Real earnings management, corporate governance and stock price crash risk: evidence from China

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Abstract

Purpose – The aim of this paper is to provide additional insights on the association between real earnings management (REM) and crash risk, particularly from the perspective of an emerging market economy. It also examines the moderating role that internal and external corporate governance may play in this area.

Design/methodology/approach – Relying on archival data from the RESSET and CSMAR databases over a timeframe from 2010 to 2018 of China listed company, the authors test the hypotheses by regressing common measures of crash risk on the treatment variable (REM) and crash risk control variables identified in the prior crash risk literature. The authors also introduce monitoring proxies (internal controls as an internal governance and institutional ownership as an external governance) and assess how effective internal and external governance moderate the relation between REM and stock price crash risk.

Findings – The results suggest firms with higher REM have a significantly greater stock price crash risk, and this association is mitigated by external monitoring. That is, greater institutional ownership, particularly pressure insensitive owners, mitigates the impact of REM on stock price crash risk. However, internal control does not mitigate the association between REM and stock price crash risk.

Originality/value – Following the passage of the Sarbanes–Oxley (SOX) Act, prior research has documented an increase in the use of REM and a positive association between REM and cash risk. The authors demonstrate that they persist in one of the largest emerging markets where institutional regulations, market conditions and corporate behaviors are different from those in developed markets. Also, the assessment of the moderation effect of internal and external governance mechanisms could have meaningful implications for investors and regulators in Chinese and other emerging markets.

Keywords Real earnings management, Stock price crash risk, Internal control quality, Institutional ownership

Paper type Research paper
1. Introduction

The phenomenon of stock price crash occurs when managers withhold and accumulate negative information or hold on to bad investment projects. “Bad news hoarding” can continue until the firm reaches a tipping point [1], at which time it must instantaneously disclose the totality of bad news and outcomes. This bad news dump causes a rapid decline in the firm’s stock price. Prior research attributes this phenomenon to the principle-agent conflict, which exacerbates information asymmetry because the agent can generate high rents from possessing private information. Once a firm’s privately held bad news is made public, an equilibrium shift occurs, causing a stock price crash.

Extensive research investigates the association between earnings management/quality and stock price crash risk, using discretionary accruals, accounting conservatism, restatements and internal control weaknesses as measures of earnings management/quality (e.g. Hutton, Marcus, & Tehranian, 2009; Kim & Zhang, 2014; Zhou, Kim, & Yeung, 2014; Andreou, Antoniou, Horton, & Louca, 2016; Chen, Chan, Dong, & Zhang, 2016; Hamm, Li, & Ng, 2018; Kim & Zhang, 2016; Zhang, Wang, & Jiang, 2017). Results generally show a positive association between accruals-based earnings management and stock price crash risk, suggesting that managers use discretionary accruals to hoard negative information.

Despite the extensive research into accruals-based earnings management, limited attention has been paid to real earnings management (hereafter REM). Similar to accruals-based earnings management, “real operations can be used to hide bad news about performance and prospects” (Francis, Hasan, & Li, 2016). However, since REM is less vulnerable to regulators’ and auditors’ scrutiny, managers prefer it over accruals-based earnings management (Graham, Harvey, & Rajgopal, 2005).

We investigate the association between REM and subsequent stock price crash risk. For a sample of 12,365 firm-year observations between 2010–2018 from all firms listed on either the Shanghai Stock Exchange (SHSE) or the Shenzhen Stock Exchange (SZSE), we find that firms with higher REM are strongly correlated with a greater risk of future stock price crash. We further fail to find a significant association between stock price crash risk and REM in the presence of adequate internal controls. Additional analysis however, finds a positive and significant association between stock price crash risk and REM for the highest internal control groups, suggesting that these firms could not restrict REM through high-quality internal controls, which in turn could exacerbate future crash risks.

We also assess the influence that external monitoring plays in the REM stock price crash risk relationship and find that greater institutional ownership mitigates the association between REM and stock price crash risk. Our additional analysis reveals that this finding is somewhat driven by “pressure insensitive” ownership that is more likely to discipline managers.

This paper contributes to the literature in several ways. First, prior research has found an increase in the magnitude of REM (Cohen, Dey, & Lys, 2008) as well as a shift from accruals earnings management to REM following the passage of Sarbanes–Oxley (SOX) (see, e.g. Zang, 2012; Ge & Kim, 2014a, b) and has found a positive association between REM and stock price crash risk, in a US (SOX) setting. This finding is not necessarily generalizable to a non-SOX Chinese environment due to the many distinguishing features of this market relative to the US. For instance, beginning in 2007, all listed A-share Chinese firms were required to shift to new reporting standards that conform to international financial reporting standards (IFRS), moving away from local generally accepted accounting principles (GAAP) reporting. The shift from a rules-based to a principles-based reporting format may influence the quality of financial reporting, thus affecting the association between REM and crash risk. Further, A-share firms listed on Chinese stock exchanges include some state-owned enterprises (SOEs). Some SOEs may tend to suppress bad news due to political incentives (Bushman, Piotroski, & Smith, 2004; Piotroski, Wong, & Zhang, 2015). Also, the cash compensation restrictions on executives of SOEs were a key driver of perks (and excessive ones) as a form of...
executive incentive compensation. These perks allow managers to divert firm resources and reduce financial reporting transparency and quality, while simultaneously increasing managers’ incentives to hide bad news thereby increasing future stock price crash risks (Xu, Li, Yuan, & Chan, 2014).

Second is our interest in assessing crash risk in one of the largest emerging market context where institutional regulations, market conditions and corporate behaviors are different from those in developed markets. Further, regulatory authorities more rely on accounting numbers to regulate China’s stock market (Pistor & Xu, 2005), thus providing an incentive for managers to engage in REM to meet regulatory thresholds.

Finally, our assessment of the influence of China’s internal and external governance mechanisms on the association between REM and stock price crash risk provides new insights on this triangular relationship. Given the distinct governance and business standards of this emerging market relative to the US, our findings could have meaningful implications for investors and regulators in Chinese and other emerging markets.

The rest of the paper is organized as follows: in section 2, we review the literature on REM and stock price crash risk; in section 3 we develop our hypotheses; section 4 discusses our sample collection process and our research design; section 5 presents our key empirical findings; and section 6 details robustness checks and additional tests. We conclude with a summary of our findings and implications in section 7.

2. The related literature
2.1 Financial reporting opacity and stock price crashes
Managers have incentives to conceal or delay the disclosure of bad news while accelerating the disclosure of good news. This asymmetric disclosure strategy may come at a cost. Withholding negative information may hinder outside investors from forcing managers to walk away from poor investment projects earlier in their life cycle, rather than accumulate larger losses over time. This asymmetric approach to information dissemination also has a finite life: the concealed information will eventually be disclosed. The resulting state of symmetry may result in large negative return outliers, which is referred to as a stock price crash.

Research has analyzed how transparent financial reporting environments, or lack thereof (referred to as opaqueness [2]), affect subsequent stock price crashes. Results suggest that the lack of transparency enables managers to conceal bad news for extended periods of time. The resulting stockpile of negative information is eventually revealed, causing an extreme decline in stock prices. Kim and Zhang (2014), using multiple measures of firm-specific financial reporting opacity [3], find that opacity is significantly associated with a steeper implied volatility smirk, suggesting that opacity increases investors’ perceptions of future crash risk.

At a macro-level, Jin and Myers (2006) predict and find that opaque reporting in a given national market [4] incentivizes managers to withhold bad news for extended periods of time. The resulting stockpile of negative information is eventually revealed, causing an extreme decline in stock prices. Jin and Myers’ (2006) findings from a historical cost accounting perspective, Bleck and Liu (2007) argue that managers in opaque financial markets can use historical cost accounting to mask or delay the disclosure of bad news, which in turn leads to more frequent and severe asset price crashes. At a micro-level, Hutton et al. (2009) use accrual earnings management as a measure of firm-specific opacity [6], finding that opaque firms are more prone to stock price crashes, consistent with the macro-level predictions of Jin and Myers (2006) and Bleck and Liu (2007).

Specific to the association between opacity and stock price crash risk in the Chinese market [7], Pan, Dai, and Lin (2011) find that opaque Chinese firms [8] are more prone to stock price crashes whereas Zhang et al. (2017) find that accounting information quality [9] is one of
the strongest deterrents of crash risk in China. Both findings are consistent with the findings of Jin and Myers (2006) and Hutton et al. (2009).

2.2 REM and crash risk

Earnings management can occur through accruals manipulation, which has no direct cash flow consequence. However, managers may also manage earnings through real activities manipulation, which has cash flow implications. Real activities manipulation is defined as “management actions that deviate from normal business practices, undertaken with the primary objective of meeting certain earnings thresholds” (Roychowdhury, 2006, p. 336). Common REM tools include abnormal discounts to temporarily increase sales, overproduction to report lower cost of goods sold and reduced discretionary expenditures in the form of changes in delivery time, postponement of R&D and maintenance expenditures (Fudenberg & Tirole, 1995; Healy & Wahlen, 1999; Dechow & Skinner, 2000; Roychowdhury, 2006).

