Do external labour market incentives constrain bad news hoarding? The CEO's industry tournament and crash risk reduction

Hasibul Chowdhury*
UQ Business School, The University of Queensland,
Brisbane, Queensland 4072, Australia.
h.chowdhury@business.uq.edu.au
*Corresponding author, Tel.: +61 7 344 31250

Allan Hodgson
UQ Business School, The University of Queensland,
Brisbane, Queensland 4072, Australia.
a.hodgson@business.uq.edu.au

Shams Pathan
School of Economics, Finance and Property
Curtin University, Perth, Australia
m.pathan@curtin.edu.au

Acknowledgements

We thank Bart Lambrecht (editor) and two anonymous reviewers for their constructive and insightful comments. We also thank Robert Faff, Mark Humphery-Jenner (8th FIRN Annual Conference 2018 discussant), Lily Nguyen (FMCG 2018 discussant), Jon Williams (11th IAFDS discussant), Hoang Luong, Mostafa Hasan, Chris Florackis, Charlie Cai, and participants of the 8th FIRN Annual Conference 2018, the Financial Markets and Corporate Governance (FMCG) Conference 2018 and 11th IAFDS 2018 for their helpful comments and suggestions. Hasibul Chowdhury acknowledges the financial support received from Australian Government Endeavour Post Graduate Research Scholarship. Allan Hodgson acknowledges research support from the Australian Research Council (ARC) Award # DP130103299. The authors are responsible for any remaining errors.

Do external labour market incentives constrain bad news hoarding? The CEO's industry tournament and crash risk reduction

ABSTRACT

We find that a CEO's industry tournament incentives (CITI) induce a CEO to undertake strategies that reduce the propensity of a firm incurring future stock price crash risk. CITI also has a mitigating effect on accounting techniques (such as, accrual manipulation, real earnings management, and financial restatement) used as channels for obfuscation and, therefore, is associated with a lower tendency to withhold bad news. CITI is more effective to reduce crash risk propensity when there is lower information quality and weaker external monitoring. Results are robust to firm governance controls, gender monitoring, and the specific personal attributes of CEOs. In short, CITI imposes on CEOs an incentive to brand themselves according to sustained visibility concepts.

Keywords**:** Industry tournament incentives, crash risk, bad news hoarding, non-competition agreement

JEL classification: G12; G32; G34; M52

Do external labour market incentives constrain bad news hoarding? The CEO's industry tournament and crash risk reduction

1. Introduction

This study examines whether and to what extent, CEOs' industry tournament incentives (hereafter, CITI) affect the propensity of firm-level future stock price crash risk.[1] CITI captures a CEO's external labour market incentives, by measuring the compensation gap between a CEO and the highest paid CEO in the same industry (Kubick and Lockhart, 2016; Coles et al., 2018). The external labour market potentially impacts internal strategies by incentivising CEOs to undertake corporate decisions that maximize their labour market visibility. These strategies take various constructs. For example, CEOs that face a high CITI might look to improve external labour market value by enacting economic policies that induce superior firm financial performance (Coles et al., 2018) and by increasing product market benefits from cash holdings (Huang et al., 2017). By extension, CITI then engenders hiring norms that attract high quality candidates and invokes policies to retain CEOs with established ability.

Although prior studies indicate that CITI has a feedback influence on corporate policies, there is no clear direction or channel examined by which external labour market incentives affect a CEO's disclosure practices. For example, a CEO can strategically shape corporate disclosure policies to increase labour market reputation by informing stakeholders of good news, such as enhanced future earnings, reduced operational uncertainties, and potential increases in firm value (Gelb and Zarowin, 2002). On the other hand, a CEO also has incentives to hide bad news for extended periods with the hope that future good news will "bury" current bad news (Kothari et al., 2009). Such a bad news concealing tactic can lead to overvaluation and distortion of a firm's signal of fundamental value. However, after accumulated bad

[1] We define firm-level stock price crash risk as the propensity of stock price crashes, primarily measured by the conditional skewness or the third moment of return distributions (Chen et al., 2001; Kim et al., 2014). Our study does not focus on the occurrences of stock price crashes or downside tail risk (Diemont et al., 2016). For detailed discussions on differences between the conditional skewness of return distribution and downside tail risk, please see Chen et al. (2001, p. 348), Kim et al. (2014, p. 1), and Diemont et al. (2016, p. 213).

news reaches a tipping point, a CEO can no longer withhold the aggregated bad news, which then cascades onto the market and increases firm-level stock price crash risk (Hutton et al., 2009).

Empirical studies reveal several accounting-based mechanisms that a CEO can apply to hide bad news. For example, with opaque financial reporting, accrual manipulation, earnings smoothing, and ambiguous annual reports, managers induce short-term gains at the expense of future crash risk (Hutton et al., 2009; Zhu, 2016; Chen et al., 2017; Ertugrul et al., 2017). Moreover, a CFO's equity incentives and a CEO's age and the level of inside debt holdings can also affect a firm's future crash risk propensity through bad news withholding channel (Kim et al., 2011; He, 2015; Andreou et al., 2017b).

Despite the possibility that a CEO's external labour market incentives can affect future stock price crash risk through bad news hoarding, no empirical studies have addressed this issue. We fill this gap by investigating whether and how CITI impacts the probability of firm-level future stock price crashes. Consequently, we ask what role does the external labour market play in proactively revealing "bad" information to markets? Do high labour market incentives, reflected by CITI, induce a CEO to adopt bad news hoarding to improve short-term market perceptions, or will the CEO reveal all, address operational problems, and focus on long-term reputation?

Specifically, external labour market incentives can affect a CEO's disclosure practices in two competing ways. A CEO can decide to hide more bad news in order to artificially inflate short-term labour market value. Stein (1988) and Bushee (1998) define such behaviour as managerial myopia, whereby managers prefer inflated short-term gains at the cost of long-term benefits. We label such phenomenon as a short-term visibility preference hypothesis, which predicts a positive relation between CITI and the propensity of future stock price crash risk. On the other hand, a CEO can ensure timely disclosure of all value relevant information to stakeholders by revealing bad news in order to sustain reliability, trust and a proactive operation strategy that maintains a long-term labour market reputation. This alternative perspective is labelled as a sustained visibility preference hypothesis, which implies a negative association between CITI and propensity of future stock price crashes.

To test the above hypotheses, we use 16,763 firm-year observations for public firms listed on U.S. stock markets from 1994 through 2015. Results support the sustained visibility preference hypothesis by showing that CITI significantly decreases future stock price crash risk propensity in economically meaningful ways. Specifically, for one standard deviation increase in CITI, crash risk decreases by 0.03, which is 37.50 percent of the mean value of crash risk propensity (0.08). This result is robust to alternative specifications of CITI and stock price crash risk, time-invariant firm-specific factors, CEO characteristics and to additional tests that address omitted variable bias, reverse-causality, and self-selection bias. Furthermore, results remain consistent with baseline findings when we apply a quasi-natural experiment design with a change in the non-competition agreement.

Hence, our basic conclusion is that CITI motivates CEOs not to hide bad news. A derivative finding is to establish the mitigating effect of CITI on several specific accounting based channels which CEOs customarily use to manipulate and conceal bad news. As one example, Andreou et al. (2017b) argue that a break in an earnings string that results in heightened crash risk, is due to bad news hoarding. After employing this test, we find that high CITI firms have fewer breaks in earnings strings. Moreover, our tests show that CITI reduces a CEO's propensity to suddenly release bad news and to undertake discretionary accruals manipulation. Furthermore, consistent with Francis et al. (2016), we show that CITI reduces a CEO's proclivity to undertake real earnings management. Our final accounting based tests reveal a negative relationship between CITI and aggressive financial restatements and overinvestments. Collectively, these results support the contention that external labour market incentives constrain a CEO's use of manipulative accounting techniques as a channel to withhold bad news.

Using cross-sectional tests, we further drill down to uncover circumstances where CITI's influence on crash risk is more effective. We find the disciplinary constraint of the external labour market through CITI is stronger for firms that are opaque and have low information quality. Moreover, using analysts and institutional investors as external monitors, we report that the disciplinary effect of CITI is more pronounced for firms with weaker external monitoring.

In further robustness analysis, we activate a number of omitted variables that might separately account for a reduced propensity of future stock price crash risk, for example, executives' equity incentives (Bergstressert and Philippon, 2006), a CFO's ability to constrain a CEO's earnings management (Kim et al., 2011, Li and Zeng, 2019), and risk and corporate governance levels. In all regressions, CITI remains robust as a significant explanator over and above these potential mitigating factors. In short, a consistent outcome from our study is that the external labour market, through CITI, motivates CEOs not to restrain bad news dissemination and encourages to undertake value enhancing endeavours that reduce the probability of firm-specific future stock price crashes.

Our research delivers four unique contributions. First, we contribute to the industry tournament literature by documenting that CEOs take a long-term and sustained (and not a short-term and temporary) approach to external labour market incentives, thus refuting any relation between managerial myopia and CITI. Second, we contribute to the stock price crash risk literature by reporting when and how external labour market incentives are associated with reduced stock price crash risk. Prior research by Kothari et al. (2009) and Baginski et al. (2018) focus on the relation between *within-firm* managerial career concerns and the tendency to withhold bad news. Specifically, Kothari et al. (2009) report that managers tend to hide bad news when faced with internal career concerns, and Baginski et al. (2018) find that managers delay bad news release when they perceive bad news will reduce their existing compensation. These two empirical studies do not consider any direct relation between career concerns and future stock price crash risk and are limited to exploring the association between firm-level managerial career concerns and delaying bad news disclosure.[2] Our study extends these studies to an external labour market focus and shows that the external labour market is the more powerful inducement

[2] There is also debate on the use of proxies. Most studies define career concern as the probability that current and future compensation will be affected by the current performance of managers (Hermalin and Weisbach, 2007; Kothari et al., 2009; Baginski et al., 2018). On the other hand, Kothari et al. (2009) use firm-level distress risk as a proxy for managerial career concern, but Baginski et al. (2018) counter that this measure of career concern does not capture "executives' prospects" but indicates "firms' prospects" and, hence, is not an effective proxy for *within-firm* managerial career concern.

for CEOs to enact timely disclosure of bad news, which is a significant constraint on the propensity of future stock price crash risk.

Third, we establish in the stock price crash risk literature that managerial decisions can have a different impact on stock price volatility (the second moment) and on the propensity of stock price crash risk (the third moment). For example, Coles et al. (2018) show that CITI increases firm risks (stock volatility). We extend by showing that CITI also incentivises CEOs to enhance value-increasing risk management strategies so that future stock price crash risk decreases. This provides valuable information to investors in determining risky investment portfolios.

Finally, we contribute to the existing accounting literature by establishing that CITI increases information transparency via a reduction in manipulations such as earnings string breaks, sudden release of bad news, and accruals and real earnings management. Specifically, we are the first to make this conceptual and empirical link.

We structure the remainder of the paper as follows. Section 2 discusses the literature review and establishes hypotheses. Section 3 describes the data and provides summary statistics. Section 4 and 5 report empirical results and additional analyses. Section 6 presents robustness analyses. Finally, Section 7 concludes.

2. Literature review and hypotheses development

In two competing hypotheses, we assess whether CEOs with high external labour market incentives place a higher value on a long-term reputation or focus on short-term benefits. An active labour market for CEOs offers the ability for an incumbent CEO to benchmark skills against other candidates in the same industry (Kubick and Lockhart, 2016). In this regard, Karlsson and Neilson (2009) report that CEO mobility is on the increase with more than twenty percent of CEO hirings derived from functioning CEOs during 2007 and 2009—up from one percent in 1989. Moreover, the labour market provides an incentive for increased mobility—executives with prior CEO experience who join a new firm receive almost a two-fold increase in compensation (Gudell, 2011).

The extent of a CEO's labour market incentives (CITI) also plays a feedback role by influencing internal corporate policies. For example, interviews by Graham et al. (2005) record that CEOs assess how the results of their decisions will influence their labour market value and future mobility. Moreover, the CITI offers incentives to a CEO to shape corporate policy even if the CEO does not intend to move. Coles et al. (2018) report that CEOs use the industry pay gap to bargain for increased compensation to remain in the same firm. Hence, if CITI influences a CEO's decisions, the question is whether CITI constrains or induces strategies that have a negative firm impact.

One economically important impact, and our primary focus, is the level of stock price crash risk, represented by the propensity of extreme future price decreases, which is driven by the outcome from strategic management decisions and is an important negative signal for investors (Zhu, 2016). Our primary tests build on prior studies that identify bad news hoarding as a contributing factor to crash risk (Jin and Myers, 2006; Kothari et al., 2009; Hutton et al., 2009; Kim et al., 2011; Callen and Fang, 2015). The perception is that CEOs obtain short-term private benefits when they hide bad news based on expectations that: (i) they can bury current bad news within future good news, (ii) timely disclosure of bad news makes a CEO less competitive in the external labour market, and (iii) by hiding bad news they can maintain short-term compensation reward perquisites (Kothari et al., 2009; Kim et al., 2011; Callen and Fang, 2015). This behaviour is consistent with a managerial myopia theory that managers tend to forgo long-term value for a short-term benefit (Stein, 1988; 1989; Bushee, 1998).

However, if managers cannot recurrently hide bad news from the market and 'adequate' offsetting good news does not subsequently arrive, then a tipping point occurs with a bad news cascade that substantially corrects previous overvaluation (Hutton et al., 2009; Kim et al., 2011). Hence, a short-term policy by CEOs that encompasses bad news hoarding and reduced external visibility, implies a positive relation between CITI and the probability of future stock price crash risk. Hence, our first hypothesis is:

HYPOTHESIS 1**:** *CITI increases the propensity of firm-level future stock price crash risk, ceteris paribus.*

On the other hand, concern for long-term reputation in the external labour market and litigation risk may motivate CEOs to disclose bad news on a timely basis in order to ensure transparency about firm operations. That is, CEOs are aware of the potential for bad news hoarding and associated price overvaluation to generate subsequent sharp price declines, which then culminate in a substantial reduction of personal reputation (Skinner, 1994; Kasznik and Lev, 1995; Kothari et al., 2009). In essence, a CEO undertakes a long-term cost-benefit analysis of the disadvantages of hiding bad news from the market on labour market adjudication and industry recognition (Hermalin and Weisbach, 2007; Kubick and Lockhart, 2016; Coles et al., 2018). In a long-term analysis, the CEO may also want to create a fair image in the market by ensuring effective disclosures of firm ventures and risk-taking.

For the CEO, pragmatic outcomes from hoarding bad news, subsequently revealed to the market, include a loss of competitive advantage and the acquisition of reputations for dishonesty, secrecy, and ineffective management. Therefore, to create a sustained long-term reputation in the labour market, CEOs with high industry tournament incentives might not withhold bad news, but rather effectively communicate it with proper and unambiguous explanations on how they plan to rectify in the future. Thus, a sustained visibility hypothesis predicts a negative relation between CITI and bad news hoarding that potentially leads to a decrease in the probability of future stock price crash risk:

HYPOTHESIS 2: *CITI decreases the propensity of firm-level future stock price crash risk, ceteris paribus*.

The above hypotheses are designed to uncover a relationship between the level of CITI and the propensity of future stock price crash risk. Once the direction is uncovered, a multitude of questions will be raised as to how CITI engages CEOs in specific channels used to hide or mitigate bad news hoarding and how it affects other internal strategic decisions. We know from past research that accounting numbers are important valuation mechanisms but are somewhat opaque to most market participants (Sloan, 1996), and following the highly publicised corporate failures of 2001-2002, manipulations are a primary channel used by management to hide bad news (Dechow and Dichev, 2002; Dechow et al., 2011). We are also aware that certain accounting techniques, such as accruals and real earnings management, are associated with increased stock price crash risk (Zhu, 2016; Chen et al., 2017). Hence, our intention is to triangulate accounting techniques with crash risk and CITI, and examine how CITI interacts with accounting methods used to hide bad news that consequently affects the probability of a firm's future stock price crash risk.

In addition, we expect that the disciplinary effect of external labour market incentives, through CITI, might vary in firms with low versus high quality information environments and strong versus weak external monitoring. Moreover, internal governance metrics such as firm incentive schemes, the competing monitoring interests of CFOs and female executives are possible mitigating factors in controlling bad news hoarding and crash risk. Inherent CEO attributes such as ability, tenure, age, and (over)confidence might also prove to be factors that intervene to negate the impact of CITI on firm crash risk. At this stage, we do not propose formal hypotheses but leave it to a battery of tests to throw light on these issues.

3. Data and summary statistics

3.1. Sample procedure

We collect data from the intersection of three databases – ExecuComp, Compustat, and CRSP. Our initial sample consists of 37,885 firm-year observations of CITI from 1992 through 2015. After taking a one-year lag of CITI, we retain 34,260 firm-year observations from 1993 through 2015 and then deduct 3,419 firm-year observations when the CEO was not in office for the entire year.[3] Next, we merge CITI with our primary measure of the probability of future stock price crash risk, NCSKEW (Equation 2) and after merging with financial variables from non-financial firms in Compustat, our final sample consists of

[3] We apply this filter to prevent "artificially" high CITI due to low CEO compensation (Bebchuk et al., 2011). However, our results remain qualitatively the same if we do not use this filter.

16,763 firm-year observations with 2,078 unique firms and 3,622 unique CEOs during 1994 through 2015. We winsorize continuous variables at the 1% level for both upper and lower tails to remove the impact of the outliers.

3.2. Industry tournament measures

Following previous studies on CITI (Coles et al., 2018; Huang et al., 2017; Kubick and Lockhart, 2016), we calculate CITI as the natural logarithm of the difference between the total compensation (TDC1) of the second-highest paid CEO[4] in the same size adjusted Fama-French 48 industry group and the total compensation of a firm's CEO. We use net sales (SALE) as a proxy for firm size. This size adjusted CITI captures a CEO's external labour market incentives based on the firms of the same size within an industry.

3.3. Stock price crash risk measures

We use four measures of the probability of stock price crashes – negative conditional return skewness (NCSKEW), down-to-up volatility (DUVOL), crash count (COUNT), and extra sigma (EXTRASIG), based on the residuals from the following market-based return model (Kim et al., 2011; Andreou et al., 2017b):

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

where $r_{i,w}$ is the return on stock i in week w, and $r_{m,w}$ is the return on the CRSP value-weighted market index in week w. Following Dimson (1979), we reduce biases from non-synchronous trading by including two lags ($r_{m,w-2}$, $r_{m,w-1}$) and two leads ($r_{m,w+1}$, $r_{m,w+2}$) of $r_{m,w}$ in Equation (1). Next, we compute firm-specific weekly returns, $W_{i,w}$, for firm i in week w as the natural logarithm of one plus the residual term ($\varepsilon_{i,w}$) of Equation (1).

[4] See Coles et al. (2018) for the justification of using the compensation of the second-highest paid CEO instead of using that of the highest paid CEO. As a robust check, we also use the total compensation (TDC1) of the highest paid CEO in unreported results and our findings remain qualitatively the same.

Our primary measure of the probability of stock price crash risk is NCSKEW, which is calculated for each firm *i* in a year as the negative of the third moment of firm-specific weekly returns divided by the standard deviation of those returns during the year raised to the third power (Chen et al., 2001; Kim et al., 2011). Specifically, we use the following formula to calculate NCSKEW:

$$NCSKEW_{i,t} = \frac{-\left[n(n-1)^{\frac{3}{2}} \sum W_{i,w}^{3}\right]}{(n-1)(n-2)\left(\sum W_{i,w}^{2}\right)^{\frac{3}{2}}} \tag{2}$$

where n is the total number of firm-specific weekly returns ($W_{i,w}$) during the year t.

We use three further measures as proxies for the probability of crash risk. Our next and second measure, DUVOL, is calculated in a three-step process (Chen et al., 2001; Kim et al., 2011). First, for each firm i in year t, we identify the "down" weeks when the firm-specific weekly returns ($W_{i,w}$) are below the annual mean. Next, using these "down" weeks, we calculate the standard deviation for each firm i in year t. Second, we identify "up" weeks and calculate the standard deviation for each firm i in year t when $W_{i,w}$ is above the annual mean. Third, we compute DUVOL as the natural logarithm of the ratio of the standard deviations of "down" weeks to "up" weeks.

Our third measure of the probability of crash risk, COUNT, is the difference between the number of downside and upside frequencies (Bhargava et al., 2017) for each firm i during year t. We define a downside (upside) frequency when $W_{i,w}$ is 3.09 standard deviations below (above) the annual mean.[5]

Our fourth measure of crash risk propensity, EXTRASIG, is the negative of the worst deviations between $W_{i,w}$ and annual mean, divided by the standard deviations of $W_{i,w}$ over the year (Bradshaw et al., 2010; Andreou et al., 2017b). Specifically, we use the following formula:

[5] We use 3.09 standard deviations to generate a frequency of 0.1% in the normal distribution (Jin and Myers, 2006; Hutton et al., 2009).

$$EXTRASIG_{i,t} = -MIN\left[\frac{W_{i,w} - MEAN_t}{\sigma_W}\right] \quad (3)$$

where $MEAN_t$ is the average and σ_W is the standard deviations of $W_{i,w}$ over the year t. For all four measures, larger values indicate a higher probability of stock price crash risk.

3.4. Empirical method

To test our hypotheses, we use the following baseline regression model:

$$CRASH_{i,t} = \alpha + \beta_1 CITI_{i,t-1} + \delta_i X_{i,t-1} + INDUSTRY\ FE + YEAR\ FE + \varepsilon_{i,t} \quad (4)$$

where $CRASH_{i,t}$ represents any of our four crash risk propensity measures (NCSKEW, DUVOL, COUNT, and EXTRASIG) for firm i in year t, α is the constant term, $CITI_{i,t-1}$ is the lagged CEO industry tournament incentives and also the independent variable of interest, X is the vector of control variables, β_1 and δ_i ($i =$ 1, 2, … , 16) are the parameters we need to estimate, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

We include sixteen control variables related to firm, CEO, and investor characteristics, which prior literature establishes as the predictors of the propensity of future stock price crash risk. Specifically, we control for firm age ($FIRMAGE_{t-1}$) because more experienced firms tend to have lower stock price crash risk due to a higher capability for risk management (Andreou et al., 2017b). We measure firm opacity ($OPAQUE_{t-1}$), which has a positive relation with the probability of stock price crash risk, as a three-year moving sum of absolute discretionary accruals (Hutton et al., 2009). As high past returns are associated with an increased likelihood of future stock price crash risk, we control for average firm-specific returns ($RETURN_{t-1}$) in year t-1 (Chen et al., 2001). Return volatility ($SIGMA_{t-1}$) is measured as the standard deviation of the firm-specific weekly returns ($W_{i,w}$) over the year t-1 (Chen et al., 2001). We also control for a firm's innovation intensity and operational opacity, measured by research and development intensity (RD_{t-1}) (Andreou et al., 2017b). We measure firm complexity ($SEGMENT_{t-1}$) by the number of business segments the firm operates in. As firm complexity provides managers incentives to hide bad news, we expect a positive relationship between firm complexity and stock price crash risk (Andreou et al., 2017b).

Moreover, consistent with past research, further controls are added for lags in firm size ($SIZE_{t-1}$), firm growth (MB_{t-1}), financial leverage ($LEVERAGE_{t-1}$), and past negative conditional return skewness ($NCSKEW_{t-1}$), together with current operating performance (ROA_t) (see Chen et al., 2001; Hutton et al., 2009). Further, as our concentration is on how a CEO's industry tournament incentives (CITI) affect the propensity for firm-level stock price crash risk through a CEO's reaction, we directly control for CEO characteristics such as CEO age ($CEOAGE_{t-1}$), CEO tenure ($TENURE_{t-1}$), and whether a CEO is a departing CEO ($FINALYR_t$) because in absence of controlling these CEO characteristics, CITI might capture their potential impact on future stock price crash risk.[6]

Consistent with Chen et al. (2001), we also control for investor characteristics with detrended turnover variable ($DTURN_{t-1}$) as a measure of investors' difference in opinion, a behavioural factor associated with increased probability of future stock price crash risk. Further, we use industry homogeneity ($INDUSTRYHOM_{t-1}$) and Fama-French 48-industry dummies to control for industry fixed effects because Finkelstein and Hambrick (1989) suggest that idiosyncratic differences among industries can affect a manager's ability to hide bad news. Finally, year dummies capture time fixed effects in our models.

3.5. Summary statistics

Panel A of Table 1 reports summary statistics. The mean (median) of our first proxy for the probability of crash risk, $NCSKEW_t$, is 0.0801 (0.0153), which is comparable to the mean (median) of 0.068 (0.021) of Kim et al. (2016). The mean (median) of our second proxy of crash risk propensity, $DUVOL_t$, is -0.0150 (-0.0259), which is consistent with the mean (median) of -0.0062 (-0.0160), reported in Al

[6] For example, Andreou et al. (2016) suggest that young and short-tenured CEOs have more incentives to hide bad news, which lead to high firm-specific stock price crash risk propensity. Moreover, departing CEOs (CEOs in their last year of tenure) might have incentives to improve their performance-based compensation with earnings overstatement, which might also lead to increased propensity of future stock price crashes (Ali and Zhang, 2015; Andreou et al., 2016).

Mamun et al. (2020). The mean (median) value of our independent variable of interest, $CITI_{t-1}$, is 8.1816 (8.6816), which is also comparable to the mean (median) of 9.035 (9.051) of Kubick and Lockhart (2016).

[Table 1 about here]

Panel B provides the year and industry distributions of number of observations and mean values of CITI and crash risk propensity for the period 1994-2015. Specifically, Panel B.1 shows a consistent increase in the percentage of yearly observations with the lowest number of observations (2.19%) in 1994 with gradual increases to the highest level in 2010 (5.92%), whereby numbers then remain relatively steady. For CITI, we find an increasing trend in the time-series distribution of Mean CITI reported in Column (3) of Panel B.1. In essence, this represents the temporal increase in a CEO's external labour market incentives.

Both measures of firm-specific crash risk propensity (NCSKEW and DUVOL), however, have a good deal of variation across the sample years. For example, mean values of crash risk propensity are high until 2002 and then gradually declines, indicating the disciplining effect of Sarbanes-Oxley Act to curb bad news withholding propensity (Fang et al., 2009; Callen and Fang, 2013; Callen and Fang, 2017). Firm-specific crash risk propensity again increases during financial crisis in 2008, then declines, and again peaks in 2012, which is consistent with Callen and Fang (2017) and Habib and Hasan (2017). Overall, our time-series distribution of crash risk propensity is comparable with prior literature (Callen and Fang, 2013; Callen and Fang, 2017; Habib and Hasan, 2017).

In Panel B.2, we present industry distributions of our sample for the top ten Fama-French 48 industries based on number of observations. We then aggregate remaining industries in an "Other industries" category. Column (2) shows that Business Services industry represents the highest number of firms (11.53%) followed by Electronic Equipment (8.32%) and Retail (7.58%). Industry decomposition is also instructive for revealing relative industry differentials in external labour market incentives and propensity for crash risk. For example, CITI in Column (3) exhibits that CEOs in Business Services

(Chemicals) industry have the highest (lowest) external labour market incentives. Similarly, industry distribution of crash risk propensity shows that the Retail (Machinery) is the most (least) crash-prone industry in our sample.

Finally, Panel C of Table 1 reports the correlation matrix. The statistically significant negative correlation between $CITI_{t-1}$ and $NCSKEW_t$ provides initial support to the sustained visibility preference hypothesis (Hypothesis 2) that a CEO's industry tournament incentives reduce the probability of firm-level future stock price crash risk. In addition, variance inflation factors (VIF) calculation shows that the highest VIF is 1.65 and the mean VIF is 1.34, which indicates multicollinearity is not a concern.

4. Main results

4.1. Pooled OLS estimates – baseline results

Table 2 reports the baseline regression results of Equation (1) on the relation between CITI and the propensity of future stock price crash risk. Columns (1) and (2) show pooled ordinary least squares (OLS) regression estimates with industry and year fixed effects (FE), columns (3) and (4) display the results with firm and year FE, and columns (5) and (6) present the results with CEO and year FE.

[Table 2 about here]

In column (1), we regress NCSKEW on the one-year lag of CITI and other control variables. The coefficient on $CITI_{t-1}$ is negative (-0.0089) and highly statistically significant at the 1% level. In column (2), we use an alternative measure of the propensity for stock price crash risk, DUVOL, as the dependent variable. The coefficient on $CITI_{t-1}$ still remains negative (-0.0034) and highly statistically significant at the 1% level. Taken together, both columns (1) and (2) strongly support the sustained visibility preference hypothesis (Hypothesis 2) that CITI is negatively associated with the propensity of future stock price crash risk. In terms of economic significance, $NCSKEW_t$ ($DUVOL_t$) decreases by 0.03 (0.01) for one standard deviation increase in $CITI_{t-1}$.[7] Given that from Table 1, the mean values of $NCSKEW_t$ and $DUVOL_t$ are 0.08 and -0.02, respectively, the economic magnitude of the impact is highly significant.

4.2. Fixed effects estimates – identification approach (1)

Columns (3) and (4) of Table 2 report regression estimates of the baseline equation with firm FE. We use firm FE to address the concern that time-invariant firm characteristics can be responsible for the findings in the pooled OLS regression estimates. For example, firms with high CITI can have certain firm-specific characteristics, which make it difficult for the CEOs to hoard bad news, causing lower stock price crash risk. In this way, the relation between CITI and the probability of future stock price crash risk might be spurious. However, negative and highly significant coefficients on $CITI_{t-1}$ at the 1% level in columns (3) and (4) alleviate this concern.