The survey findings of Bruns and Merchant (1990) and Graham et al. (2005) indicate a greater willingness by managers to manipulate earnings through real activities than accruals, despite its substantial impact on the firm’s operating cash flow and the likelihood of a negative impact on the company’s future performance (Gunny, 2005; Li and Zhang, 2009a). Early empirical research finds that firms reduce R&D spending to increase short-term earnings (Dechow & Sloan, 1991) and meet earnings benchmarks (Baber, Fairfield, & Haggard, 1991; Bushee, 1998). More recent research expands on real activities manipulations scenarios, finding evidence of a significant association between earnings management and abnormal price discounts, overproduction and reduction in discretionary expenditures (see, e.g. Graham et al., 2005; Roychowdhury, 2006; Cohen et al., 2008; Cohen & Zarowin, 2010; Gunny, 2010; Zang, 2012).

Assessment and finding of a significant association between discretionary accruals earnings management and future stock price crashes by Hutton et al. (2009) lead Francis et al. (2016) to suggest that real activities manipulation can be used as an alternative form of earnings management. Given that REM can be used for an extended period of time compared to accruals earnings management, Francis et al. (2016) argue that REM can also be a significant predictor of future stock price crashes. Indeed, using REM models, the authors not only find evidence of a significant association between REM and future stock price crashes, but also that this association is stronger than that between accruals earnings management and crash risk. Within the Chinese market, Li and Zhang (2008, 2009a, b) find that REM tools (discretionary cost manipulation, sales manipulation and production activities) are associated with serious economic consequences on future performance.

3. Hypothesis development

3.1 Hypothesis 1

The association between REM and stock price crash risk among A-share listed Chinese firms may be impacted by reforms, ownership structures and the compensation system, which differs from that of publicly listed US firms. From a reforms perspective, the split share structure reform (SSSREF) [10] which separated firms’ stocks into tradable and non-tradable was intended to produce an alignment effect and in turn strengthen corporate governance, enhance financial disclosures and thus restricting firm information withholding abilities (Hou, Kuo, & Lee, 2012; Kuo, Ning, & Song, 2014). Kuo et al. (2014) find that this reform constrained firms’ discretionary accruals usage which resulted in a shift towards REM because it is less detectable. They conclude that the reform has not fundamentally improved financial reporting quality.
Another reform effected on January 1, 2007 required all listed A-share firms to follow new accounting standards that conform with IFRS (principles-based reporting), thus transitioning away from local GAAP (a rules-based reporting) \[1\], with a goal of improving financial reporting quality. However, this is still up for debate in China. One side of the debate suggests that more comprehensive disclosure requirements under IFRS could result in greater reporting transparency (Daske & Gebhardt, 2006; Ding, Hope, Jeanjean, & Stolowy, 2007; Daske, Hail, Leux, & Verdi, 2008). In addition, there is more flexibility to choose accounting outcomes that better reflect firm performance, thus improving financial reporting quality (Schipper, 2003). This change may also reduce opportunistic earnings management and improve audit quality (Ashbaugh & Pincus, 2001; Barth, Landsman, & Lang, 2008).

On the other side of the debate, opponents of IFRS argue that principles-based standards require greater judgment by managers and auditors which could reduce consistency and comparability of financial information, thereby creating more opportunities for managers to manipulate accounting numbers (Financial Accounting Standards Board, 2002; Barth et al., 2008). The work of Ewert and Wagenhofer (2005) and Cohen et al. (2008) suggest that more rigorous accounting standards and/or stricter reporting regimes could motivate firms to substitute accruals-based with REM, as evidenced by Ho, Liao, and Taylor (2015) in China. Overall, research evidence suggests that both reforms are associated with a shift from accruals earnings management to REM in the Chinese market.

Furthermore, A-share firms listed on China’s stock exchanges include some SOEs which tend to have opaque reporting practices and suppress bad news due to political incentives (Bushman et al., 2004; Bushman & Piotroski, 2006). In addition, the cash compensation restrictions imposed on executives of SOEs resulted in a perk system (memberships, luxury cars, lavish offices, entertainment and travel costs, . . .) as a form of incentive compensation. Xu et al. (2014) suggest that excessive perks are a way for executives to divert firm resources and to misappropriate firm surplus without outside detection. Further, they suggest that excess perks could reduce the level of transparency as some of these perks can be disguised under production enhancing expenditures. Research finds a significant negative association between excess perks and firm productivity, operating efficiency and financial reporting quality (Cai, Fang, & Xu, 2011; Luo, Zhang, & Zhu, 2011; Gul, Cheng, & Leung, 2011). More so, the perk system that exists in China may exacerbate managers’ focus on short-term results, which in turn may increase the likelihood of bad news hoarding. Xu et al. (2014) find that bad news hoarding incentives arising from perk consumption incrementally contribute to crash risk.

As indicated above, the opportunity for A-share firms listed on Chinese stock exchanges to hide or delay disclosing bad news may be more tenable through REM, as opposed to accruals earning management which has been restricted by many reforms in China. Consistent with the logic developed in Francis et al. (2016), outsiders have a limited ability to distinguish between opportunistic operating decisions and legitimate ones made in good faith, thus creating an opportunity for firms to hide bad news through REM. Furthermore, this inability of outsiders to distinguish between good and bad decisions may mitigate outside pressure on managers to promptly liquidate bad projects (Bleck & Liu, 2007; Kuo et al., 2014), thus exacerbating the compilation of bad news. Finally, given the established association between bad news hoarding and stock price crash risk in China, we presume a positive and significant association between firm REM and stock price crash risk for A-share firms listed on the Chinese stock exchanges. Based on the above arguments, we present our first hypothesis (in the alternative form):

\[
H1. \text{For A-share firms listed on the public stock exchanges in China, firms with higher levels of real earnings management will have a higher probability of subsequent stock price crashes.}
\]
3.2 Hypothesis 2
Firms’ internally developed/implemented monitoring mechanisms (e.g. internal control system) as well as externally imposed monitoring mechanisms (e.g. blockholders and institutional ownership) may alleviate agency costs. Given that the role of these monitoring mechanisms is to reduce information asymmetry between managers and investors, we assess the effect of these governance measures on the association between REM and subsequent stock price crash risk.

Well-designed and implemented internal controls can facilitate the implementation of an enterprise’s overall strategy and provide a roadmap for meeting operating, compliance and reporting objectives. Therefore, internal controls may play a critical role in improving the firm’s financial reporting environment and potentially restraining managerial opportunistic behavior and misconduct, such as the hoarding of bad news (Jensen & Meckling, 1976; La Porta, Lopez-De-Silanes, Shleifer, & Vishny, 2002). Prior research finds that effective (deficient) internal controls are positively (negatively) associated with accounting conservatism and financial reporting transparency (see, e.g. Doyle, Ge, & McVay, 2007; Ashbaugh-Skaife, Collins, Kinney, & LaFond, 2008; Beneish, Billings, & Hodder, 2008; Goh & Li, 2011; Mitra, Jaggi, & Hossain, 2013; Qi, Li, Zhou, & Sun, 2017) [12]. This monitoring role can influence investor confidence in the manager’s financial reporting decisions (Beneish et al., 2008) [13], which in turn has been associated with changes in stockholder wealth (Zhang & Chen, 2014; Zhang, Zhao, & Tian, 2015).

The issuance of the BICNE “China SOX” in June of 2008, and its full implementation following the government’s issuance of “The Implementation Guidelines” [14] required companies to self-assess and report on the effectiveness of their internal controls. This reform environment, with more emphasis on internal monitoring, may restrict managerial opportunistic behaviors (e.g. earnings manipulations and REM). Furthermore, firms with adequate internal controls may be less able to conduct real activities manipulation without detection, whereas firms with identified weak internal controls may be more prone to these manipulations, as this weaker monitoring environment provides an opportunity for REM activities without detection.

Another logic, and counter to the above reasoning, is that the reform environment with its additional restrictions on earnings management may entice managers to manipulate firm performance by shifting away from the more detectable accruals earnings management towards a less observable earnings management technique, REM (the “substitution effect”). If this is the case, the restrictive environment may exacerbate the “substitution effect” even in the presence of adequate internal monitoring and controls.

Finally, given the self-disclosure nature of the effectiveness of firm internal controls, it could also be the case that this reformed environment does not influence managerial opportunistic behaviors.

Recent evidence on the association between internal controls and REM post reform is somewhat consistent with the notion of adequate (deficient) internal controls are negatively (positively) linked to REM in China. Specifically, Jarvinen and Myllymaki (2016) find evidence that material weaknesses in firm internal controls signal an environment in which managers are more inclined to rely on REM [15]. Further, Lenard, Petruska, Alam, and Yu (2016) find that firms with weak internal controls use REM, and Li, Li, Xiang, and Djajadikerta (2020) find a positive and significant association between the presence of internal control deficiencies and REM and further find that the severity of the deficiency is also positively associated with REM. On the other hand, contrary to the notion that a weak control environment creates an opportunity for REM, Fan, Zhang, and Liu (2013) find that high-quality internal control does not restrict REM practices.

Prior research also indicates that the lack of effective internal monitoring has been linked with subsequent stock price crashes. Specifically, Kim, Yeung, and Zhou (2015) find that
firms with internal control weaknesses are more prone to stock price crashes. Although indirect, Zhang et al. (2017) develop an index of investor protection which includes a measure of internal control effectiveness and find that firms that gave investors the best protection were the least likely to experience a crash risk.

Given the predominant finding that effective internal controls have on enhanced reporting quality, improved accounting transparency and reduced managerial opportunism, we posit that the presence of effective internal controls in the reformed China corporate environment will help to mitigate a potential positive association between REM and subsequent crash risk. Therefore, we present our second hypothesis (in the alternative form):

**H2.** For firms listed on the public stock exchanges in China, higher internal control quality will mitigate the positive association between real earnings management and the probability of subsequent stock price crashes.

### 3.3 Hypothesis 3
External monitoring is another means of reducing agency costs between managers and owners. Institutional ownership is one such form of external monitoring, since parties with large holdings have more incentive to invest in the costly monitoring of managers (Callen & Fang, 2013). Indeed, Shleifer and Vishny (1986) note that institutional owners may have greater incentives to monitor managers than the board of directors itself, given the limited wealth the board invests in the firm relative to institutional owners. Hence, with the resources available to monitor and influence managerial actions, some research has found evidence that institutional monitoring is associated with enhanced firm performance and reduced opportunistic behavior by managers (see, e.g. McConnell & Servaes, 1990; Nesbitt, 1994; Smith, 1996; Del Guercio & Hawkins, 1999) [17].

Specific to financial reporting, institutional investors with strong regulatory incentives can influence managerial behavior and improve the quality and transparency of earnings (Zhang, 2008; Bo & Wu, 2009; Ye, Li, & Ding, 2009). Cui (2004) shows that firms with institutional investors in the top ten of shareholding owners have higher information transparency. Similarly, Yin (2010) finds that institutional investors increase the information content of stock price, thereby reducing the risk of stock prices crash. With regards to the effect of institutional ownership on earnings management, Ramalingegowda, Ukte, and Yu (2021) find that common institutional ownership is negatively associated with earnings management. Specific to REM, and for a sample of publicly listed high-tech Chinese firms, Gao, Li, Mao, and Shi (2020) find that REM under the supervision of stable institutional investors could be easily identified by shareholders.

In sum, effective monitoring provided by institutional investors may mitigate information asymmetry, improve information transparency, and therefore, reduce managers’ ability to hoard bad news. Thus, we posit that effective institutional monitoring may weaken the positive association between REM and subsequent stock price crash risk. We present our third hypothesis (in the alternative form):

**H3.** For firms listed on the public stock exchanges in China, greater institutional monitoring will mitigate the positive association between real earnings management and the probability of subsequent stock price crashes.

### 4. Empirical methodology

#### 4.1 Data and sample description
Firm-specific weekly stock return data are derived from the RESSET finance database, and annual financial data are sourced from the China Stock Market and Accounting Research
(CSMAR) database. Our selection criteria includes publicly listed firms on the SHSE and the SZSE. After excluding firm-year observations in the financial sector, firms with fewer than 26 weeks of consecutive returns, and firms with missing financial statement and internal control data, our final sample consists of 12,365 firm-year observations from fiscal years 2010–2018 [18]. Table 1 presents the sample distribution by year and industry.

Table 1 Panel A provides the annual sample distribution, whereas Panel B provides the industry distribution of our sample. Panel A of Table 1 illustrates the development trend of China’s listed firms. Specifically, in 2010 only 930 listed firms entered our sample while in 2018 this number increased to 1,938. This increase in number of firms was gradual throughout our sample period.

According to Panel B of Table 1, 61.19% of our sample firms are from the manufacturing sector (Industry code C), consistent with China’s status as a global manufacturing powerhouse. The second largest sector is the wholesale and retail industries (Industry code F) at 6.61%, followed by the real estate industry (Industry code K) at 5.95% of the sample.

4.2 REM metric
Roychowdhury (2006, p. 337) defines real activities manipulation as “the departure from normal operational practices, motivated by managers’ desire to mislead at least some stakeholders into believing certain financial reporting goals have been met in the normal course of operations.” Consistent with this definition and prior research, our proxy for REM is an aggregate measure of the sum of abnormal production costs (AbPROD), abnormal discretionary expenditures (AbDISX) and abnormal cash flows from operating activities (AbCFO) resulting in one proxy RM, as follows [19]:

\[ RM_{i,t} = \text{AbPROD}_{i,t} - \text{AbDISX}_{i,t} - \text{AbCFO}_{i,t} \] (1)

where \( RM_{i,t} \) is the proxy for REM for firm \( i \) in year \( t \); AbPROD\(_{i,t}\) is the abnormal production costs from operating activities for firm \( i \) in year \( t \); AbDISX\(_{i,t}\) is the abnormal discretionary expenditures for firm \( i \) in year \( t \) and AbCFO\(_{i,t}\) is the abnormal cash flow from operations for firm \( i \) in year \( t \). We use RM by taking its absolute value: the greater the index value, the higher the degree of REM. Finally, following Hutton et al. (2009), we modify the RM proxy by determining the moving sum of the above value in the prior three years, as follows:

\[ RM\_SUM = |RM_{t-1}| + |RM_{t-2}| + |RM_{t-3}| \] (2)

4.3 Crash risk metrics
Following Chen, Hong, and Stein (2001), Hutton et al. (2009) and Kim, Li, and Zhang (2011a) and Kim, Song, and Zhang (2011b), we use two measures of crash likelihood for each firm year: negative conditional return skewness (NCSKEW) and down-to-up volatility (DUVOL). To determine these firm-specific crash risk measures, we first estimate firm-specific weekly returns for each firm year. Specifically, the firm-specific weekly return for firm \( j \) in week \( t \), denoted by \((W_{j,t})\) is defined as the natural log of one plus the residual return from the expanded market model regression as follows:

\[ r_{j,t} = \alpha_t + \beta_1 r_{mt,-1} + \beta_2 r_{mt} + \beta_3 r_{mt+1} + \beta_4 r_{i,t-1} + \beta_5 r_{i,t} + \beta_6 r_{i,t+1} + \epsilon_{i,t} \] (3)

where \( r_{j,t} \) is the return of stock \( j \) in week \( t \), \( r_{mt} \) is the return of value-weighted market index from China A share, \( r_{i,t} \) is the return of Fama and French value-weighted industry index from China A share. We include the lead and lag terms for the market index return to allow for nonsynchronous trading (Dimson, 1979).
Our first measure of crash risk is the negative conditional return skewness (NCSKEW) calculated as follows:

$$NCSKEW_{jt} = \frac{-n(n-1)\sum W_{jt}^3}{(n-1)(n-2)\left(\sum W_{jt}^2\right)^{3/2}}$$

Specifically, $NCSKEW$ for a given firm in a fiscal year is the negative of the third moment of firm-specific weekly returns for each sample year, divided by the standard deviation of

<table>
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<th>Year</th>
<th>$N$</th>
<th>Percent</th>
<th>Cumulative percent</th>
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<tr>
<td>2010</td>
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<td>7.52</td>
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<tr>
<td>2011</td>
<td>1,061</td>
<td>8.58</td>
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<td>25.27</td>
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<td>1,370</td>
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<td>1,704</td>
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<td>2018</td>
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<td>Total</td>
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Panel A: Yearly sample distribution

<table>
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<td>B</td>
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<td>D</td>
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<td>E</td>
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<td>G</td>
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</table>

Panel B: Industry sample distribution

**Note(s):** The industry classification is based on the Guidelines for the Industry Classification of Listed Companies 2001, where A represents agriculture, forestry, animal husbandry and fishery industries; B represents the mining industry; C represents the manufacturing industry; D represents the electric power, heat, gas and water production and supply industries; E represents the construction industry; F represents wholesale and retail industries; G represents transport, storage and postal service industries; I represents the information transmission, software and information technology services industries; K represents the real estate industry; L represents leasing and business services industry; M represents scientific research and technology services industries; N represents the water conservancy, environment and public facilities management industries; P represents the education industry; Q represents the health and social work industries; R represents the culture, sports and entertainment industries; S represents the comprehensive industry
firm-specific weekly returns raised to the third power. Greater NCSKEW values indicate greater negative skewness, suggesting a higher probability of a stock price crash.

Our second measure of crash risk is down-to-up volatility (DUVOL), which is the natural logarithm of the ratio of the standard deviation in the “down” weeks to the standard deviation in the “up” weeks, calculated as follows:

\[
DUVOL_{jt} = \log \left( \frac{(n_{up} - 1) \sum_{down} W_{jt}^2}{n_{down} - 1} \sum_{up} W_{jt}^2 \right)
\]

(5)

where \( n_{up} \) and \( n_{down} \) are the number of up and down weeks in year \( t \). This is used to describe the stock price volatility. An “up” week occurs when the return is higher than the annual mean. A “down” week occurs when the return is lower than the annual mean. Larger DUVOL indicates a greater tendency of a stock price crash.