Another potential concern with the baseline pooled OLS results is that unobservable managerial characteristics, such as CEO skill and talent, can be correlated with a CEO's bad news hoarding ability and thus drive the relation between CITI and the probability of future stock price crash risk. We address this concern with CEO FE in columns (5) and (6) and report that the coefficients on $CITI_{t-1}$ are still negative and significant at the 5% level. Overall, firm and CEO FE estimates reaffirm our baseline finding that CITI is associated with a reduced propensity for future stock price crash risk.

4.3. Propensity score matching – identification approach (2)

We also address the issue that the systematic differences among firms led by CEOs with high and low CITI could possibly drive our baseline results by using a propensity score matching technique (Humphery-Jenner et al., 2016). Table 3 reports regression estimates. Column (1) shows regression estimates for the first-stage logistic regression model where the dependent variable is $HIGHCITI_{t-1}$. The estimates from

[7] Using an alternative method of reporting economic significance, we also find similar results. For example, following Kini and Williams (2012), we first compute the dollar amount of the industry pay gap 0.5 standard deviation above and below the mean and label them high and low pay gap. Next, we take the natural logarithm of these two values and calculate the difference between them, which is 1.823. We then multiply this value with the coefficient on $CITI_{t-1}$ and divide by the standard deviation of NCSKEW (DUVOL). Finally, we obtain for a one standard deviation increase of $CITI_{t-1}$ centered on its mean, NCSKEW (DUVOL) decreases by 0.02 (0.02) standard deviations.

this stage capture the propensity that a firm's $CITI_{t-1}$ is within the top two quartiles of the same Fama-French 48 industry group in a given year. Next, we use the propensity scores from the first-stage model to run a second-stage OLS regression, where the dependent variable is $NCSKEW_t$ in column (2) and $DUVOL_t$ in column (3). In both regressions, we use $HIGHCITI_{t-1}$ as our independent variable of interest.

[Table 3 about here]

The significant negative coefficients on $HIGHCITI_{t-1}$ for both $NCSKEW_t$ and $DUVOL_t$ in columns (2) and (3) respectively confirm our results in Table 2. Similarly, the economic magnitude of the probability of crash risk coefficient from the second-stage propensity score matching model remains the same as that from the baseline regression. For example, for one standard deviation (0.50) increase in $HIGHCITI_{t-1}$, $NCSKEW_t$ decreases by 0.02, which is the same magnitude we report for the baseline regression.

4.4. Quasi-natural experiment – identification approach (3)

As a further robustness test of our baseline result, we design a quasi-natural experiment using an exogenous shock to CITI due to a change of the enforceability of the non-competition agreement in three states – Florida, Texas, and Louisiana. The purpose of the non-competition agreement is to prevent executives from accepting job offers from rival firms (Garmaise, 2011; Jeffers, 2017; Huang et al., 2017). Thus, a regulatory change in the enforceability of the non-competition agreement also becomes a shock to CITI (Huang et al., 2017). For example, a leniency in the enforceability of the non-competition agreement increases a CEO's industry tournament incentives by alleviating the restrictions of job-switching. So, an increase in the enforceability of the non-competition agreement attenuates CITI's impact on reducing future stock price crash risk, and vice versa.

The enforceability of the non-competition agreement does not vary much after its introduction in different states. During our sample period, only three states experienced a change in the enforceability of the non-competition agreement. For example, enforceability decreased in Texas in June 1994 and in

Louisiana during June 2001. Given the decreased enforceability, we predict that the impact of CITI on reducing future stock price crash risk will strengthen in Texas after 1994 and in Louisiana after 2001. However, on the other side of the spectrum, the enforceability of the non-competition agreement increased in Florida in May 1996. In addition, Louisiana experienced a switch in enforceability as the state later re-introduced a non-competition agreement from 2003. We predict that this change effectively decreases the impact of CITI on crash risk propensity for firms headquartered in Florida after 1996 and in Louisiana after 2003. To test these two sets of predictions, we design the following difference-in-differences (DiD) regression equation.

$$CRASH_{i,t} = \begin{cases} \alpha + \beta_1 CITI_{i,t-1} + \beta_2 SHOCK_{i,t} + \beta_3 SHOCK_{i,t} \times CITI_{i,t-1} + \delta_i X_{i,t-1} \\ + \lambda_{i,t} S_{i,t} + INDUSTRY\ FE + YEAR\ FE + \varepsilon_{i,t} \end{cases} \quad (5)$$

where $CRASH_{i,t}$ indicates $NCSKEW_t$ or $DUVOL_t$ for firm i in year t. Depending on the change of the enforceability in a specific state, $SHOCK_{i,t}$ is either $SHOCK\ FL_{i,t}$ for Florida, or $SHOCK\ TX_{i,t}$ for Texas, or $SHOCK\ LA_{i,t}$ for Louisiana. $SHOCK\ FL_{i,t}$ takes a value of one if firm i is headquartered in Florida after 1996, otherwise zero. $SHOCK\ TX_{i,t}$ assumes the value of negative one if firm i is headquartered in Texas after 1994, otherwise zero. $SHOCK\ LA_{i,t}$ has a value of negative one if firm i is headquartered in Louisiana between 2002 and 2003, and one if firm i is headquartered in Louisiana in 2004 and onwards, otherwise zero. $X_{i,t}$ are the baseline control variables and $S_{i,t}$ incorporates two state level variables—state unemployment rates and the natural logarithm of per capita personal income in each state. We use these two variables to control for state-level economic and labour market conditions. We also control for industry and year fixed effects. Finally, to address concerns that the error terms in this state-level research design can be autocorrelated within states, we cluster the standard errors by state (Garmaise, 2011; Bertrand et al., 2004).

In Equation (5), our coefficient of interest is β_3. For firms headquartered in Texas and Louisiana, we expect β_3 to be negative, and for firms in Florida, we expect β_3 to be positive. Panel A of Table 4 reports regression estimates.[8]

[Table 4 about here]

Column (1) shows DiD estimation results for Texas, where the treatment group is the firms with headquarters in Texas after 1994 and the control group is the remaining firms headquartered in other states. The coefficient on SHOCK TX × $CITI_{t-1}$ in column (1) is significantly negative. This indicates that an exogenous increase in CITI due to a decrease in the enforceability of the non-competition agreement in Texas magnifies the negative impact of CITI on the probability of crash risk. In column (2), the coefficient on SHOCK LA × $CITI_{t-1}$ is also negative and statistically significant for Louisiana. However, in column (3), the coefficient on SHOCK FL × $CITI_{t-1}$ is significantly positive, indicating CITI no longer reduces the propensity of future stock price crash risk when enforceability of the non-competition agreement increases in Florida. In the next columns, we apply two alternative specifications by separately pooling the states with negative and positive shocks with regard to the enforceability of the non-competition agreement.

Particularly, in column (4), we use a dummy variable NEG SHOCK with the value of negative one if the firms are headquartered in either of two states (Texas during 1995 and afterwards and Louisiana during 2002 and 2003) that have a reduction in the enforceability of the non-competition agreement and otherwise NEG SHOCK is set to zero. A significantly negative coefficient on NEG SHOCK × $CITI_{t-1}$ is consistent with the previous result that a reduction in the enforceability of non-competition agreement further intensifies the negative relation between CITI and the probability of future stock price crash risk. Similarly, in column (5), we employ a dummy variable POS SHOCK with the value of one for firms headquartered in either of the two states (Louisiana during 2004 and afterwards and Florida during 1997

[8] For brevity we only report regression estimates for NCSKEW as the dependent variable. However, results for DUVOL remain consistent with NCSKEW.

and afterwards) that have an increase in the enforceability of non-competition agreement and zero otherwise. A positive and statistically significant coefficient on POS SHOCK × $CITI_{t-1}$ supports our prior conjecture that CITI's effect on reducing future crash risk propensity becomes weaker when an increase in the enforceability of non-competition agreement constrains a CEO's external labour market incentives.

The key condition to satisfy the validity of the DiD estimate is to have a parallel trend in the outcome variable for both the treatment and control groups before the exogenous treatment event (Roberts and Whited, 2013). We test this parallel trend assumption in Panel B. Specifically, in columns (1) through (5), we include additional dummy variables to capture the trend during each of the two years before the change in the enforceability of the non-competition agreement. For example, SHOCK TX_{Before} is an indicator variable with the value of negative one for the firms headquartered in Texas during each of the two years prior to the reduction in non-competition agreement enforceability. Other time trend indicator variables in columns (2) through (5) are similarly defined based on a two-year window prior to the event. The coefficients on the interactions between CITI and all these time-trend variables are statistically insignificant in columns (1) through (5), suggesting that the treatment and control groups do not have different trends in the propensity of crash risk prior to the change in the enforceability of the non-competition agreement. However, in all these regressions, the coefficients on the interactions between CITI and shock dummies are statistically significant in the predicted directions. Collectively, these results show that our DiD satisfies the parallel trend assumption and, hence, the treatment effect on the probability of future crash risk can be attributed to a change in CITI caused by changes in the enforceability of non-competition agreements.

4.5. Generalised method of moments (GMM) – identification approach (4)

Next, we use the generalised method of moments (GMM) with two instrumental variables to rule out the possibility that omitted variables and reverse causality potentially bias our baseline OLS regression estimates. Our two instrumental variables are: (i) the natural logarithm of the mean CEO compensation of other industries headquartered within 250 kilometres of the firm (GEOCOMP250),[9] and (ii) the natural logarithm of the total CEO compensation of other firms, except the firm of the second highest paid CEO, in the same size adjusted Fama-French 48 industry group (INDCEOCOMP) (Coles et al., 2018; Kubick and Lockhart, 2016).[10]

Both instruments satisfy the relevance and exclusion conditions. For example, GEOCOMP250 affects CITI as Bouwman (2013) shows that local competition among executives affects their compensation. In addition, there is no economic channel to explain that compensation in firms of other industries headquartered within 250 kilometres of the firm can affect the probability of firm-level future stock price crash risk. Thus, we may expect GEOCOMP250 influences crash risk only through its impact on CITI. The second instrument, INDCEOCOMP, shows how much an industry can pay a CEO (Kubick and Lockhart, 2016; Coles et al., 2018). Thus, INDCEOCOMP directly influences CITI as the industry CEO compensation determines firm-level CEO compensation (Dickens and Katz, 1987). Again, total CEO compensation in an industry has no direct influence on firm-level future stock price crash risk propensity. Thus, INDCEOCOMP can affect the probability of firm-level future stock price crash risk only by its effect on CITI. Table 5 reports regression results of the GMM estimation with these two instrumental variables.

[Table 5 about here]

Columns (1) and (2) show second-stage results of GMM estimation with $NCSKEW_t$ and $DUVOL_t$, respectively. For both crash risk measures, the coefficient on $CITI_{t-1}$ is significantly negative reaffirming our baseline result that CITI reduces the propensity of firm-level future crash risk. This result remains robust even after applying more restrictive model specifications such as firm FE in columns (3) and (4) and CEO FE in columns (5) and (6). The economic significance of the coefficients on CITI also

[9] We do not include the CEOs in the same Fama-French 48 industry to avoid any mechanical relation. Alternatively, we also use the mean CEO compensation of other industries headquartered within 500 kilometres of the firm and results remain qualitatively the same.

[10] We exclude the total compensation of the second highest paid CEO in the same industry because it is included in the CITI calculation.

improves from the baseline equation. For example, for one (sample) standard deviation (3.23) increase in $CITI_{t-1}$, $NCSKEW_t$ decreases by 0.09 given the mean value of NCSKEW of this sample is 0.07.

In addition, all the diagnostic statistics in Table 5 support the validity of the results. For example, statistically significant Hausman test statistics in columns (1) through (6) favour GMM over OLS estimation, the significant Kleibergen-Paap rk LM statistic and Kleibergen-Paap rk Wald F statistic shows the GMM model is neither under identified nor weakly identified, and the insignificant Hansen J statistic in all models justify the use of these two instruments. Overall, our GMM estimates confirm that neither omitted variables nor reverse causality drives the negative relation between CITI and the probability of future crash risk.

5. Additional analyses

5.1. Test of bad news withholding channels

This section examines whether CITI reduces bad news concealment by evaluating two direct tests – *earnings string breaks* and *sudden bad news release*, and four indirect tests – *accrual manipulation*, *real earnings management practices, aggressive financial restatements, and overinvestments*.

5.1.1. Earnings string breaks

Managers have incentives to maintain a consecutive increase in earnings (a string) for longer periods by withholding bad news (Myers et al., 2007; Andreou et al., 2017b). As a mechanism to increase earnings in consecutive years, managers overestimate earnings increasing accruals to hide underlying bad news (Hutton et al., 2009; Zhu, 2016). Prior research shows that a firm experiences crash risk when these consecutive increases of earnings break in a year (Andreou et al., 2017b). Thus, combining a measure for a break of consecutive increase in earnings and subsequent crash risk provides an event-based foundation to test managerial bad news hoarding behaviour. Following Andreou et al. (2017b), we create a dummy variable “Break” with the value of one if a firm’s earnings decrease in the current year after consecutively increasing in the previous two years. We then multiply our primary measure of the probability of crash risk, $NCSKEW_t$, with “Break” and create a new variable “Break of earnings string” to capture the propensity of a crash during the year that a break in consecutive earnings occurs. Hence, if the reason for the negative relation between $CITI_{t-1}$ and crash risk is due to a CEO's withholding of bad news, we would expect a negative relation between "Break of earnings string" and $CITI_{t-1}$. Column (1) of Table 6 supports this prediction with a negative coefficient on $CITI_{t-1}$.

[Table 6 about here]

5.1.2. Sudden release of bad news

Our second test of a bad news hoarding channel examines CITI's impact on a firm's propensity to release unexpected extreme bad news in the future. Accordingly, we determine firms which are not very likely to reveal bad news in the current year based on their previous year's disclosures and, hence when such bad news is revealed, the market recognises it as unexpected (Chang et al., 2017). We estimate the dependent variable (SUR) for this test in two steps. First, we calculate "unexpected earnings" of a firm as the ratio of the change in income before extraordinary items over year t and t-1, divided by the market value of equity at year t-1 (Kothari et al., 2006). Second, we estimate SUR as a dummy variable with the value of one if a firm has unexpected earnings in the bottom decile during year t but it has non-negative unexpected earnings during year t-1, otherwise SUR is set to zero (Chang et al., 2017). The probit regression result is reported in column (2) of Table 6 after controlling for variables reported as determinants of managerial bad news hoarding and earnings management in prior literature. The significantly negative coefficient on $CITI_{t-1}$ shows that external labour market incentives reduce a CEO's propensity to suddenly release extreme bad news in the future.