4.4 Governance metrics

4.4.1 Internal governance mechanisms. In China, firms are required by the Enterprise Internal Control Evaluation Guidelines, EICEG, to self-assess the effectiveness of their internal controls and disclose these annual self-evaluation reports. In addition, the EICEG demand that Certified Public Accountants disclose significant deficiency findings during their audit of a client’s internal controls. Many proxies of internal control quality have been used in the literature [20]. Our proxy for internal control quality/adequacy is the internal control index from the DIB database constructed by Shenzhen DIB Enterprise Risk Management Technology. This index is a composite score reflecting the internal control quality based on listed firms’ internal control disclosure, internal control assessment and auditing/assurance reports, with a higher index suggesting greater internal control quality.

4.4.2 External governance mechanisms. Our proxy for external monitoring is the level of institutional monitoring of a firm, measured by the proportion of the firm’s outstanding shares owned by institutional investors (INST). Institutional investors are more sophisticated than individual investors and act as external firm monitors (Bo & Wu, 2009; Ye et al., 2009; Shi & Tong, 2009).

4.5 Empirical models

The models below are used to test our hypotheses:

\[
CRASH_{i,t} = \alpha_0 + \alpha_1 RM_{SUM,i,t-1} + \gamma * Controls + \gamma * Year + \gamma * Industry + \epsilon_{i,t}
\]

(6)

\[
CRASH_{i,t} = \alpha_0 + \alpha_1 RM_{SUM,i,t-1} + \alpha_2 ICA_{Index,i,t-1} + \alpha_3 (ICA_{Index} * RM_{SUM})_{i,t-1} + \gamma * Controls + \gamma * Year + \gamma * Industry + \epsilon_{i,t}
\]

(7)

\[
CRASH_{i,t} = \alpha_0 + \alpha_1 RM_{SUM,i,t-1} + \alpha_2 INST_{i,t-1} + \alpha_3 (INST * RM_{SUM})_{i,t-1} + \gamma * Controls + \gamma * Year + \gamma * Industry + \epsilon_{i,t}
\]

(8)

where \( CRASH \), the dependent variable, is crash risk measured using NCSKEW and DUVOL; \( RM_{SUM} \) is the aggregate REM variable; \( ICA_{Index} \) is the internal control index constructed by Shenzhen DIB Enterprise Risk Management Technology. \( INST \) is the percentage of institutional ownership in the firm. Models 6 through 8 include a vector of crash risk determinants (Controls) and dichotomous variables for firm year and industry to control for fixed effects.
The vector of crash risk determinants is based on prior research (Chen et al., 2001; Hutton et al., 2009; Francis et al., 2016). \( DTURN \) is the de-trended average monthly stock turnover in year \( t-1 \); \( SIGMA \) is the standard deviation of firm-specific weekly returns over the fiscal year \( t-1 \); \( RET \) is the arithmetic average of firm-specific weekly returns in year \( t-1 \); \( SIZE \) is the log of the market value of equity in year \( t-1 \); and \( MB \) is the market value of equity divided by the book value of equity in year \( t-1 \), and \( ACCR \) is the absolute value of discretionary accruals in year \( t-1 \). Consistent with prior research we predict a positive and significant association between future stock price crashes and \( DTURN, SIGMA, RET, SIZE, MB \) and \( ACCR \). The variable \( LEV \) is the total long-term debt, divided by total assets. \( ROE \) is income before extraordinary items, divided by lagged total equity. Hutton et al. (2009) find that financial leverage and operating performance are both negatively associated with future stock crash risk.

To test \( H1 \), we rely on Model 6 above and regress our measures of crash risk \( (NCSKEW_t, DUVOL_t) \) on REM \( (RM\_SUM_{t-1}) \), while controlling for crash risk determinants at time \( t-1 \). \( H1 \) predicts a positive and significant coefficient on \( \alpha_1 \) in Equation (6). To test \( H2 \) and \( H3 \), we rely on Equations (7) and (8) above and regress the measures of crash risk on the interaction of REM and governance quality, both internal \( (ICA\_Index_{t-1}) \) and external \( (INST_{t-1}) \). \( H2 \) predicts that the coefficient \( \alpha_3 \) in Equation (7) is negative and significant, and \( H3 \) predicts that the coefficient \( \alpha_3 \) in Equation (8) is also negative and significant.

### 5. Results

#### 5.1 Descriptive statistics
Panel A in Table 2 reports the descriptive statistics for all variables. The mean values of the crash risk measures \( NCSKEW \) and \( DUVOL \) are \( -0.340 \) and \( -0.226 \), respectively. The sample firm-year observations have a mean three-year moving sum absolute value of REM \( (RM\_SUM) \) of 0.398, mean change in yearly trading volume (as a percentage of shares outstanding) \( (DTURN) \) of \( -0.029 \) and mean weekly return \( (RET) \) of \( -12.3\% \). The mean (median) for log size \( (SIZE) \) is 22.47 (22.29); market-to-book ratio \( (MB) \) is 2.60 (2.02), and leverage \( (LEV) \) is 0.465 (0.469). The average return on net assets \( (ROE) \) is approximately 0.07 and the average ICA index score \( (ICA\_Index) \) is 6.566. On average 7.1\% of firm shares are owned by institutional investors \( (INST) \), and 1.5\% received a non-standard audit opinion \( (OPINION) \). To eliminate the possible effects of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

#### 5.2 Real earnings management and crash risk
Table 3 reports the results of our analysis of \( H1 \) assessing the association between ex ante REM and contemporaneous stock price crash risk. Model 1 of Table 3 uses contemporaneous \( NCSKEW \) as a measure of stock price crash risk, whereas Model 2 uses contemporaneous \( DUVOL \) as an alternative measure of crash risk. All models control for years and industry.

We first briefly revisit the association between our measures of crash risk \( (NCSKEW \) and \( DUVOL) \) and crash risk determinants. In line with the findings of Chen et al. (2001) and Chen, Zhang, and Shen (2009), we find a significant positive association between the level of stock price volatility \( (SIGMA) \) and stock price crash risk, albeit marginal association between \( DUVOL \) and \( RM\_SUM \), consistent with Francis et al. (2016). We also find a positive association between \( MB \) and both \( NCSKEW \) and \( DUVOL \) \( (p\text{-value} < 0.01) \), consistent with the expectation of the "stochastic bubble theory", which suggests that stocks with historically high cumulative returns and high growth rates are more prone to collapse (Harvey & Siddique, 2002). We also find a consistent negative association between \( LEV \) and crash risk (both \( NCSKEW \) and \( DUVOL \), \( p\text{-values} < 0.01 \), consistent with Kim et al. (2011a). Finally, we
**Panel A: Descriptive statistics**

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCSKEW</td>
<td>12,365</td>
<td>-0.340</td>
<td>-0.295</td>
<td>-2.427</td>
<td>1.547</td>
<td>0.706</td>
</tr>
<tr>
<td>DUVOL</td>
<td>12,365</td>
<td>-0.226</td>
<td>-0.228</td>
<td>-1.359</td>
<td>0.923</td>
<td>0.463</td>
</tr>
<tr>
<td>RM_SUM</td>
<td>12,365</td>
<td>0.398</td>
<td>0.303</td>
<td>0.011</td>
<td>2.034</td>
<td>0.321</td>
</tr>
<tr>
<td>ICA_Index</td>
<td>12,365</td>
<td>6.566</td>
<td>6.731</td>
<td>0.000</td>
<td>9.953</td>
<td>1.121</td>
</tr>
<tr>
<td>INST</td>
<td>12,365</td>
<td>0.071</td>
<td>0.048</td>
<td>0.000</td>
<td>0.630</td>
<td>0.076</td>
</tr>
<tr>
<td>DTURN</td>
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<td>-0.029</td>
<td>-0.029</td>
<td>-0.592</td>
<td>0.664</td>
<td>0.228</td>
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<tr>
<td>SIGMA</td>
<td>12,365</td>
<td>0.045</td>
<td>0.041</td>
<td>0.016</td>
<td>0.106</td>
<td>0.018</td>
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<tr>
<td>RET</td>
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<td>SIZE</td>
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<td>22.291</td>
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<td>2.022</td>
<td>0.377</td>
<td>11.191</td>
<td>1.989</td>
</tr>
<tr>
<td>LEV</td>
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<td>0.469</td>
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<td>0.862</td>
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</tr>
<tr>
<td>ROE</td>
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<td>0.067</td>
<td>-0.421</td>
<td>0.315</td>
<td>0.095</td>
</tr>
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<td>1.000</td>
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<td>0.038</td>
<td>0.000</td>
<td>1.000</td>
<td>0.279</td>
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**Panel B: Correlation table**