5.1.3. Accrual earnings management

Prior accounting literature shows that the cash component of earnings is more reliable than accrual components because estimation of accrual components requires greater subjective judgment from managers (Dechow and Dichev, 2002; Dechow et al., 2011). Further, Zhu (2016) shows that firms, maintaining high accruals to hide bad news over the years, experience crashes when accumulated bad news spills on to the market all at once. If CEOs with high CITI have a lower incentive for bad news hoarding, they are expected to maintain lower accruals.[11] Thus, we predict a negative relation between CITI and accruals. In an untabulated test, we find support for this prediction with a significantly negative coefficient on $CITI_{t-1}$ (-0.0012).

A stronger test is the use of discretionary accruals which captures the proclivity for managerial earnings manipulations better than total accruals. Specifically, Hutton et al. (2009) show that managers hide bad news by employing accruals earnings management through aggressive use of discretionary accruals, and this is associated with the propensity of future stock price crashes. Consistent with the finding that CITI reduces a CEO's propensity to withhold bad news, we predict a negative relation between CITI and discretionary accruals. Following Hutton et al. (2009), we estimate discretionary accruals as a moving sum of the absolute value of yearly discretionary accruals for three years. Column (3) reports regression estimates. A statistically significant negative coefficient on $CITI_{t-1}$ is consistent with our conjecture that CEOs are reluctant to hide bad news by using accruals based earnings management techniques when they have high external labour market incentives. We also reaffirm this finding in column (4) using the modified Dechow and Dichev (2002) discretionary accruals model.

5.1.4. Real earnings management

If accrual management is apparent, managers can defer obscuration of bad news by manipulation through real earnings management (Francis et al., 2016). Specifically, by employing real earnings management techniques, managers can misguide external parties to wrongly conceive that financial reporting targets are achieved during regular business activities (Roychowdhury, 2006). The financial statement effect of these real earnings management strategies is to increase income which then provides a facade to bury bad news in more optimistic but inaccurate disclosures (Huang et al., 2019). Arguably, if our documented negative CITI-future crash risk relation is due to a CEO's less bad news withholding behaviour, we can predict a negative relation between CITI and real earnings management.

[11] We define accruals as a ratio of change in net operating assets (AT – CHE – LT + DLC + DLTT) to total assets (Dechow et al., 2008; Richardson et al., 2006; Zhu, 2016).

Following Roychowdhury (2006), we measure real earnings management by three proxies – (a) production of goods more than the expected demand in order to inflate earnings by lowering the reported cost of goods sold, (b) abnormal reduction of discretionary R&D, advertising, and selling, general, and administrative expenditures to increase reported earnings, and (c) temporary increase in sales by offering price discounts or easy credit terms. These variables are defined in Appendix A.1 and the regression estimates are reported in columns (5) and (6). Consistent with predictions, we find significantly negative coefficients (-0020; -0.0054) on $CITI_{t-1}$, indicating real earnings management (with overproduction and reduction of discretionary expenditures[12]) decreases when firms have CEOs with high external labour market incentives. However, in an untabulated result, we find no evidence that CITI affects sales manipulation decisions.

Prior studies show that real earnings management reduces long-term firm value. For example, a firm can curtail discretionary spending like R&D in the current period to match earnings goals but this can reduce a firm's competitiveness against the peers, leading to operating underperformance in the long-term (Bhojraj et al., 2009; Cheng et al., 2016; Cohen and Zarowin, 2010). Our result in this section is consistent with these findings from prior real earnings management literature and with extant CITI literature (Coles et al., 2018) that CITI reduces the propensity of future crash risk and improves firm performance by lowering a CEO's incentives to engage in real earnings manipulations.

5.1.5. Aggressive financial restatements

The previous section explains how managers can conceal bad news with earnings management practices. However, at some point, accumulation of bad news piles up and managers eventually need to restate earnings to their intrinsic values and thus release bad news that might lead to an increased probability of future stock price crashes (Kim and Zhang, 2014). Financial restatements can be of two types – (a) intentional misstatements or aggressive financial restatements, and (b) unintentional errors (Hennes et

[12] For the ease of interpretation, we use the negative of the residuals of the discretionary expenditure model so that a negative relation between $CITI_{t-1}$ and these residuals indicates a reduction in real earnings management (Cheng et al., 2016).

al., 2008). Kim and Zhang (2014) find that only intentional misstatements capture bad news hoarding incentives and therefore affect a firm's crash risk propensity. In similar spirit, we examine whether CEOs with high external labour market incentives have a lower probability of bad news hoarding through intentional misstatements.[13] As expected, untabulated results show a significant negative coefficient on CITI (-0.2168), confirming that external labour market incentives restrain a CEO from intentional misstatements and bad news hoarding.

5.1.6. Overinvestments

Prior literature also shows that managers increase overinvestments by withholding investment related bad news for prolonged periods (Kedia and Philippon, 2009; McNichols and Stubben, 2008). For example, to maintain private benefits, managers conceal bad news on loss-making negative NPV projects for extended periods resulting in continued overinvestments (Khurana et al., 2018). Further, Benmelech et al. (2010) conjecture that managers cannot disguise overinvestments for unlimited periods, and when such bad news is suddenly assessed by the market, the stock price drops substantially. As we hypothesise that CEOs with high industry tournament incentives do not suppress and accumulate bad news for longer periods, we predict a negative relation between CITI and overinvestments.[14] Untabulated results with a significantly negative coefficient on $CITI_{t-1}$ (-0.0042) support this prediction.

5.2. Cross-section analysis

By examining cross-sectional variations in CITI-crash risk propensity relation, we add further credence to our argument that CITI reduces the probability of future crash risk due to the disciplinary role of external labour market incentives on a CEO's strategic decisions within a firm.

[13] We collect intentional misstatements data from https://kelley.iu.edu/bpm/activities/errorandirregularity.html.
[14] We calculate overinvestments following Richardson (2006) and Blaylock (2016). The detailed process is in Appendix A.1.

5.2.1. High versus low information environment quality

As insiders, managers have better access to private information regarding firm policies and prospects than investors (Kothari et al., 2009). Managers also have different incentives to disclose or hide their private information (Healy and Palepu, 2001). For example, managers often reduce information asymmetry between them and outsiders by revealing private information in order to lower the cost of capital (Verrecchia, 2001; Healy and Palepu, 2001). Therefore, we conjecture that industry tournament incentives induce CEOs in high information asymmetry firms to disseminate and disclose information that reduces the probability of future stock price crashes.

To test this conjecture, we divide our sample into quartiles based on financial reporting opacity ($OPAQUE_{t-1}$, Hutton et al., 2009) and create a dummy variable labelled as high opacity (low-quality information environment) with the value of one for the firms in the top quartile. The variable is set to zero for the firms in the bottom quartile, indicating high-quality information environment. Following Kim et al. (2016), we exclude observations in the middle two quartiles (third and second quartile). Panel A of Table 7 reports regression results.

[Table 7 about here]

In Panel A, regression estimates for $NCSKEW_t$ and $DUVOL_t$ are reported in columns (1) – (2) and columns (3) – (4) for low and high information quality subgroups. As predicted, the coefficient on $CITI_{t-1}$ is negatively significant only for the low information quality subgroup in both measures of the probability of future crash risk. Moreover, the test of difference of the coefficients on $CITI_{t-1}$ in the low versus high group is statistically significant at the 5% level ($p = 0.0258$) for $NCSKEW_t$ and at the 10% level ($p = 0.0525$) for $DUVOL_t$. Collectively, these results suggest that the disciplinary constraint of external labour market incentives on bad news hoarding is stronger for firms with low information quality when compared to firms that already operate in a high-quality information environment.

5.2.2. High versus low external monitoring

Monitoring from external stakeholders can restrain managers from withholding bad news (Kim et al., 2016). Specifically, as an external monitor, analysts can reduce a firm's propensity to manage earnings (Yu, 2008) and alleviate crash risk (Kim et al., 2019). Similarly, monitoring from institutional shareholders can substantially mitigate the propensity of firm-level future crash risk (Callen and Fang, 2013). On these grounds, if the negative CITI-crash risk relation is due to the disciplinary role of external labour market incentives on a CEO with regard to restraining bad news holding, we posit a stronger CITI-crash risk relation (hence, greater disciplinary effect) for the firms with low external monitoring. We empirically test this conjecture in Panel B (analyst coverage) and Panel C (institutional holdings).

In order to identify firms with low and high external monitoring, we divide the sample into quartiles based on analyst coverage and institutional shareholders and define firms in the bottom (top) quartile as the firms with low (high) external monitoring. Data on analyst coverage is collected from I/B/E/S and institutional shareholdings from Thomson Reuters. Consistent with predictions, the negative CITI-crash risk propensity relation is statistically significant only in the low external monitoring subgroups for both in Panel B (analyst coverage) and C (institutional shareholdings). Furthermore, the test of difference between low and high external monitoring groups for both measures of crash risk (NCSKEW and DUVOL) are also statistically significant,[15] suggesting that CITI's disciplinary effect in reducing crash risk is much stronger for firms with low external monitoring than for firms with high external monitoring.

[15] In Panel B with analysts as the external monitors, the difference between the coefficients on $CITI_{t-1}$ in low versus high external monitoring group is significant at the 5% level for both measures of crash risk (p = 0.0306 with $NCSKEW_t$ and p = 0.0380 with $DUVOL_t$). In Panel C with institutional shareholders, the coefficient difference with CITI in low versus high group is statistically significant at the 5% level (p = 0.0276) for $NCSKEW_t$ and at the 1% level (p = 0.0011) for $DUVOL_t$.

6. Further robustness analyses

6.1. Alternative measures

Thus far, we only report results for $NCSKEW_t$ and $DUVOL_t$ as proxies for the probability of future stock price crash risk. Appendix A.2 reports our baseline results with two more cash risk proxies – $COUNT_t$ and $EXTRASIG_t$. Definitions of COUNT and EXTRASIG are provided in Appendix A.1.

Consistent with our main results, the coefficients on $CITI_{t-1}$ for both $COUNT_t$ and $EXTRASIG_t$ in columns (1) and (2) are significantly negative. The coefficient on $CITI_{t-1}$ also remains significantly negative after controlling for firm FE in columns (3) and (4) and CEO FE in columns (5) and (6).

6.2. Omitted variable bias

To further address omitted variables bias, we examine whether our baseline results still hold after the inclusion of sixteen additional controls grouped in four categories: equity-based incentives of a CEO and a CFO,[16] other controls related to a CEO and a CFO, corporate governance and monitoring, higher market pressure and inherent riskiness. All variables are defined in Appendix A.1 and Table 8 presents regression estimates.[17]

[Table 8 about here]

Kim et al. (2011) report that executives' equity incentives (sensitivity of the value of options portfolio to the change in stock price) can increase the propensity of future stock price crash risk. Therefore, to alleviate the concern that $CITI_{t-1}$ might merely capture the lack of a CEO's high equity incentives, we control for a CEO's incentive ratios with options ($CEOOPT_{t-1}$) and stocks ($CEOSTK_{t-1}$) in column (1) (Bergstresser and Philippon, 2006; Kim et al., 2011). Moreover, we also control for a CFO's equity incentives ($CFOOPT_{t-1}$, $CFOSTK_{t-1}$) in column (1) because Kim et al. (2011) show that the

---

[16] As ExecuComp database only reports whether an exeutive is a CFO with "CFOANN" data item from 2006, we identify all CFOs before 2006 using ExecuComp's TITLEANN data item. Specifically, we check and identify an executive as a CFO if the executive's title consists of any of the following terms – "CFO, chief financial officer, treasurer, controller, finance, and vp finance" (Kim et al., 2011).

[17] For brevity, we report regression results with $NCSKEW_t$ as the dependent variable in this table. However, all these results remain consistent with $DUVOL_t$.

effect of a CFO's equity incentives on the propensity of future stock price crash risk is more pronounced than a CEO's equity incentives because CFOs are in a good position to influence the flow of accounting information. However, the negatively significant coefficient on $CITI_{t-1}$ in column (1) shows that a CEO's external labour market incentives still reduce the probability of future stock price crash risk even after executives' equity incentives are taken into consideration.

Next, we employ additional CEO and CFO related controls in column (2) to mitigate the possibility that CITI-crash risk negative relation is spurious due to other characteristics pertaining to CEO and non-CEO executives. Specifically, a recent study shows that the *internal* promotion tournament of non-CEO executives increases future crash risk (Jia, 2018). Furthermore, as the "specialist in accounting information", a CFO might have a certain preference for bad news disclosure and thus can affect future crash risk when faced with high external labour market incentives.[18] With a similar argument, Li and Zeng (2019) show that female CFOs reduce future crash risk. In addition, a CEO's gender and the extent of power to influence corporate decisions could explain the variations in industry pay gap of a CEO and hence might be another source of omitted variable bias if not controlled. Accordingly, we control for $PAYGAP_{t-1}$, $CFOITI_{t-1}$, $POWER_{t-1}$, $CEOFEMALE_{t-1}$, $CFOFEMALE_{t-1}$, and $CEODUAL_{t-1}$ in column (2). The coefficient on $CITI_{t-1}$ continues to load statistically significantly at the 1% level. More importantly, the statistically insignificant coefficient on $CFOITI_{t-1}$ suggests that a CFO's external labour market incentives do not drive a CFO's bad news hoarding behaviour and future crash risk propensity. This finding is not surprising because a CFO is mostly likely to be promoted within a firm and hence internal promotion tournament is far more important to a CFO than an external labour market "promotion competition." [19]

[18] We thank an anonymous reviewer for this suggestion.

[19] Our data indicates that a CFO's average annual industry pay gap in dollar terms is 3.43 times lower than the average annual industry pay gap of a CEO. Therefore, a CFO's external labour market incentives are relatively lower than those of a CEO. Moreover, an analysis by Spencer Stuart shows that 69 percent of Fortune 500 CFOs in 2016 were internal successors with firms tending to develop CFOs by internal rotation because internally promoted CFOs are better informed about corporate policies than any externally hired CFOs (source: https://www.spencerstuart.com/-/media/pdf-files/profile-of-the-fortune-500-cfo-today-and-in-the-future_21jun2017.pdf). Given that, high CITI by nature provides an elevated remuneration signal in industry that demands high quality, competitive and astute candidates with the result, CEO turnover has significantly

We also employ an alternative method to address the concern that executives' characteristics might be responsible for the documented negative relation between CITI and future crash risk. It can be argued that it is not the external labour market incentives rather a CEO's time variant and inherent time invariant characteristics determine the level of CEO pay compared to industry and therefore, by construct, CITI picks up the effect of CEO attributes on crash risk.[20] We approach this issue in two steps. First, we run the following regression model:

$$CITI_{i,t-1} = \alpha + \beta_1 ABILITY_{i,t-1} + \beta_2 TENURE_{i,t-1} + \beta_3 CEOAGE_{i,t-1} + \beta_4 OVERCON_{i,t-1} + \beta_5 POWER_{i,t-1} + \beta_6 CEOFEMALE_{i,t-1} + INDUSTRY\ FE + YEAR\ FE + \varepsilon_{i,t} \quad (6)$$

where $ABILITY$ is a CEO's managerial ability (Demerjian et al., 2012), $TENURE$ is a CEO's experience as a CEO of the firm, $CEOAGE$ is the age of a CEO, $OVERCON$ is a dummy variable indicating whether a CEO is overconfident, $POWER$ is CEO power index, and $CEOFEMALE$ captures CEO gender. All these variables are defined in Appendix A.1.

Next, we take lag of the residuals from the above model and use it in Equation (4) replacing $CITI_{t-1}$. These residuals capture variations in CITI which cannot be explained by CEO-specific traits. An untabulated regression result shows that the coefficient on the lagged residuals with both $NCSKEW_t$ (-0.0082) and $DUVOL_t$ (-0.0031) are negatively significant at the 1% level. The absolute values of these coefficients on lagged residuals are slightly smaller than those on $CITI_{t-1}$ with $NCSKEW_t$ (-0.0089) and $DUVOL_t$ (-0.0034) reported in columns (1) and (2) of Table 2, indicating that CEO traits do have some impact on the propensity of firm-level future crash risk. However, as these values are not substantially different from each other in magnitude, we can say that the variations in CITI which cannot be explained

increased over the last few decades with lower tenure, suggesting CEOs have strong external labour market incentives than CFOs (Karlsson and Neilson, 2009). Hence, if according to Baker et al. (2019) and Feng et al. (2011) CFOs are simply CEO's agents, stand more to lose from loss of employment, and face powerful CEOs with high external labour market incentives, then it stands to reason that the CFO's comparative power, specifically with regards to external labour market incentives, to influence the propensity of future crash risk is comparatively lower.

[20] For example, CEOs with low compensation compared to industry might be entrenched in their firms and, therefore, receive other forms of perks and benefits for which they could be insensitive to bad news withholding which might drive negative CITI-crash risk propensity relation. We thank an anonymous reviewer for suggesting this alternative explanation.

by CEO traits and hence, are most likely to capture a CEO's external labour market incentives are significantly responsible to reduce the propensity of a firm's future stock price crash risk.

There could be a possibility that firms with strong corporate governance maintain lower CEO pay compared to the industry. Hence, the negative CITI-crash risk propensity relation might pick up the effects of strong corporate governance. To address this concern, we control for several proxies of corporate governance (takeover index (CG), Cain et al., 2017; institutional investor stability (INSTD), Callen and Fang, 2013; accounting conservatism (CSCORE), Andreou et al., 2016) in column (3). Moreover, we control for firm-level internal governance through which non-CEO executives can influence corporate decisions and outcomes (e.g, propensity of future crash risk) by disciplining a CEO's actions (Cheng et al., 2016). However, $CITI_{t-1}$ remains significantly negative at the 1% level.

Next, in column (4), we control for the potential effects of higher market pressure and inherent riskiness of the firms that might affect a CEO's decision to maintain an opaque information environment within the firm. Specifically, we control for product market competition ($FLUIDITY_{t-1}$), distance -to - default (DD_{t-1}) capturing a firm's bankruptcy possibility, and forward-looking measure of R&D intensity ($INNOVATION_{t-1}$) (Bharath and Shumway, 2008; Hoberg et al., 2014; Kogan et al., 2017). Consistent with previous results, the coefficient on $CITI_{t-1}$ is negative and statistically significant at the 1% level. In column (5), the negative CITI-future crash risk propensity relation still prevails after combining all these sixteen additional controls, along with the baseline controls in the same model. However, we note a significant drop in the number of observations in columns (4) and (5) because innovation data ends in 2010 and is not available for all firms in our sample.

7. Conclusion

We investigate and find that the external labour market through CITI has a powerful effect on CEO internal strategies that reduce the probability of future stock price crash risk, measured by negative conditional return skewness (NCSKEW) and down-to-up volatility (DUVOL). Focusing on two competing hypotheses (short-term visibility preference vs. sustained visibility preference), we first show that CEOs with high industry tournament incentives have a lower tendency to withhold bad news and this leads to a lower probability of future stock price crash risk. Results are robust to identification problems. Our study extends research that concentrates on internal career incentives and bad news hoarding (Kothari et al., 2009; Baginski et al., 2018) and reveal that the external labour market induces an information focused and longer-term branding approach by CEOs.

Supplementary tests designed to target and uncover specific channels where bad news hoarding might occur shows that CITI reduces the propensity of earning string breaks, sudden releases of bad news, and the use of discretionary accruals, real earnings management, aggressive financial restatements, and overinvestments. In addition, as a disciplinary mechanism, CITI is more effective in firms with low quality information environment and when there is lower external monitoring by analysts and institutions.

In short, the external labour market incentive provided by CITI proves to be a dominant factor that induces CEOs to control bad news hoarding and use other strategic issues which result in a reduced probability of future firm specific crash risk. These findings are important to academics, investors, and policy makers on several fronts. Academically, we complement Coles et al. (2018) and Huang et al. (2017) by documenting CITI's positive value implications for shareholders through a reduction in extreme negative return outcomes. We also add to Andreou et al. (2017b), Hutton et al. (2009), and Chang et al. (2017) by establishing a link between CITI and its ability to mitigate the manipulation of accounting variables used to hide bad news hoarding. Specifically, unlike similar studies of crash risk, we not only show "whether" CITI affects crash risk propensity but also identify the channels as to "how" CITI reduces the probability of future crash risk.

For investors, we provide indicators how they can screen out shares of firms with high crash risk rather than employing diversification techniques. Specifically, finding a negative relation between CITI and the probability of crash risk provides signals to investors to undertake more effective asset allocation decision and portfolio formulation. Moreover, boards should also be aware of the implications of CITI when designing executives' compensation contracts and retaining high quality CEOs. Additionally, whilst Graham et al. (2005) find that 78% of managers prefer short-term gains at the expense of long-term benefits, but our research shows that CEOs with high industry tournament incentives are the exception. Our final contribution is to highlight the disciplinary mechanisms of the external labour market on value-adding corporate decision making.

One caveat is necessary. Specifically, an important qualifying note is that the use of continuous variables, such as NCSKEW and DUVOL, captures both extreme positive and negative returns, and hence might not exclusively show the left-side tail risk (Diemont et al., 2016; Kim et al., 2014). Moreover, NCSKEW and DUVOL measure both large and small crashes. Hence, the use of these continuous variables identifies the propensity for, not the occurrences of, actual stock price crashes (Andreou et al., 2017a). Whilst we argue that the approach of using continuous variables to measure the probability of stock price crash risk provides pre-emptive signals for managers and investors to identify and mitigate forthcoming risk concerns, the association of CITI and occurrences of crashes is not covered. Hence, future research that examines the association of a CEO's external labour market incentives with the occurrence of actual crashes is recommended. Another promising avenue of future research is related to whether investors, ex ante, recognise the effect of a CEO's external labour market incentives on crash risk, captured by the option-based implied volatility smirk.

References

Adams, R. B., Almeida, H., Ferreira, D., 2005. Powerful CEOs and their impact on corporate performance. *Review of Financial Studies*, 18(4), 1403-1432.

Al Mamun, M., Balachandran, B., Duong, H. N., 2020. Powerful CEOs and stock price crash risk. *Journal of Corporate Finance*, 62, 101582.

Ali, A., Zhang, W., 2015. CEO tenure and earnings management. *Journal of Accounting and Economics*, 59(1), 60-79.

Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.

Andreou, P. C., Antoniou, C., Horton, J., Louca, C., 2016. Corporate governance and firm-specific stock price crashes. *European Financial Management*, 22(5), 916-956.

Andreou, P. C., Cooper, I., Louca, C., Philip, D., 2017a. Bank loan loss accounting treatments, credit cycles and crash risk. *British Accounting Review*, 49(5), 474-492.

Andreou, P. C., Louca, C., Petrou, A. P., 2017b. CEO age and stock price crash risk. *Review of Finance*, 21(3), 1287-1325.

Baginski, S. P., Campbell, J. L., Hinson, L. A., Koo, D. S., 2018. Do career concerns affect the delay of bad news disclosure? *Accounting Review*, 93(2), 61-95.

Baker, T. A., Lopez, T. J., Reitenga, A. L., Ruch, G. W., 2019. The influence of CEO and CFO power on accruals and real earnings management. Review of Quantitative Finance and Accounting, 52(1), 325-345.

Bebchuk, L. A., Cremers, K. M., Peyer, U. C., 2011. The CEO pay slice. *Journal of Financial Economics*, 102(1), 199-221.

Benmelech, E., Kandel, E., Veronesi, P., 2010. Stock-based compensation and CEO (dis) incentives. *Quarterly Journal of Economics*, 125(4): 1769–1820.

Bergstresser, D., Philippon, T., 2006. CEO incentives and earnings management. *Journal of Financial Economics*, 80(3), 511-529.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1), 249-275.

Bharath, S. T., Shumway, T., 2008. Forecasting default with the Merton distance to default model. *Review of Financial Studies*, 21(3), 1339-1369.

Bhargava, R., Faircloth, S., Zeng, H., 2017. Takeover protection and stock price crash risk: Evidence from state antitakeover laws. *Journal of Business Research*, 70, 177-184.

Bhojraj, S., Hribar, P., Picconi, M., McInnis, J., 2009. Making sense of cents: An examination of firms that marginally miss or beat analyst forecasts. *Journal of Finance*, 64(5), 2361-2388.

Blaylock, B., 2016. Is tax avoidance associated with economically significant rent extraction among U.S. firms? *Contemporary Accounting Resea*rch, 33(3):1013-1043.

Bouwman, C., 2013. The geography of executive compensation. *Unpublished working paper. Texas A&M University*.

Bradshaw, M. T., Hutton, A. P., Marcus, A. J., Tehranian, H., 2010. Opacity, crash risk, and the option smirk curve. *Unpublished working paper, Boston College*.

Bushee, B. J., 1998. The influence of institutional investors on myopic R&D investment behavior. *Accounting Review*, 73(3), 305-333.

Cain, M. D., McKeon, S. B., & Solomon, S. D., 2017. Do takeover laws matter? Evidence from five decades of hostile takeovers. *Journal of Financial Economics*, 124(3), 464-485.

Callen, J. L., Fang, X., 2013. Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking and Finance*, 37(8), 3047-3063.

Callen, J. L., Fang, X., 2015. Short interest and stock price crash risk. *Journal of Banking and Finance*, 60, 181-194.

Callen, J. L., Fang, X., 2017. Crash risk and the auditor–client relationship. *Contemporary Accounting Research*, 34(3), 1715-1750.

Chang, X., Chen, Y., Zolotoy, L., 2017. Stock liquidity and stock price crash risk. *Journal of Financial and Quantitative Analysis*, 52(4), 1605-1637.

Chen, C., Kim, J. B., Yao, L., 2017. Earnings smoothing: Does it exacerbate or constrain stock price crash risk? *Journal of Corporate Finance*, 42, 36-54.

Chen, J., Hong, H., Stein, J. C., 2001. Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, 61, 345–381.

Cheng, Q., Lee, J., Shevlin, T., 2016. Internal governance and real earnings management. *Accounting Review*, 91(4), 1051-1085.

Cohen, D. A., Zarowin, P., 2010. Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50(1), 2-19.

Coles, J. L., Li, Z., Wang, A. Y., 2018. Industry tournament incentives. *Review of Financial Studies*, 31(4), 1418-1459.

Dechow, P., Dichev, I., 2002. The quality of accruals and earnings: the role of accrual estimation errors. *Accounting Review*, 77(s1), 35–59.

Dechow, P., Ge, W., Larson, C., Sloan, R., 2011. Predicting material accounting misstatements. *Contemporary Accounting Research*, 28(1), 17–82.

Dechow, P., Richardson, S. A., Sloan, R. G., 2008. The persistence and pricing of the cash component of earnings. *Journal of Accounting Research*, 46(3), 537-566.

Demerjian, P., Lev, B., McVay, S., 2012. Quantifying managerial ability: A new measure and validity tests. *Management Science*, 58(7), 1229-1248.

Dickens,W., Katz, L., 1987. Inter-industry wage differences and industry characteristics. In: Lang, K., Leonard, J. (Eds.), Unemployment and the Structure of Labor Markets. Basil Blackwell, New York, pp. 48–89.

Diemont, D., Moore, K., Soppe, A., 2016. The downside of being responsible: Corporate social responsibility and tail risk. *Journal of Business Ethics*, 137(2), 213-229.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7, 197–226.

Ertugrul, M., Lei, J., Qiu, J., Wan, C., 2017. Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis*, 52(2), 811-836.

Fang, X., Liu, Y., Xin, B., 2009. Accounting Conservatism, the Sarbanes-Oxley Act, and crash risk. Working paper, University of Toronto.

Feng, M., Ge, W., Luo, S., Shevlin, T., 2011. Why do CFOs become involved in material accounting manipulations? *Journal of Accounting and Economics*, 51(1-2), 21-36.

Finkelstein, S., Hambrick, D. C., 1989. Chief executive compensation: A study of the intersection of markets and political processes. *Strategic Management Journal*, 10(2), 121-134.

Francis, B., Hasan, I., Li, L., 2016. Abnormal real operations, real earnings management, and subsequent crashes in stock prices. *Review of Quantitative Finance and Accounting*, 46(2), 217-260.

Garmaise, M. J., 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *Journal of Law, Economics, and Organization*, 27(2), 376-425.

Gelb, D. S., Zarowin, P., 2002. Corporate disclosure policy and the informativeness of stock prices. *Review of Accounting Studies*, 7(1), 33-52.

Graham, J. R., Harvey, C. R., Rajgopal, S., 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40(1), 3-73.

Gudell, S. M., 2011. Serial CEOs and their career concerns. *Working paper, University of Rochester*.

Habib, A., Hasan, M. M., 2017. Business strategy, overvalued equities, and stock price crash risk. *Research in International Business and Finance*, 39, 389-405.

Han, S., Nanda, V. K., Silveri, S., 2016. CEO power and firm performance under pressure. *Financial Management*, 45(2), 369-400.