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<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
<th>(12)</th>
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<tr>
<td>NCSKEW (1)</td>
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<td></td>
<td></td>
<td></td>
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<td>DUVOL (2)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>RM_SUM (3)</td>
<td>0.06</td>
<td>0.05</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>DTURN (4)</td>
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<td>-0.07</td>
<td>-0.01</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>SIGMA (5)</td>
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<td>0.00</td>
<td>0.57</td>
<td>1.00</td>
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</tr>
<tr>
<td>RET (6)</td>
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<td>0.02</td>
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<td>-0.40</td>
<td>-0.74</td>
<td>1.00</td>
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<td></td>
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</tr>
<tr>
<td>SIZE (7)</td>
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<td>-0.08</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.25</td>
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<td></td>
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</tr>
<tr>
<td>MB (8)</td>
<td>0.10</td>
<td>0.10</td>
<td>0.15</td>
<td>0.38</td>
<td>-0.29</td>
<td>-0.43</td>
<td>1.00</td>
<td></td>
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</tr>
<tr>
<td>LEV (9)</td>
<td>-0.06</td>
<td>-0.07</td>
<td>0.00</td>
<td>-0.03</td>
<td>-0.07</td>
<td>-0.02</td>
<td>0.49</td>
<td>-0.10</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ROE (10)</td>
<td>-0.06</td>
<td>0.05</td>
<td>0.22</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.07</td>
<td>0.14</td>
<td>0.06</td>
<td>-0.07</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOA (11)</td>
<td>0.01</td>
<td>0.00</td>
<td>0.11</td>
<td>0.00</td>
<td>-0.07</td>
<td>0.06</td>
<td>0.20</td>
<td>-0.11</td>
<td>-0.18</td>
<td>0.21</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>OPINION (12)</td>
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<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.04</td>
<td>0.07</td>
<td>0.05</td>
<td>-0.15</td>
<td>-0.05</td>
<td>1.00</td>
<td>0.05</td>
</tr>
<tr>
<td>ACGR (13)</td>
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<td>0.03</td>
<td>0.19</td>
<td>-0.02</td>
<td>0.07</td>
<td>-0.07</td>
<td>-0.05</td>
<td>0.08</td>
<td>0.07</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.06</td>
</tr>
</tbody>
</table>

**Note(s):** This table reports the summary statistics for the variables used in the analyses (Panel A) and the Pearson correlation coefficients among the main variables (Panel B). The Spearman and Pearson correlation coefficients are presented in Panel B. Figures in italics are significant at the 5% level. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix 2.
find a positive and significant association between \textit{ACCR} and crash risk (\textit{p}-value < 0.01 in Model 1 and \textit{p}-value < 0.05 in Model 2), indicating that companies with accruals earning management practices are more susceptible to the risk of stock price crashes.

After controlling for crash risk determinants as well as year and industry variations on crash risk, our OLS regression results reported in Table 3 find a positive and significant association between \textit{RM\_SUM} and stock price crash risk (both \textit{p}-value < 0.01). These combined results, specifically after controlling for managerial accruals earnings management, suggests that managers ability to pursue real activity manipulation among Chinese listed firms contributes significantly to future stock price crash risk, consistent with the predictions of our first hypothesis.

### 5.3 Role of monitoring

Table 4 reports the results of our analysis of H2 and H3, the effect that monitoring mechanisms have on the association between REM and subsequent stock price crash risk. Using the two alternative measures of crash risk (\textit{NCSKEW} and \textit{DUVOL}), Models 1 and 2 of Table 4 provide a test of H2 using a continuous internal control quality measure (\textit{ICA\_Index}). Models 3 and 4 of Table 4 provide a test of H3 using the percentage of institutional firm ownership (\textit{INST}) to assess the external monitoring effect.

According to H2, we predict that stronger internal control quality will mitigate the association between REM and subsequent stock price crash risk. To test this hypothesis, we interact our measure of REM (\textit{RM\_SUM}) with our measure of internal control quality (\textit{ICA}) and regress our measures of crash risk on this interaction term, after controlling for the main effects and the crash risk determinants. We still find a positive and significant association between REM and stock price crash risk (\textit{DUVOL}) in Model 2 of Table 4, consistent with our

### Table 3.

Real earnings management and stock price crash risk

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 \textit{NCSKEW}, H1</th>
<th>Model 2 \textit{DUVOL}, H1</th>
</tr>
</thead>
<tbody>
<tr>
<td>\textit{RM_SUM}_{t-1}</td>
<td>0.073*** (3.47)</td>
<td>0.047*** (3.58)</td>
</tr>
<tr>
<td>\textit{DTURN}_{t-1}</td>
<td>0.005 (0.15)</td>
<td>0.028 (1.08)</td>
</tr>
<tr>
<td>\textit{SIGMA}_{t-1}</td>
<td>1.631** (2.50)</td>
<td>0.733* (1.79)</td>
</tr>
<tr>
<td>\textit{RET}_{t-1}</td>
<td>0.002 (0.03)</td>
<td>0.026 (0.55)</td>
</tr>
<tr>
<td>\textit{SIZE}_{t-1}</td>
<td>0.007 (0.88)</td>
<td>-0.006 (1.24)</td>
</tr>
<tr>
<td>\textit{MB}_{t-1}</td>
<td>0.026*** (5.84)</td>
<td>0.017*** (5.70)</td>
</tr>
<tr>
<td>\textit{LEV}_{t-1}</td>
<td>-0.150*** (3.11)</td>
<td>-0.105*** (3.44)</td>
</tr>
<tr>
<td>\textit{ROE}_{t-1}</td>
<td>0.009 (0.62)</td>
<td>0.165** (3.47)</td>
</tr>
<tr>
<td>\textit{NOA}_{t-1}</td>
<td>0.009 (0.62)</td>
<td>0.000 (0.04)</td>
</tr>
<tr>
<td>\textit{OPINION}_{t-1}</td>
<td>0.020 (0.37)</td>
<td>-0.001 (0.05)</td>
</tr>
<tr>
<td>\textit{ACCR}</td>
<td>0.397*** (3.05)</td>
<td>0.206** (2.31)</td>
</tr>
<tr>
<td>\textit{Intercept}</td>
<td>-0.862*** (4.27)</td>
<td>-0.258** (1.99)</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>\textit{N}</td>
<td>12,365</td>
<td>12,365</td>
</tr>
<tr>
<td>Adjusted \textit{R}^2</td>
<td>0.054</td>
<td>0.059</td>
</tr>
<tr>
<td>Model</td>
<td>19.75***</td>
<td>22.63***</td>
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</table>

\textbf{Note(s):} \textit{T} statistics are reported in parentheses. ***, ** and * denote statistical significance at 1, 5 and 10\%, respectively.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1 NCSKEW, H2</th>
<th>Model 2 DUVOL, H2</th>
<th>Model 3 NCSKEW, H3</th>
<th>Model 4 DUVOL, H3</th>
</tr>
</thead>
<tbody>
<tr>
<td>RM_SUMt−1</td>
<td>−0.067 (−0.50)</td>
<td>0.079** (2.16)</td>
<td>0.083*** (2.80)</td>
<td>0.045*** (2.45)</td>
</tr>
<tr>
<td>ICA_Indext−1</td>
<td>−0.009 (−0.97)</td>
<td>0.000 (0.04)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(ICA_Index*RM_SUM)t−1</td>
<td>0.020 (1.08)</td>
<td>−0.035 (−0.92)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INSTt−1</td>
<td>0.010 (0.23)</td>
<td>0.028 (1.08)</td>
<td>0.037* (0.93)</td>
<td>0.048* (1.84)</td>
</tr>
<tr>
<td>SIGMATt−1</td>
<td>1.546** (2.36)</td>
<td>0.729* (1.78)</td>
<td>1.069* (1.65)</td>
<td>0.381*** (0.94)</td>
</tr>
<tr>
<td>RETt−1</td>
<td>−0.003 (−0.04)</td>
<td>0.026 (0.54)</td>
<td>−0.030 (−0.39)</td>
<td>0.005 (0.12)</td>
</tr>
<tr>
<td>SIZEt−1</td>
<td>0.009 (1.08)</td>
<td>−0.006 (−1.24)</td>
<td>−0.020** (−2.48)</td>
<td>−0.024*** (−4.49)</td>
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<tr>
<td>MBt−1</td>
<td>0.032*** (6.11)</td>
<td>0.017*** (5.69)</td>
<td>0.013*** (3.01)</td>
<td>0.009*** (2.96)</td>
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<tr>
<td>LEVt−1</td>
<td>−0.152*** (−3.15)</td>
<td>−0.107*** (−3.48)</td>
<td>−0.095** (−2.02)</td>
<td>−0.070** (−2.33)</td>
</tr>
<tr>
<td>ROEt−1</td>
<td>0.282*** (3.59)</td>
<td>0.168*** (3.53)</td>
<td>0.132* (1.73)</td>
<td>0.064 (1.36)</td>
</tr>
<tr>
<td>NOAt−1</td>
<td>0.008 (0.60)</td>
<td>0.000 (0.05)</td>
<td>−0.007 (−0.53)</td>
<td>−0.010 (−1.07)</td>
</tr>
<tr>
<td>OPINIONt−1</td>
<td>0.024 (0.44)</td>
<td>−0.005 (−0.15)</td>
<td>0.041 (0.76)</td>
<td>0.011*** (0.33)</td>
</tr>
<tr>
<td>ACR</td>
<td>0.406*** (2.83)</td>
<td>0.206*** (2.41)</td>
<td>0.399*** (3.12)</td>
<td>0.210*** (2.51)</td>
</tr>
<tr>
<td>Intercept</td>
<td>−0.846*** (−3.96)</td>
<td>−0.202 (−1.50)</td>
<td>−0.255 (−1.27)</td>
<td>0.126 (0.57)</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>12,365</td>
<td>12,365</td>
<td>12,365</td>
<td>12,365</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.055</td>
<td>0.059</td>
<td>0.071</td>
<td>0.074</td>
</tr>
<tr>
<td>Model</td>
<td>18.84***</td>
<td>21.46***</td>
<td>25.52***</td>
<td>28.69***</td>
</tr>
</tbody>
</table>

**Note(s):** T statistics are reported in parentheses. ***, ** and * denote statistical significance at 1, 5 and 10%, respectively.