He, G., 2015. The effect of CEO inside debt holdings on financial reporting quality. *Review of Accounting Studies*, 20(1), 501-536.
Healy, P. M., Palepu, K. G., 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1), 405-440.
Hennes, K. M., Leone, A. J., Miller, B. P., 2008. The importance of distinguishing errors from irregularities in restatement research: The case of restatements and CEO/CFO turnover. *Accounting Review*, 83(6), 1487-1519.
Hermalin, B. E., Weisbach, M. S., 2007. Transparency and corporate governance. NBER Working Paper No. 12875. DOI: 10.3386/w12875.
Hoberg, G., Phillips, G., Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. *Journal of Finance*, 69(1), 293-324.
Huang, J., Jain, B., Kini, O., 2017. Industry tournament incentives and the product market benefits of corporate liquidity. *Journal of Financial and Quantitative Analysis*. Forthcoming
Huang, S., Roychowdhury, S., Sletten, E., 2019. Does litigation deter or encourage real earnings management? *Accounting Review*, In-Press.
Humphery-Jenner, M., Lisic, L. L., Nanda, V., Silveri, S. D., 2016. Executive overconfidence and compensation structure. *Journal of Financial Economics*, 119(3), 533-558.
Hutton, A. P., Marcus, A. J., Tehranian, H., 2009. Opaque financial reports, R^2, and crash risk. *Journal of Financial Economics*, 94(1), 67-86.
Jeffers, J. S., 2017. The impact of restricting labor mobility on corporate investment and entrepreneurship. *Working Paper, University of Chicago*.
Jia, N., 2018. Tournament incentives and stock price crash risk. *Accounting Horizons*, 32(3), 101-121.
Jin, L., Myers, S., 2006. R^2 around the world: New theory and new tests. *Journal of Financial Economics*, 79(2), 257–292.
Karlsson, P. O., Neilson, G. L., 2009. CEO succession 2008: Stability in the storm. *Strategy+ Business*, 55, 59-69.
Kasznik, R., Lev, B., 1995. To warn or not to warn: Management disclosures in the face of an earnings surprise. *Accounting Review*, 70(1), 113-134.
Kedia, S., Philippon, T., 2009. The economics of fraudulent accounting. *Review of Financial Studies*, 22(6), 2169–2199.
Khan, M., Watts, R. L., 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics*, 48(2-3), 132-150.
Khurana, I. K., Pereira, R., Zhang, E. X., 2018. Is real earnings smoothing harmful? Evidence from firm-specific stock price crash risk. *Contemporary Accounting Research*, 35(1), 558–587
Kim, J. B., Li, L., Lu, L. Y., Yu, Y., 2016. Financial statement comparability and expected crash risk. *Journal of Accounting and Economics*, 61(2), 294-312.
Kim, J. B., Lu, L. Y., Yu, Y., 2019. Analyst coverage and expected crash risk: Evidence from exogenous changes in analyst coverage. *Accounting Review*, 94(4), 345-364.
Kim, J. B., Zhang, L., 2014. Financial reporting opacity and expected crash risk: Evidence from implied volatility smirks. *Contemporary Accounting Research*, 31(3), 851-875.
Kim, J., Li, Y., Zhang, L., 2011. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, 101(3), 713–730.
Kim, Y., Li, H., Li, S., 2014. Corporate social responsibility and stock price crash risk. *Journal of Banking and Finance*, 43, 1-13.
Kini, O., Williams, R., 2012. Tournament incentives, firm risk, and corporate policies. *Journal of Financial Economics*, 103(2), 350-376.
Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2), 665-712.

Kothari, S. P., Lewellen, J., Warner, J. B., 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics*, 79(3), 537-568.
Kothari, S. P., Shu, S., Wysocki, P. D., 2009. Do managers withhold bad news? *Journal of Accounting Research*, 47(1), 241-276.
Kubick, T., Lockhart, G., 2016. Do external labor market incentives motivate CEOs to adopt more aggressive corporate tax reporting preferences? *Journal of Corporate Finance*, 36, 255-277.
Li, Y., Zeng, Y., 2019. The impact of top executive gender on asset prices: Evidence from stock price crash risk. *Journal of Corporate Finance*, 58, 528-550.
McNichols, M. F., 2002. Discussion of the Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *Accounting Review*, 77 (s1), 61-69.
McNichols, M., Stubben, S., 2008. Does earnings management affect firms' investment decisions? *Accounting Review*, 83(6), 1571–1603.
Myers, J. N., Myers, L. A., Skinner, D. J., 2007. Earnings momentum and earnings management. *Journal of Accounting, Auditing and Finance*, 22(2), 249-284.
Parrino, R., 1997. CEO turnover and outside succession a cross-sectional analysis. *Journal of Financial Economics*, 46(2), 165-197.
Richardson, S., 2006. Over-investment of free cash flow. *Review of Accounting Studies*, 11(2-3): 159–89.
Richardson, S., Sloan, R. G., Soliman, M. T., Tuna, I., 2006. The implications of accounting distortions and growth for accruals and profitability. *Accounting Review*, 81(3), 713-743.
Roberts, M. R., Whited, T. M., 2013. Endogeneity in empirical corporate finance. In Handbook of the Economics of Finance (Vol. 2, pp. 493-572). Elsevier.
Roychowdhury, S., 2006. Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), 335-370.
Skinner, D. J., 1994. Why firms voluntarily disclose bad news. *Journal of Accounting Research*, 32(1), 38-60.
Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings?. *Accounting Review*, 71(3), 289-315.
Stein, J. C., 1988. Takeover threats and managerial myopia. *Journal of Political Economy*, 96(1), 61-80.
Stein, J. C., 1989. Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *Quarterly Journal of Economics*, 104(4), 655-669.
Verrecchia, R. E., 2001. Essays on disclosure. *Journal of Accounting and Economics*, 32(1), 97-180.
Yu, F. F., 2008. Analyst coverage and earnings management. *Journal of Financial Economics*, 88(2), 245-271.
Zhu, W., 2016. Accruals and price crashes. *Review of Accounting Studies*, 21(2), 349-399.

Table 1
Summary statistics and correlation matrix

This table reports descriptive statistics of the variables, year and industry distribution, and correlation matrix. Panel A shows the distribution of the variables with mean (column 2), standard deviation (column 3), first quartile (column 4), median (column 5), and third quartile (column 6). Panel B reports year and industry distribution of the key variables of interest. Panel C provides Pearson pair-wise correlation coefficients for the selected variables of interest. Bold values in Panel C indicate correlation coefficients significant at 5% level or better. Appendix A.1 includes variable definitions.

Panel A: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Obs.	Mean	Std.Dev.	1st Quartile	Median	3rd Quartile
Panel A.1: Crash risk propensity proxies						
$NCSKEW_t$	16,763	0.0801	1.0240	-0.5655	0.0153	0.6544
$DUVOL_t$	16,763	-0.0150	0.3793	-0.2698	-0.0259	0.2195
Panel A.2: Other variables						
$CITI_{t-1}$	16,763	8.1816	3.1694	7.9385	8.6816	9.4633
$FIRMAGE_{t-1}$	16,763	27.7778	16.4638	14.0000	23.0000	42.0000
$CEOAGE_{t-1}$	16,763	55.6115	7.2875	51.0000	56.0000	60.0000
$TENURE_{t-1}$	16,763	7.5274	7.6117	2.0000	5.0000	10.0000
$OPAQUE_{t-1}$	16,763	0.2226	0.1636	0.1155	0.1794	0.2771
$RETURN_{t-1}$	16,763	-0.0802	0.7083	-0.4534	-0.0686	0.3165
$SIGMA_{t-1}$	16,763	0.0494	0.0252	0.0314	0.0435	0.0607
$DTURN_{t-1}$	16,763	0.0040	0.0738	-0.0199	0.0029	0.0275
RD_{t-1}	16,763	0.0326	0.0549	0.0000	0.0021	0.0443
$SEGMENT_{t-1}$	16,763	14.7913	9.4737	6.0000	14.0000	21.0000
ROA_t	16,763	0.0439	0.0988	0.0209	0.0519	0.0892
$SIZE_{t-1}$	16,763	7.3851	1.5670	6.2826	7.2548	8.4027
MB_{t-1}	16,763	3.0360	3.1570	1.4816	2.2234	3.5637
$LEVERAGE_{t-1}$	16,763	0.1819	0.1632	0.0188	0.1653	0.2855
$INDUSTRYHOM_{t-1}$	16,763	0.2281	0.1218	0.1271	0.1854	0.3229

Panel B: Year and industry distribution of CITI and crash risk propensity

Panel B.1: Year distribution

Year	(1) Number of observations	(2) Percentage	(3) Mean CITI	(4) Mean NCSKEW	(5) Mean DUVOL
1994	367	2.19%	6.6905	0.0200	-0.0376
1995	476	2.84%	7.1422	0.2440	-0.0360
1996	536	3.20%	7.1932	0.0178	-0.1049
1997	540	3.22%	7.7566	0.2441	-0.0236
1998	575	3.43%	8.0401	0.1679	-0.0723
1999	592	3.53%	8.0502	0.2218	-0.0514
2000	603	3.60%	8.3688	-0.0510	-0.0209
2001	686	4.09%	8.7590	-0.0631	0.0401
2002	733	4.37%	8.6964	0.1590	0.1028
2003	748	4.46%	8.3891	0.0675	-0.0142
2004	801	4.78%	8.2434	0.0400	-0.0141
2005	774	4.62%	8.2916	0.1536	0.0018
2006	792	4.72%	8.3929	0.0935	-0.0327
2007	804	4.80%	8.1967	0.0718	-0.0509
2008	947	5.65%	8.4221	0.0114	0.0189
2009	970	5.79%	8.3966	-0.0198	-0.0435
2010	992	5.92%	8.1822	-0.0213	-0.0301
2011	970	5.79%	8.1011	0.0314	-0.0266
2012	989	5.90%	8.2090	0.2436	0.0570
2013	975	5.82%	8.2635	0.0834	0.0030
2014	989	5.90%	8.2520	0.0591	-0.0462
2015	904	5.39%	8.2573	0.1018	-0.0185
Total	16,763	100%			

Panel B.2: Industry distribution

Industry	(1) Number of observations	(2) Percentage	(3) Mean CITI	(4) Mean NCSKEW	(5) Mean DUVOL
Business Services	1,932	11.53%	9.7992	0.0974	-0.0035
Electronic Equipment	1,395	8.32%	9.0046	0.0937	-0.0137
Retail	1,271	7.58%	9.0705	0.1646	0.0286
Machinery	881	5.26%	8.2150	0.0138	-0.0270
Petroleum and Natural Gas	819	4.89%	8.9617	0.0816	0.0080
Pharmaceutical Products	747	4.46%	8.5213	0.0522	-0.0168
Computers	679	4.05%	8.7661	0.1557	0.0090
Wholesale	653	3.90%	8.2248	0.0965	0.0000
Chemicals	651	3.88%	7.6426	0.1288	-0.0021
Transportation	559	3.33%	8.0298	0.0275	-0.0264
Other industries	7,176	42.81%	4.2585	0.0695	-0.0372
Total	16,763	100%			

Panel C: Correlation matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	NCSKEW$_{t}$	1.0000																
(2)	DUVOL$_{t}$	**0.9044**	1.0000															
(3)	CITI$_{t-1}$	**-0.0206**	-0.0070	1.0000														
(4)	FIRMAGE$_{t-1}$	-0.0072	-0.0087	**-0.0519**	1.0000													
(5)	CEOAGE$_{t-1}$	0.0060	-0.0016	**-0.0336**	**0.1560**	1.0000												
(6)	TENURE$_{t-1}$	-0.0017	-0.0006	-0.0037	**-0.1259**	**0.4367**	1.0000											
(7)	OPAQUE$_{t-1}$	0.0061	0.0044	**0.0284**	**-0.2825**	**-0.1153**	-0.0053	1.0000										
(8)	RETURN$_{t-1}$	**0.0772**	**0.1140**	-0.0029	0.0002	**-0.0178**	-0.0094	**0.0182**	1.0000									
(9)	SIGMA$_{t-1}$	**-0.0459**	**-0.0193**	**0.0544**	**-0.3729**	**-0.1151**	**0.0339**	**0.2965**	**-0.0735**	1.0000								
(10)	DTURN$_{t-1}$	**0.0187**	**0.0193**	0.0146	-0.0033	-0.0056	0.0056	**-0.0546**	0.0056	**0.1559**	1.0000							
(11)	RD$_{t-1}$	**-0.0172**	**-0.0219**	**0.0473**	**-0.2271**	**-0.1210**	0.0116	**0.2473**	-0.0126	**0.2654**	**-0.0421**	1.0000						
(12)	SEGMENT$_{t-1}$	-0.0076	**0.0328**	0.0115	**0.2686**	**0.0336**	**-0.0509**	**-0.0780**	**0.0519**	**-0.0898**	-0.0139	**0.0265**	1.0000					
(13)	ROA$_{t}$	**-0.0840**	-0.0103	**-0.0161**	**0.0515**	**0.0262**	**0.0410**	**-0.0861**	**0.2566**	**-0.2954**	**0.0298**	**-0.1682**	**0.0228**	1.0000				
(14)	SIZE$_{t-1}$	**0.0467**	**0.0554**	0.0126	**0.3465**	**0.0427**	**-0.0909**	**-0.1498**	**0.1538**	**-0.4570**	**0.0493**	**-0.0688**	**0.2496**	**0.2729**	1.0000			
(15)	MB$_{t-1}$	**0.0307**	**0.0380**	**-0.0270**	**-0.0585**	**-0.0650**	-0.0044	**0.0890**	**0.1921**	**-0.0482**	**0.0627**	**0.1623**	**-0.0418**	**0.2195**	**0.2799**	1.0000		
(16)	LEVERAGE$_{t-1}$	**-0.0235**	**-0.0258**	**-0.0554**	**0.1765**	**0.0424**	**-0.0744**	**-0.0896**	**-0.0513**	**-0.0505**	**0.0172**	**-0.2625**	-0.0056	**-0.1260**	**0.0729**	**-0.0625**	1.0000	
(17)	INDUSTRYHOM$_{t-1}$	-0.0063	-0.0007	**-0.0607**	**0.1898**	**0.0664**	**-0.0381**	**-0.0648**	-0.0019	**-0.0915**	**0.0296**	**-0.4107**	**-0.0639**	-0.0086	**0.0935**	**-0.1379**	**0.2148**	1.0000

Table 2
Effect of CITI on the propensity of stock price crashes

This table shows the impact of a CEO's industry tournament incentives (CITI) on the propensity of firm-level future stock price crash risk. Columns (1) and (2) report pooled ordinary least squares (OLS) regression results with $NCSKEW_t$ and $DUVOL_t$ as the dependent variables, respectively. Columns (3) and (4) present firm-fixed effects regression results. Columns (5) and (6) show regression results with CEO-fixed effects. $CITI_{t-1}$ is the independent variable of interest in these models. Appendix A.1 includes variable descriptions. Industry dummies capture Fama-French 48 industry classification fixed effects. Year dummies capture time fixed effects. Firm FE and CEO FE indicate firm and CEO fixed effects, respectively. Figures in parenthesis are standard errors robust to heteroskedasticity and clustered at the firm level for columns (1) through (4) and at the CEO level for columns (5) and (6). Superscripts *, **, and, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	Industry-Year FE		Firm-Year FE		CEO-Year FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
$CITI_{t-1}$	-0.0089***	-0.0034***	-0.0089***	-0.0037***	-0.0070**	-0.0030**
	(0.0026)	(0.0010)	(0.0029)	(0.0011)	(0.0031)	(0.0012)
$FIRMAGE_{t-1}$	-0.0020***	-0.0006**	-0.0326***	-0.0088***	-0.0062	-0.0008
	(0.0006)	(0.0002)	(0.0038)	(0.0014)	(0.0072)	(0.0025)
$CEOAGE_{t-1}$	-0.0006	-0.0004	-0.0009	-0.0005	0.0001	-0.0000
	(0.0013)	(0.0005)	(0.0023)	(0.0009)	(0.0060)	(0.0023)
$TENURE_{t-1}$	0.0003	0.0002	-0.0027	-0.0003	-0.0044	-0.0007
	(0.0012)	(0.0005)	(0.0022)	(0.0008)	(0.0059)	(0.0022)
$OPAQUE_{t-1}$	0.0790	0.0072	0.1059	0.0156	0.1001	0.0163
	(0.0544)	(0.0203)	(0.0741)	(0.0272)	(0.0866)	(0.0318)
$RETURN_{t-1}$	0.2159***	0.0748***	0.1016***	0.0302***	0.0632***	0.0095
	(0.0147)	(0.0055)	(0.0155)	(0.0058)	(0.0166)	(0.0061)
$SIGMA_{t-1}$	-3.1341***	-0.7532***	-2.9611***	-0.8489***	-3.0064***	-0.8578***
	(0.4457)	(0.1724)	(0.5760)	(0.2191)	(0.6769)	(0.2540)
$DTURN_{t-1}$	0.4474***	0.1108**	0.3083***	0.0879*	0.3091**	0.0881*
	(0.1131)	(0.0431)	(0.1184)	(0.0451)	(0.1250)	(0.0472)
RD_{t-1}	-1.0805***	-0.3113***	0.4232	0.0755	0.3597	0.1142
	(0.2211)	(0.0821)	(0.5023)	(0.1896)	(0.5716)	(0.2231)
$SEGMENT_{t-1}$	0.0010	0.0006	0.0042**	0.0019**	0.0069***	0.0027***
	(0.0010)	(0.0004)	(0.0020)	(0.0008)	(0.0026)	(0.0010)
ROA_t	-1.7748***	-0.2744***	-2.2790***	-0.4191***	-2.2578***	-0.4177***
	(0.1094)	(0.0384)	(0.1405)	(0.0491)	(0.1430)	(0.0525)
$SIZE_{t-1}$	0.0332***	0.0090***	0.4541***	0.1055***	0.5575***	0.1303***
	(0.0067)	(0.0026)	(0.0218)	(0.0080)	(0.0269)	(0.0099)
MB_{t-1}	0.0076**	0.0020*	0.0010	0.0007	-0.0013	-0.0012
	(0.0032)	(0.0011)	(0.0040)	(0.0014)	(0.0042)	(0.0015)
$LEVERAGE_{t-1}$	-0.2376***	-0.0539**	0.2067**	0.0493	0.1338	0.0188
	(0.0590)	(0.0217)	(0.1022)	(0.0374)	(0.1240)	(0.0458)
$INDUSTRYHOM_{t-1}$	-0.2959	-0.0624	-1.1077**	-0.1972	0.2455	0.1263
	(0.1832)	(0.0694)	(0.5281)	(0.1982)	(0.6625)	(0.2281)
$FINALYR_t$	0.1553***	0.0442***	0.1384***	0.0395***	0.1406***	0.0350***
	(0.0268)	(0.0099)	(0.0277)	(0.0104)	(0.0311)	(0.0117)
$NCSKEW_{t-1}$	0.0622***	0.0184***	-0.0507***	-0.0263***	-0.1205***	-0.0538***
	(0.0108)	(0.0039)	(0.0112)	(0.0041)	(0.0117)	(0.0043)
Constant	0.1637	-0.0212	-1.8946***	-0.4367***	-3.3022***	-0.8124***
	(0.3170)	(0.0897)	(0.2313)	(0.0874)	(0.3802)	(0.1404)
Industry FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
CEO FE	No	No	No	No	Yes	Yes
R^2	0.0505	0.0400	0.0970	0.0569	0.1152	0.0708
No. of observations	16,763	16,763	16,763	16,763	16,761	16,761

Table 3
Propensity score matching (PSM)

This table presents regression estimates of the baseline model using propensity score matching (PSM) regression technique. Column (1) shows the first-stage logit model and columns (2) and (3) present the second-stage OLS with the matched sample where $NCSKEW_t$ and $DUVOL_t$ are the dependent variables. $HIGHCITI_{t-1}$ is a dummy variable equal to one if a firm's $CITI_{t-1}$ is in the top two quartiles of the specific Fama-French 48 industry during the year and otherwise $HIGHCITI_{t-1}$ is set to zero. Appendix A.1 shows definitions of all variables. Industry dummies capture Fama-French 48 industry group fixed effects. Year dummies capture time fixed effects. Figures with parentheses are standard errors robust to heteroskedasticity and clustered at the firm level. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	$HIGHCITI_{t-1}$	CRASH RISK	
Explanatory variables	(1)	(2)	(3)
	First-stage Logit	Second-stage PSM	Second-stage PSM
		$NCSKEW_t$	$DUVOL_t$
$HIGHCITI_{t-1}$		-0.0471***	-0.0102*
		(0.0161)	(0.0062)
$FIRMAGE_{t-1}$	0.0059***	-0.0017***	-0.0005**
	(0.0013)	(0.0006)	(0.0002)
$CEOAGE_{t-1}$	0.0029	-0.0005	-0.0003
	(0.0027)	(0.0013)	(0.0005)
$TENURE_{t-1}$	-0.0003	0.0004	0.0002
	(0.0025)	(0.0012)	(0.0005)
$OPAQUE_{t-1}$	0.0735	0.0921	0.0155
	(0.1180)	(0.0564)	(0.0210)
$RETURN_{t-1}$	-0.0878***	0.2202***	0.0775***
	(0.0321)	(0.0154)	(0.0057)
$SIGMA_{t-1}$	-3.6687***	-2.7722***	-0.5931***
	(1.0393)	(0.4662)	(0.1809)
$DTURN_{t-1}$	0.2892	0.4164***	0.1009**
	(0.2471)	(0.1152)	(0.0439)
RD_{t-1}	-5.0446***	-0.8741***	-0.2336***
	(0.4600)	(0.2292)	(0.0872)
$SEGMENT_{t-1}$	0.0066***	0.0009	0.0006
	(0.0024)	(0.0010)	(0.0004)
ROA_t	-0.5203**	-1.8732***	-0.2958***
	(0.2070)	(0.1166)	(0.0411)
$SIZE_{t-1}$	0.4530***	0.0301***	0.0078***
	(0.0151)	(0.0071)	(0.0028)
MB_{t-1}	-0.0490***	0.0103***	0.0026**
	(0.0063)	(0.0032)	(0.0011)
$LEVERAGE_{t-1}$	1.0325***	-0.2389***	-0.0550**
	(0.1164)	(0.0598)	(0.0219)
$INDUSTRYHOM_{t-1}$	-0.9372**	-0.2609	-0.0521
	(0.3856)	(0.1862)	(0.0699)
$FINALYR_t$	-0.0599	0.1509***	0.0436***
	(0.0541)	(0.0273)	(0.0101)
$NCSKEW_{t-1}$	0.0231	0.0608***	0.0181***
	(0.0209)	(0.0110)	(0.0040)
Constant	-4.5692***	0.7684***	0.0665
	(1.0948)	(0.1122)	(0.0420)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2/Pseudo R^2	0.0976	0.0486	0.0387
No. of observations	16,752	16,180	16,180

Table 4
Quasi-natural experiment

This table presents difference-in-differences (DiD) estimates using the change in non-competition agreement enforceability as a source of a quasi-natural experiment in Panel A. $CITI_{t-1}$ is a CEO's industry tournament incentives. In column (1), SHOCK TX is a dummy variable with the value of negative one if firms are headquartered in Texas from 1995 to onwards, otherwise zero. In column (2) SHOCK LA is an indicator variable with the value of negative one if firms are headquartered in Louisiana in the year 2002 and 2003, with the value of one for the firms headquartered in Louisiana from 2004 onwards, otherwise zero. In column (3), SHOCK FL is a dummy variable with the value of one if the firms are headquartered in Florida from 1997 to onwards, otherwise zero. In column (4), NEG SHOCK is a dummy variable with the value of negative one if firms are headquartered in Texas from 1995 to onwards and in Louisiana in the year 2002 and 2003, otherwise zero. In column (5), POS SHOCK is a dummy variable with the value of one if firms are headquartered in Louisiana during 2004 onwards and in Florida during 1997 onwards, otherwise zero. In Panel B, we test the parallel trend assumption of the DiD analyses. Control variables include all baseline controls, STATE UNEMP (indicating unemployment rate of the states), and LOG STATE INC (the natural logarithm of per capita personal income in the states) in Panels A and B, and additionally the time trend dummies in Panel B (SHOCK TX_{Before}, SHOCK LA_{Before}, SHOCK FL_{Before}, NEG $SHOCK_{Before}$, POS $SHOCK_{Before}$) in columns (1) through (5), respectively. Appendix A.1 shows definitions of all variables. Industry and Year dummies capture industry and time fixed effects. Figures with parentheses are standard errors robust to heteroskedasticity and clustered at the state level. All models include a constant. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: DiD analyses					
			$NCSKEW_t$		
Explanatory variables	(1) TEXAS	(2) LOUISIANA	(3) FLORIDA	(4) Negative shocks	(5) Positive shocks
$CITI_{t-1}$	-0.0108***	-0.0102***	-0.0098***	-0.0098***	-0.0096***
	(0.0022)	(0.0021)	(0.0022)	(0.0024)	(0.0021)
SHOCK TX	0.1255***				
	(0.0238)				
SHOCK TX × $CITI_{t-1}$	-0.0139***				
	(0.0023)				
SHOCK LA		0.1353***			
		(0.0478)			
SHOCK LA × $CITI_{t-1}$		-0.0319***			
		(0.0039)			
SHOCK FL			-0.1194***		
			(0.0281)		
SHOCK FL × $CITI_{t-1}$			0.0177***		
			(0.0029)		
NEG SHOCK				0.1112***	
				(0.0262)	
NEG SHOCK × $CITI_{t-1}$				-0.0126***	
				(0.0024)	
POS SHOCK					-0.0980***
					(0.0315)
POS SHOCK × $CITI_{t-1}$					0.0135**
					(0.0052)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0510	0.0516	0.0527	0.0510	0.0510
No. of observations	15,850	14,259	14,698	16,551	16,551

Panel B: Test of parallel trend					
			$NCSKEW_t$		
Explanatory variables	(1) TEXAS	(2) LOUISIANA	(3) FLORIDA	(4) Negative shocks	(5) Positive shocks
$CITI_{t-1}$	-0.0107***	-0.0096***	-0.0098***	-0.0089***	-0.0096***
	(0.0022)	(0.0021)	(0.0022)	(0.0024)	(0.0021)
SHOCK TX_{Before} × $CITI_{t-1}$	0.0021				
	(0.0100)				
SHOCK TX × $CITI_{t-1}$	-0.0138***				
	(0.0022)				
SHOCK LA_{Before} × $CITI_{t-1}$		0.0133			
		(0.0101)			
SHOCK LA × $CITI_{t-1}$		-0.0325***			
		(0.0039)			
SHOCK FL_{Before} × $CITI_{t-1}$			0.0019		
			(0.0125)		
SHOCK FL × $CITI_{t-1}$			0.0178***		
			(0.0029)		
NEG $SHOCK_{Before}$ × $CITI_{t-1}$				0.0093	
				(0.0069)	
NEG SHOCK × $CITI_{t-1}$				-0.0098**	
				(0.0043)	
POS $SHOCK_{Before}$ × $CITI_{t-1}$					0.0002
					(0.0097)
POS SHOCK × $CITI_{t-1}$					0.0135**
					(0.0052)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0510	0.0519	0.0527	0.0511	0.0510
No. of observations	15,850	14,259	14,698	16,551	16,551

Table 5
Generalised method of moments (GMM) estimation

This table reports regression estimates using generalised method of moments (GMM) instrumental variables (IV) method. Columns (1) – (6) show second-stage of the regression estimates with the dependent variables $NCSKEW_t$ and $DUVOL_t$. $CITI_{t-1}$ is a CEO's industry tournament incentives. Appendix A.1 shows definitions of all variables. $GEOCOMP250_{t-1}$ and $INDCEOCOMP_{t-1}$ are the two instrumental variables used in the first stages of columns (1) – (6). $GEOCOMP250_{t-1}$ is the natural logarithm of the average CEO compensation of firms in other industries with headquarters within 250 kilometres of the firm. $INDCEOCOMP_{t-1}$ is the natural logarithm of the total compensation received by the CEOs in the same size adjusted industry group excluding the firm's CEO and the second-highest paid CEO in the industry. Industry dummies capture Fama-French 48 industry group fixed effects. Year dummies capture time fixed effects. Firm FE and CEO FE indicate firm and CEO fixed effects, respectively. Figures with parentheses are standard errors robust to heteroscedasticity. Standard errors in columns (5) and (6) are clustered at the CEO level. All other models have standard errors clustered at the firm level. All models include a constant. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Industry-Year FE		Firm-Year FE		CEO-Year FE	
Explanatory variables	(1) $NCSKEW_t$	(2) $DUVOL_t$	(3) $NCSKEW_t$	(4) $DUVOL_t$	(5) $NCSKEW_t$	(6) $DUVOL_t$
$CITI_{t-1}$	-0.0290***	-0.0093**	-0.0384***	-0.0148***	-0.0308**	-0.0121**
	(0.0094)	(0.0036)	(0.0125)	(0.0048)	(0.0145)	(0.0055)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
CEO FE	No	No	No	No	Yes	Yes
R^2	0.0469	0.0357	0.0809	0.0435	0.1062	0.0621
No. of observations	10,705	10,705	10,656	10,656	10,363	10,363
Model diagnostics:						
Test of endogeneity						
Hausman test	5.820**	3.361*	7.283***	6.507**	3.726*	3.565*
Under identification test						
Kleibergen-Paap rk LM statistic	279.905***	279.905***	190.255***	190.255***	180.316***	180.316***
Weak identification test						
Kleibergen-Paap rk Wald F statistic	268.896***	268.896***	191.508***	191.508***	149.325***	149.325***
Over identification test						
Hansen J statistic	0.283	0.053	1.822	0.336	1.076	0.431