Table 4 presents the effect of monitoring on the relationship between real earnings management and stock price crash risk. Models 1 and 3 use NCSKEW, and Models 2 and 4 use DUVOL as crash risk measures. Models 1 and 2 analyze the impact of adequate internal controls (ICA_Indext−1) on the association between real earnings management and stock price crash risk (H2) and Models 3 and 4 analyze the impact of the percentage of institutional ownership (INSTt−1) on the association between real earnings management and stock price crash risk (H3). All variables are defined in Appendix 2. Year and industry dichotomous controls are included in all models.
findings in Table 3 and in support of H1. Counter to our expectations, we find no significant association between crash risk and internal control quality (ICA_Index) in both Models 1 and 2. Furthermore, we find that the presence of adequate internal controls does not mitigate the association between REM and stock price crash risk, as indicated by the insignificant association between crash risk and the interaction terms $ICA_Index \times RM\_SUM$ in both models 1 and 2. This interaction finding suggests that the presence of adequate internal controls does not restrict managerial ability to manipulate real activities, which could indicate that managerial hoarding of bad news is not constrained and thus still contributes to future crash risks [22]. This finding may suggest that in the Chinese corporate environment internal control quality does not restrict REM practices.

Another explanation is that the new control regulations introduced among publicly listed Chinese firms may limit managers ability to manage earnings through accruals and may result in them more aggressively managing earnings through real activities. In other words, the presence of adequate internal controls may exacerbate the substitution effect. To assess the potential substitution effect, we divide our sample into high and low internal control quality firms [23] and assess the differences in the magnitude of discretionary accruals (ACCR) among the two subgroups. Untabulated t-test and non-parametric analyses both reveal that ACCR is significantly greater for the high internal control quality subgroup relative to the low internal control quality subgroup, suggesting that the substitution effect is not driving our H2 findings.

According to H3, we predict that stronger external monitoring quality will also mitigate the association between REM and subsequent stock price crash risk. To test this hypothesis, we interact RM_SUM with our measure of external monitoring (INST) and regress crash risk measures on the main effects of the interaction term, the interaction term itself and crash risk controls. The results of Models 3 and 4 of Table 4 indicate that the main effect INST is positively and significantly associated ($p$-value < 0.01) with crash risk (both NCSKEW and DUVOL), consistent with the result of Kim et al. (2011a). Furthermore, we find that the interaction effect (INST*RM_SUM) is negative and significant ($p$-value < 0.05) in Model 3 (crash risk measure is NCSKEW), whereas the interaction effect is insignificantly associated with DUVOL. The negative and significant interaction effect in Model 3 suggests that the presence of external monitoring, specifically the presence of institutional ownership, may restrict managers ability to manipulate real activities, thus resulting in a decline in the association between REM and future crash risk. We find some evidence consistent with H3 which states that the relationship between real earning management and risk of stock price crash is less pronounced as institutional monitoring increases.

6. Robustness tests and additional analysis
6.1 Hypothesis 1 robustness checks
6.1.1 Alternative REM measures. In the analyses reported in Tables 3 and 4, we rely on the measures of Roychowdhury (2006) and Cohen et al. (2008) to construct RM_SUM. We repeat our Table 3 (H1) analysis using two alternative aggregate REM measures based on Cohen and Zarowin (2010) and Zang (2012): RM_SUM_1 and RM_SUM_2 [24]. In untabulated results, after regressing each measure of crash risk (NCSKEW and DUVOL) on disaggregated REM measures (RM_SUM_1 and RM_SUM_2), we find a positive and significant association between both crash risk measures and RM_SUM_1 ($p$-value < 0.01) and an insignificant association with RM_SUM_2 [25]. This finding of the crash risk-REM association being driven by abnormal production and abnormal discretionary expenditures could be attributed to the fact that the majority of our sample firms are in the manufacturing industry.
6.2 Hypothesis 2 robustness checks

6.2.1 Additional ICA analysis. To further evaluate the influence of internal controls on the association between REM and stock price crash risk, we conduct the following additional analysis. First, presented in Panel A of Table 5, we replace the continuous ICA Index measure with two alternative high internal control quality measures (H_ICA) and revisit the association between $H_ICA \times RM_SUM$ and stock price crash risk. The first $H_ICA$ measure is equal to 1 if the firm-specific ICA Index is greater than or equal to the industry-median ICA index score and 0 otherwise, and the second $H_ICA$ measure is equal to 1 if the firm-specific ICA Index is in the highest industry quartile of ICA index scores and 0 otherwise. According to the results presented in Models 1 and 2 in Panel A of Table 5, we find that the main effect RM_SUM is not significantly associated with crash risk (both NCSKEW and DUVOL), the presence of high internal control quality ($H_ICA$), is negative and significantly associated and crash risk (both NCSKEW and DUVOL) in 3 out of the 4 models presented in Panel A (insignificant in Model 4). Furthermore, we find consistent evidence to suggest that the presence of high-quality internal controls enhances, rather than mitigates, the association between REM and crash risk (albeit marginally significant when using the industry median cutoff point to measure high internal control quality). This finding is consistent with our explanations above that the presence of internal control quality does not restrict managers ability to manipulate real activities.

Second, presented in Panel B of Table 5, we conduct subsample analysis comparing the association between REM and stock price crash risk among high and low ICA index firm years. We use the same ICA index score cutoff points as in Panel A of Table 5 (median in Models 1 and 2 and 3rd quartile in models 3 and 4) to classify firms as high vs low. For brevity, we present our findings using NCSKEW as the dependent variable. Across all models in Table 5 Panel B, we find a positive and significant association between REM and stock price crash risk, ($p$-value < 0.01 for $H_ICA$ subgroups and $p$-value < 0.10 for L_ICA subgroups). This is also consistent with our explanations presented above.

6.3 Hypothesis 3 robustness checks

In our assessment of the impact of institutional monitoring on the association between crash risk and REM, we used the proportion of the institutional investors as a whole as our measure of institutional monitoring. However, there is a great deal of variation in the monitoring roles of different institutional investors. Recent studies suggest that not all institutional investors are equal (Brickley, Lease, & Smith, 1988; Almazan, Hartzell, & Starks, 2005; Chen, Harford, & Li, 2007; Cornett, Marcus, Saunders, & Tehranian, 2007). Brickley et al. (1988) find that compared to “pressure-sensitive” institutional investors that the company has business dealings with (such as banks and insurance companies), public pension funds, mutual funds and other “pressure-insensitive” institutional investors are more likely to discipline managers. Using a sample of 874 Chinese-listed firms from 2005–2009, Mao, Wang, and Wang (2011) find only mutual fund ownership to be significantly and positively related to executive compensation and pay performance sensitivity, while other institutional investors (security companies, insurance companies, QFII and social security funds) are not significantly correlated. We rely on the WIND financial database’s classification of institutional/blockholder investors as follows: mutual funds, insurance companies, security companies, QFII and social security funds and revisit the role of these different institutional ownership subgroups in mitigating the relation between REM and stock price crash risk. According to Table 6, we find that REM is positively associated with crash risk (both NCSKEW and DUVOL) in all models ($p$-value < 0.01), consistent with H1. We also find that the presence of different types of institutional ownership (with the exception of QFII) is associated with a significant positive future stock price crash risk ($p$-value < 0.01), consistent
### Table 5: Robustness checks

#### Panel A: Subsample analysis

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NCSKEW(_t)</td>
<td>DUVO(_t)</td>
<td>NCSKEW(_t)</td>
<td>DUVO(_t)</td>
</tr>
<tr>
<td>(RM_SUM_{t-1})</td>
<td>0.033 (1.07)</td>
<td>0.023 (1.16)</td>
<td>0.038 (1.47)</td>
<td>0.028* (1.78)</td>
</tr>
<tr>
<td>(H_ICA_{t-1})</td>
<td>-0.049** (-2.37)</td>
<td>-0.031** (-2.41)</td>
<td>-0.048** (-2.06)</td>
<td>-0.015 (-1.00)</td>
</tr>
<tr>
<td>((H_ICA\times RM_SUM)_{t-1})</td>
<td>0.068* (1.89)</td>
<td>0.042* (1.78)</td>
<td>0.106*** (2.78)</td>
<td>0.057** (2.27)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.885*** (-4.34)</td>
<td>-0.274*** (-2.09)</td>
<td>-0.869*** (-4.15)</td>
<td>-0.228* (-1.69)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(N)</td>
<td>12,365</td>
<td>12,365</td>
<td>12,365</td>
<td>12,365</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.055</td>
<td>0.059</td>
<td>0.055</td>
<td>0.059</td>
</tr>
<tr>
<td>Model</td>
<td>19.15***</td>
<td>21.75***</td>
<td>19.22***</td>
<td>21.64***</td>
</tr>
</tbody>
</table>

#### Panel B: Subsample analysis

<table>
<thead>
<tr>
<th>ICA(_\text{Index}) &lt; industry median</th>
<th>ICA(_\text{Index}) &lt; industry Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>Model 1</td>
</tr>
<tr>
<td></td>
<td>NCSKEW(_t)</td>
</tr>
<tr>
<td>(RM_SUM_{t-1})</td>
<td>0.073*** (2.90)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.000*** (-3.82)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry</td>
<td>Yes</td>
</tr>
<tr>
<td>(N)</td>
<td>6,119</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.068</td>
</tr>
<tr>
<td>Model</td>
<td>12.90***</td>
</tr>
</tbody>
</table>

**Note(s):** \(T\) statistics are reported in parentheses. \(**, **\) and * denote statistical significance at 1, 5 and 10%, respectively.

Table 5 revisits the conclusions of \(H_2\) analysis presented in Table 4. In Panel A, we replace the ICA\(_\text{Index}\) measure with two indicator variables: 1. equal to 1 if the firm-specific ICA\(_\text{Index}\) measure is above the industry median ICA\(_\text{Index}\) and 0 otherwise (Models 1 and 2); equal to 1 if the firm-specific ICA\(_\text{Index}\) measure is above the industry 3rd quartile ICA\(_\text{Index}\) and 0 otherwise (Models 3 and 4). Both measures represent proxied for high internal control quality (H\_ICA). In Panel B, we conduct subsample analysis and divide our sample into high and low ICA\(_\text{Index}\) measures, using the industry median and 3rd quartiles are cut-off points for these classifications. Models 1 and 2 use the industry median as the cut-off for high and low ICA\(_\text{Index}\), whereas Models 3 and 4 use the industry 3rd quartile as the cut-off for high and low ICA\(_\text{Index}\). All variables are defined in Appendix 2. Year and industry indicators are included in all models.
Table 6 presents an analysis of the impact of institutional investors on the association between stock price crash risk and real earnings management \((RM_SUM_t-1)\). The alternative crash risk dependent variables are \(NCSKEW_t\) and \(DUVOL_t\). We replace 5 institutional investor classifications (Fund, Insurance, Sec, QFII and Social) for our original institutional investor ownership percentage \((INST)\) and regress the interaction of each of these measures against the two alternative measures of crash risk. All variables are defined in Appendix 2. Year and industry indicators are included in all models.

### Table 6

<table>
<thead>
<tr>
<th>Variables</th>
<th>(RM_SUM_{t-1})</th>
<th>(INST_{t-1}(2))</th>
<th>Intercept</th>
<th>Controls</th>
<th>Year</th>
<th>Industry</th>
<th>Pseudo (R^2)</th>
<th>(N)</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>0.084***</td>
<td>1.757***</td>
<td>-0.387*</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.066</td>
<td>12,365</td>
<td>24.40***</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.052***</td>
<td>0.555**</td>
<td>0.043***</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.070</td>
<td>12,365</td>
<td>27.35***</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.078***</td>
<td>1.109***</td>
<td>-0.780***</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.079</td>
<td>12,365</td>
<td>21.75***</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.048***</td>
<td>3.192***</td>
<td>-0.196</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.079</td>
<td>12,365</td>
<td>20.80***</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.091***</td>
<td>3.287***</td>
<td>-0.773***</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>23.22***</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.056***</td>
<td>1.686***</td>
<td>-0.211</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>19.27***</td>
</tr>
<tr>
<td>Model 7</td>
<td>0.069***</td>
<td>2.374***</td>
<td>-0.819***</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>21.80***</td>
</tr>
<tr>
<td>Model 8</td>
<td>0.044***</td>
<td>19.20</td>
<td>-0.747***</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>0.062</td>
</tr>
<tr>
<td>Model 9</td>
<td>0.070***</td>
<td>1.300</td>
<td>-0.185</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>19.20</td>
</tr>
<tr>
<td>Model 10</td>
<td>0.042***</td>
<td>4.943***</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>0.080</td>
<td>12,365</td>
<td>21.75***</td>
</tr>
</tbody>
</table>

**Note(s):** T statistics are reported in parentheses. ***, ** and * denote statistical significance at 1, 5 and 10%, respectively.
with our aggregate findings in Table 4 above. Finally, we find that the mitigating role of institutional ownership found in Table 4, Model 3 is driven by the presence of public pension funds, mutual funds and other “pressure-insensitive” institutional investors (Fund). This finding is consistent with the argument and findings of Brickley et al. (1988) that their “pressure-insensitive” institutional owners are more likely to discipline managers, suggesting they are a stronger form of external managerial monitoring.

7. Conclusions
This paper investigates the relationship between REM and stock price crash risk for cross listed A-share Chinese firms and further assesses the influential roles that both internal controls and external monitoring plays in this association. Relying on a sample of 12,365 firm-year observations between 2010 and 2018, we find that firms with a higher level of REM have a higher stock price crash risk. This finding is consistent with bad news hoarding of stock-price risk (Jin & Myers, 2006; Hutton et al., 2009), wherein REM hinders the flow of negative information into the capital markets until the tipping point is reached, at which time all of the negative information is released and the firm’s stock price crashes.

We also find that the internal control quality does not mitigate the association between REM and stock price crash risk. Furthermore, we find some evidence to suggest that internal controls may not restrict managerial ability to manipulate earnings through REM, which in turn may exacerbate future stock price crash risk. Finally, we document that the presence of greater institutional ownership mitigates the association between REM and future stock price crash risk, consistent with the notion that institutional ownership in the Chinese market may enhance financial reporting transparency and reduce firms’ ability to hoard bad news. Our additional analysis finds that this result may be driven by institutional owners that are more likely to discipline managers, specifically, pressure insensitive owners.

Notes
1. Managerial incentives to conceal and hoard bad news include career concerns (e.g. Kothari, Shu, & Wysocki, 2009), a desire to maintain the esteem of peers (Ball, 2009), personal equity based gains (Ball, 2009; Kothari et al., 2009; Kim et al., 2011b), or an anticipation of strong future improvements that may camouflage the hoarded bad news (Graham et al., 2005).
2. Opaqueness is “the lack of information that would enable investors to observe operating cash flow and income and determine firm value” (Jin & Myers, 2006, p. 281).
3. They use three measures financial reporting opacity: (1) a measure of earnings management, (2) the presence of financial statement restatements and (3) the presence of auditor-attested material internal control weakness over financial reporting.
4. They measure country level opacity using the following proxies: (1) measure of Global Competitiveness Report, (2) auditing activity, (3) number of key accounting variables are included in financial statements, (4) the PricewaterhouseCoopers opaqueness measure and (5) an opaqueness measure based on diversity of analysts’ forecasts. For detailed information on these measures see p. 281 in Jin and Myers (2006).
5. Using returns from 40 stock markets from 1990–2001, they find a positive and significant association between country-level measures of opaqueness and crash risk.
6. They argue that accruals management it a direct measure of opacity given that accruals management obscures at least some information about firm fundamentals, and therefore, can be considered a direct firm-specific measure of opacity.
7. Factors other than opacity have also been linked to crash risk in the China setting, including investor protection (Zhang et al., 2017); share pledging (Li et al., 2019); executive compensation (Xu,
8. They use accrual earnings management as the proxy of information opacity.

9. This component is a compilation of earnings quality, accounting conservatism, the information content of earnings announcements and accounting disclosure.

10. This was enacted by the Chinese government on April 29, 2005, a split share structure reform to convert non-tradeable shares into tradable shares, and research evidence finds this reform reduced underpricing of IPOs, suggesting that it reduced information asymmetry (Khurshed, Tong, & Wang, 2018).

11. The resulting transition produced 48 new Chinese Auditing Standards and a new set of internal control standards, requiring firms listed on Shanghai and Shenzhen stock exchanges to perform systematic evaluations of their internal control systems and issue reports annually.

12. Doyle et al. (2007) finds that internal control deficiencies can lead to a decline in earnings quality and accounting information quality. Similarly, Qi et al. (2017) find that internal control deficiencies are negatively associated with accounting conservatism, accruals quality and accounting information relevance.

13. Beneish et al. (2008) examines and finds that the disclosure of a SOX 302 internal control deficiency exacerbates the uncertainty of the investors' forecast of the company's future performance, suggesting that the decline in confidence will negatively impact future stock prices.

14. Including the Guidelines for Application of Enterprise Internal Controls, the Guidelines for Assessment of Enterprise Internal Controls and the Guidelines for Audit of Enterprise Internal Controls. The guidelines generally follow the Internal Control-Integrated Framework of the Committee of Sponsoring Organizations of the Treadway Commission (COSO) in the US, with a few differences. The Guidelines established in China are set by the government, whereas it is set by COSO, a joint initiative of 5 private sector organizations. Given the governments' role in these standards, the expectation would be significant impact on reporting and earnings management behavior of firms in China. Furthermore, the disclosure requirement is mandatory for listed firms, whereas in China, it is mandatory only for large listed firms (medium and small firms may provide this information on a voluntary basis).

15. Jarvinen and Myllymaki (2016) find that companies with material weaknesses in their internal controls engage in more manipulation of real activities, relative to firms with effective internal controls and that firms tend to rely on REM after disclosing a material weakness in internal controls the prior period, suggesting that this would allow managers to mitigate the negative perception of the public to the weakness by engaging in earnings management that is not easily detected or constrained by outside stakeholders.

16. Their investor protection index is based on the quality of accounting information, the effectiveness of internal controls, the reliability of external auditor reports, operating efficiency and financial management.

17. However, Agrawal and Knoeber (1996), Karpoff, Malatesta, and Walkling (1996), Duggal and Miller (1999), and Faccio and Lasfer (2000) fail to find a significant association between institutional ownership and firm performance.

18. We start with 2010, the internal control reform period, allowing us to rely on a consistent sample across our analysis. To avoid any COVID implications on our analysis, we include data up until December 31, 2018, leaving the COVID period for future research.

19. Details are provided in Appendix 1.

20. Examples include the use of a non-standard audit opinion to proxy for internal control quality (Li, Lin, & Song, 2011; Ye, Li, & Zhang, 2012), a dichotomous variable equal to one if there are negative elaborations in the self-evaluation report and zero otherwise (Lu, Liu, & Xu, 2011), a dichotomous variable equal to one if a firm is either punished by CSRC due to the violation of the requirements of the regulating bodies, is issued a non-standard audit OPINION, required to restate its annual, semi-
annual, or quarterly financial statement due to the detection of false information and zero otherwise (Liu & Liu, 2014).

21. Hutton et al. (2009) state that this contradictory finding “most likely reflects endogeneity in firms’ capital structure choices more stable, less crash-prone firms are more willing or able to establish higher levels of indebtedness” (p. 81).

22. We also substitute the ICA_Index measure with a dichotomous variable equal to 1 if the firm has adequate internal controls and 0 if one of the following criteria of deficiency is present: (1) firm $i$ is punished by the regulating bodies, like CSRC, due to its violation of the requirements of the regulating bodies in the current year; (2) firm $i$ was issued a non-standard audit opinion by an accounting firm; (3) firm $i$’s discloses an internal control deficiency in the internal control evaluation report (ICA). We still find no significant association between crash risk and the interaction term $ICA*RM_SUM$.

23. We classify our sample as high internal control quality is the firm year ICA_Index is greater than the industry median ICA_Index.

24. $RM\_SUM\_1 = ABS(-Ab\text{DISX} + Ab\text{PROD})$ and $RM\_SUM\_2 = ABS(-Ab\text{DISX} - Ab\text{CFO})$. See Appendix 1 for variable definitions.

25. The sum of $ab\text{CFO}$ and $ab\text{PROD}$ is not considered a REM proxy variable, according to Cohen and Zarowin’s (2010) explanation that overproduction automatically leads to abnormally low CFO.


29. Although the increase in product yield is the main reason for the increase in the production costs, the increase in product yield can lead to the decrease in the unit product fixed cost. Therefore, the increase in abnormal production costs may lead to the increase in the profitability per unit of product and increase firms’ reported earnings.

References


### Appendix 1

To determine the abnormal cash flow from operation (abCFO), abnormal production costs (abPROD) and abnormal discretionary expenditures (abDISX) for Model 1, we first calculate the normal cash flows from operating activities (CFO), the normal production costs (PROD) and the normal discretionary expenditures (DISX) for firm i in year t. All variables in the following models are measured at time t (unless stated otherwise) and scaled by total assets at time t–1 (Ai,t–1).

1. Normal CFO is estimated as a linear function of sales and change in sales [26] regressed for each industry-year as follows:

   \[
   CFO_{i,t}/A_{i,t-1} = \alpha_0 + \alpha_1/A_{i,t-1} + \alpha_2MV_{i,t}/A_{i,t-1} + \alpha_3Q_{i,t}/A_{i,t-1} + \alpha_4S_{i,t}/A_{i,t-1} + \alpha_5\Delta S_{i,t}/A_{i,t-1} + \epsilon_{i,t} \tag{A.1}
   \]

   \(CFO_{i,t}\) is the normal cash flow from operations; \(MV_{i,t}\) is the market value of firm i; \(Q_{i,t}\) is the Tobins Q; \(S_{i,t}\) is the net sales; and \(\Delta S_{i,t-1}\) is the change in net sales from year \(t–1\) to \(t\).

2. Normal PROD [27] is estimated by each industry-year as follows:

   \[
   PROD_{i,t}/A_{i,t-1} = \alpha_0 + \alpha_1/A_{i,t-1} + \alpha_2MV_{i,t}/A_{i,t-1} + \alpha_3Q_{i,t}/A_{i,t-1} + \alpha_4S_{i,t}/A_{i,t-1} + \alpha_5\Delta S_{i,t}/A_{i,t-1} + \epsilon_{i,t} \tag{A.2}
   \]

   where \(PROD_{i,t}\) is the sum of the cost of goods sold in year \(t\) and the change in inventory from \(t–1\) to \(t\).

3. Normal DISX [28] is estimated by each industry-year as follows:

   \[
   DISX_{i,t}/A_{i,t-1} = \alpha_0 + \alpha_1/A_{i,t-1} + \alpha_2S_{i,t-1}/A_{i,t-1} + \alpha_2MV_{i,t}/A_{i,t-1} + \alpha_3Q_{i,t}/A_{i,t-1} + \alpha_4INT_{i,t}/A_{i,t-1} + \alpha_3\Delta S_{i,t}/A_{i,t-1} + \alpha_6\Delta S_{i,t} \times DD/A_{i,t-1} + \epsilon_{i,t} \tag{A.3}
   \]

   \(DISX_{i,t}\) is the discretionary expenditures defined as the sum of R&D expenses, advertising expenses and SG&A. \(INT_{i,t}\) is internal funds of firm \(i\).

Then abnormal CFO (AbCFO), abnormal PROD (AbPROD) [29] and abnormal DISX (AbDISX) are measured as the estimated residual from each regression, which is the deviation of dependent variables’ actual values in Models (A.1), (A.2) and (A.3) from their predicted ones.
**Variables Definition**

**Dependent variable**
- **NCSKEW**: Stock price crash risk measures for firm $i$
- **DUVOL**: The three-year moving sum of the absolute value of real earnings management for firm $i$
- **RM_SUM**: Sum of abnormal discretionary expenses and abnormal production cost for firm $i$
- **RM_SUM_1**: Sum of abnormal discretionary expenses and abnormal cash flows for firm $i$
- **ICA_Index**: A firm-specific internal control index from the DIB database constructed by Shenzhen DIB Enterprise Risk Management Technology. This index is a composite score reflecting the internal control quality based on listed firms’ internal control disclosure, internal control assessment and auditing/assurance reports, with a higher index suggesting greater internal control quality
- **INST**: The percentage of institutional ownership for firm $i$
- **DTURN**: The average monthly share turnover over the current fiscal year period minus the monthly share turnover over the previous fiscal year period for firm $i$. The monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month for firm $i$
- **SIGMA**: The standard deviation of firm-specific weekly return over the fiscal year period
- **RET**: The mean of firm-specific weekly returns over the fiscal year period for firm $i$, multiplied by 100
- **SIZE**: The natural logarithm of total assets for firm $i$
- **MB**: The ratio of market value of equity to book value of equity for firm $i$
- **LEV**: The ratio of long-term debt to total assets for firm $i$
- **ROE**: The ratio of net profit to net assets for firm $i$
- **NOA**: A dichotomous variable equal to one if the net operating asset for firm $i$ is higher than the industry average net operating assets and zero otherwise
- **OPINION**: A dichotomous variable equal to one if the non-standard audit opinion is issued by firm $i$’s auditor to firm $i$ and zero otherwise
- **ACCR**: The absolute value of discretionary accruals using the modified Jones models (Dechow, Sloan, & Sweeney, 1995)

**Note(s):**
- $^a$All dependent variables are measured at time $t$.
- $^b$All treatment and control variables are measures at time $t-1$

**Table A1.** Definition of variables

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