Table 6
Tests of bad news hoarding

This table reports regression estimates of the tests of bad news hoarding. Columns (1) and (2) provide the direct tests. Specifically, column (1) shows the regression estimates with the dependent variable Break of earnings string. Column (2) presents the regression estimates with Sudden release of bad news as the dependent variable. Columns (3) through (6) report indirect tests of bad news hoarding. Columns (3) and (4) show regression estimates with accruals earnings management as the dependent variable. Columns (5) and (6) report estimations with real earnings management. $CITI_{t-1}$ is a CEO's industry tournament incentives. Appendix A.1 shows definitions of all variables. Industry dummies capture Fama-French 48 industry group fixed effects. Year dummies capture time fixed effects. Figures with parentheses are standard errors robust to heteroscedasticity and clustered at the firm level. All models include a constant. Superscripts *, **, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Direct tests		Indirect tests			
			Accruals earnings management		Real earnings management	
Explanatory variables	(1) Break of earnings string	(2) Sudden release of bad news	(3) Discretionary accruals (Hutton et al., 2009)	(4) Discretionary accruals (Dechow and Dichev, 2002)	(5) Overproduction	(6) Abnormal discretionary expenditure
$CITI_{t-1}$	-0.0021*	-0.0173*	-0.0012*	-0.0022**	-0.0020**	-0.0054*
	(0.0013)	(0.0098)	(0.0007)	(0.0009)	(0.0010)	(0.0031)
$SIZE_{t-1}$	-0.0045*	-0.2586***	-0.0120***	-0.0010	0.0070*	0.0495***
	(0.0027)	(0.0232)	(0.0020)	(0.0035)	(0.0042)	(0.0106)
$ZSCORE_{t-1}$	-0.0007	-0.0481***	0.0009	0.0001	-0.0011	0.0002
	(0.0006)	(0.0155)	(0.0006)	(0.0016)	(0.0011)	(0.0029)
ROA_{t-1}	0.1935***	3.6553***	-0.1450***	-1.7907***	-0.8523***	-0.3502
	(0.0476)	(0.6737)	(0.0446)	(0.1216)	(0.1070)	(0.2525)
MB_{t-1}	0.0021*	-0.0316**	0.0057***	-0.0068***	-0.0087***	-0.0156***
	(0.0012)	(0.0131)	(0.0010)	(0.0019)	(0.0024)	(0.0057)
$LEVERAGE_{t-1}$	-0.0441*	0.8068***	-0.0269	0.1755***	0.0156	0.1005
	(0.0249)	(0.1835)	(0.0178)	(0.0382)	(0.0431)	(0.0965)
$LOSS_{t-1}$	-0.0314***	-0.0163	0.0516***	-0.0654***	-0.0585***	-0.0397
	(0.0088)	(0.0996)	(0.0074)	(0.0180)	(0.0226)	(0.0501)
$SALEGR_{t-1}$	0.0033	0.0351**	0.0083	0.0213**	0.0156**	0.0281
	(0.0020)	(0.0157)	(0.0058)	(0.0092)	(0.0063)	(0.0197)
$EXTRA_{t-1}$	0.0099	0.2899***	-0.0132**	-0.0137	0.0131	0.0254
	(0.0122)	(0.0998)	(0.0060)	(0.0117)	(0.0186)	(0.0514)
$SEGMENT_{t-1}$	0.0003	0.0011	-0.0012***	0.0016***	-0.0013	-0.0009
	(0.0005)	(0.0037)	(0.0003)	(0.0006)	(0.0008)	(0.0019)
RD_{t-1}	-0.0258	1.0140	0.4211***	0.5848***	-1.0142***	-2.1124***
	(0.0849)	(0.7328)	(0.0796)	(0.1773)	(0.2199)	(0.4105)
$FINALYR_t$	0.0461***	0.4053***	0.0081*	0.0072	0.0045	-0.0037
	(0.0124)	(0.0687)	(0.0042)	(0.0100)	(0.0108)	(0.0386)
Constant	-0.0363	-0.7880**	0.4673***	-0.7754***	-0.0317	-0.4357***
	(0.0253)	(0.3168)	(0.1627)	(0.0971)	(0.0549)	(0.1318)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.0129	0.1513	0.2519	0.7864	0.0679	0.1018
No. of observations	16,418	16,269	16,386	14,833	16,241	14,672

Table 7
Cross-section analysis

This table reports regression estimates with the cross-section variations. Panel A shows the impact of $CITI_{t-1}$ on future crash risk propensity for the firms with low- and high-quality information environment. Panel B reports CITI's effect on future crash risk propensity at the presence of low and high external monitoring. $CITI_{t-1}$ is a CEO's industry tournament incentives. Appendix A.1 shows definitions of all variables. Industry dummies capture Fama-French 48 industry group fixed effects. Year dummies capture time fixed effects. Figures with parentheses are standard errors robust to heteroscedasticity and clustered at the firm level. All models include a constant. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Information environment quality				
	$NCSKEW_t$		$DUVOL_t$	
Explanatory variables	(1)	(2)	(3)	(4)
	Low quality	High quality	Low quality	High quality
$CITI_{t-1}$	-0.0175***	-0.0008	-0.0067***	-0.0013
	(0.0055)	(0.0051)	(0.0021)	(0.0020)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0740	0.0614	0.0611	0.0536
No. of observations	4,190	4,191	4,190	4,191
Difference				
H_0: The coefficients on $CITI_{t-1}$ in low and high groups are equal				
$CITI_{t-1}$ (Low – High)	-0.0167**		-0.0054*	
Prob > chi2	0.0258		0.0525	

Panel B: External monitoring by analysts				
	$NCSKEW_t$		$DUVOL_t$	
Explanatory variables	(1)	(2)	(3)	(4)
	Low monitoring	High monitoring	Low monitoring	High monitoring
$CITI_{t-1}$	-0.0202***	-0.0030	-0.0072***	-0.0012
	(0.0069)	(0.0041)	(0.0025)	(0.0016)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0969	0.0433	0.0709	0.0494
No. of observations	4,691	3,941	4,691	3,941
Difference				
H_0: The coefficients on $CITI_{t-1}$ in low and high groups are equal				
$CITI_{t-1}$ (Low – High)	-0.0172**		-0.0060**	
Prob > chi2	0.0306		0.0380	

Panel C: External monitoring by institutional shareholders				
	$NCSKEW_t$		$DUVOL_t$	
Explanatory variables	(1)	(2)	(3)	(4)
	Low monitoring	High monitoring	Low monitoring	High monitoring
$CITI_{t-1}$	-0.0187***	-0.0015	-0.0086***	0.0008
	(0.0060)	(0.0051)	(0.0022)	(0.0019)
Control variables	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.0934	0.0569	0.0772	0.0477
No. of observations	4,183	4,182	4,183	4,182
Difference				
H_0: The coefficients on $CITI_{t-1}$ in low and high groups are equal				
$CITI_{t-1}$ (Low – High)	-0.0172**		-0.0094***	
Prob > chi2	0.0276		0.0011	

Table 8
Additional control variables

This table shows pooled ordinary least squares (OLS) regression estimates of the impact of CITI on the propensity of future stock price crash risk after controlling for additional executive incentives and firm-specific characteristics. In column (1), we report regression estimates after controlling for CEO and CFO equity-based incentives. In column (2), we show regression estimates after using some additional CEO and CFO related controls. In columns (3) and (4), we additionally control for corporate governance and firm-level inherent riskiness. Column (5) shows regression estimates combining all controls from columns (1) through (4). Appendix A.1 shows definitions of all variables. Industry FE captures Fama and French 48 industry group fixed effects. Year FE captures time fixed effects. Figures with parentheses are standard errors robust to heteroskedasticity and clustered at the firm level. All models include a constant. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

			$NCSKEW_t$		
Explanatory variables	(1) CEO and CFO equity-based incentives	(2) CEO and CFO related other controls	(3) Corporate governance and monitoring	(4) Higher pressure and inherent riskiness	(5) All combined
$CITI_{t-1}$	-0.0106***	-0.0128***	-0.0123***	-0.0160***	-0.0269**
	(0.0032)	(0.0042)	(0.0032)	(0.0052)	(0.0117)
$CEOOPT_{t-1}$	0.0360				-0.0443
	(0.0691)				(0.2521)
$CEOSTK_{t-1}$	0.0350				-0.0837
	(0.0435)				(0.1574)
$CFOOPT_{t-1}$	-0.0799*				0.2475
	(0.0450)				(0.3988)
$CFOSTK_{t-1}$	-0.0696				-0.0786
	(0.0720)				(0.2412)
CG_{t-1}			-0.5531**		0.1963
			(0.2268)		(0.5568)
IG_{t-1}			-0.0021		0.0216
			(0.0034)		(0.0338)
$INSTD_{t-1}$			0.0030***		1.4215**
			(0.0003)		(0.6837)
$CSCORE_{t-1}$			0.0903		-0.1157
			(0.0840)		(0.2499)
$PAYGAP_{t-1}$		0.0012			-0.0630
		(0.0129)			(0.0437)
$CFOITI_{t-1}$		-0.0045			0.0010
		(0.0037)			(0.0073)
$POWER_{t-1}$		-0.0049			-0.0040
		(0.0090)			(0.0256)
$CEOFEMALE_{t-1}$		0.0870			-0.1832
		(0.0727)			(0.2190)
$CFOFEMALE_{t-1}$		-0.0332			0.0694
		(0.0412)			(0.1328)
$CEODUAL_{t-1}$		-0.0230			-0.0659
		(0.0285)			(0.0823)
$INNOVATION_{t-1}$				-0.0075	-0.0125
				(0.0123)	(0.0209)
DD_{t-1}				-0.0001	-0.0033
				(0.0013)	(0.0022)
$FLUIDITY_{t-1}$				0.0038	-0.0032
				(0.0072)	(0.0126)
Baseline control variables	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.0557	0.0569	0.0625	0.0816	0.1478
No. of observations	11,698	10,898	10,047	3,287	1,135

Appendix A.1

Variable definitions

This table shows the definition of variables used in the empirical models. Variable names and definitions are presented in columns (1) and (2), respectively.

Variables	Definition
Panel A: Propensity of stock price crash risk proxies	
NCSKEW	The ratio of the negative of the third moment for each firm's firm-specific weekly returns during the fiscal year to the standard deviations of firm-specific weekly returns raised to the power of three. Source: CRSP.
DUVOL	The natural logarithm of the ratio of the standard deviations of the "down" and "up" weeks. A "down" ("up") week is the week with firm-specific weekly returns lower (higher) than the annual average. Source: CRSP.
COUNT	The difference between the number of downside and upside frequencies for each firm i during year t. We define a downside (upside) frequency when $W_{i,w}$ is 3.09 standard deviations below (above) the annual mean. Source: CRSP.
EXTRASIG	The ratio of the negative of the worst deviation between firm-specific and average firm-specific weekly returns to the standard deviation of the firm-specific weekly returns during the fiscal year. Source: CRSP.
Panel B: Industry tournament proxies	
CITI	Measured as the natural logarithm of the difference between the total compensation (TDC1) of the second highest paid CEO in the same size adjusted Fama-French 48 industry group and the total compensation (TDC1) of the firm's CEO. Source: ExecuComp.
HIGHCITI	A dummy variable with the value of one if a firm's $CITI_{t-1}$ is within the top two quartiles of the same Fama-French 48 industry group in a given year, otherwise set to zero. Source: ExecuComp.
CFOITI	Measured as the natural logarithm of the difference between total compensation (TDC1) of the second highest paid CFO in the same size adjusted Fama-French 48 industry group and total compensation (TDC1) of the firm's CFO. Source: ExecuComp.
Panel C: Control variables from baseline regression	
FIRMAGE	Firm age calculated as the difference between the observation year and the year in which the firm first appears in Compustat. Source: Compustat.
CEOAGE	Age of the firm's CEO. Source: ExecuComp.
TENURE	Tenure of the CEO in the firm. Source: ExecuComp.
OPAQUE	Moving sum of the previous three years' absolute value of discretionary accruals, calculated using modified Jones (1991) model. Source: Compustat.
RETURN	Mean of the firm-specific weekly returns during the fiscal year. Source: CRSP.
SIGMA	The standard deviation of the firm-specific weekly returns during the fiscal year. Source: CRSP.
DTURN	The difference between average monthly share turnover during the current fiscal year and the previous fiscal year. Source: CRSP.
SIZE	The natural logarithm of the market value of equity. Source: Compustat.
MB	The market value of equity divided by the book value of equity. Source: Compustat.

LEVERAGE	Total liabilities divided by total assets. Source: Compustat.
RD	A ratio of R&D to total assets. Source: Compustat.
INDUSTRYHOM	Industry homogeneity, calculated as mean partial correlation between a firm's stock return and equally weighted industry returns after controlling for market returns (Parrino, 1997). Source: Compustat.
SEGMENT	Number of business segments in the firm. Source: Compustat.
FINALYR	A dummy variable with the value of one for the last year of the departing CEO, otherwise the variable is set to zero. Source: ExecuComp.
ROA	The ratio of income before extraordinary items to total assets. Source: Compustat.
Panel D: Instrumental variables for CITI	
GEOCOMP250	Measured as the natural logarithm of mean compensation of the CEOs of the firms in other industries, headquartered within 250 kilometres of the firm. We collect latitude and longitude data of the firm headquarters from https://www.census.gov/geo/maps-data/data/gazetteer.html. Source: Compustat, ExecuComp.
INDCEOCOMP	Calculated as the natural logarithm of the total compensation (TDC1) obtained by the CEOs of the same size adjusted Fama and French 48 industry group. Source: ExecuComp.
Panel E: Other variables	
SHOCK TX	A dummy variable with the value of negative one if a firm's headquarter is in Texas after 1994, otherwise set to zero. Source: Compustat.
SHOCK LA	An indicator variable with the value of negative one if a firm's headquarter is in Louisiana in the year 2002 and 2003, and with the value of one if the firm's headquarter is in Louisiana after the year 2003 and, otherwise set to zero. Source: Compustat.
SHOCK FL	A dummy variable with the value of one if a firm's headquarter is in Florida after 1996, otherwise set to zero. Source: Compustat.
NEG SHOCK	A dummy variable with the value of negative one if firms are headquartered in Texas from 1995 to onwards and in Louisiana in the year 2002 and 2003, otherwise zero. Source: Compustat.
POS SHOCK	A dummy variable with the value of one if the firms are in Louisiana during 2004 onwards and in Florida during 1997 onwards, otherwise zero. Source: Compustat.
STATE UNEMP	State-level unemployment rate. Source: Bureau of Labor.
LOG STATE INC	Calculated as the natural logarithm of state-level per capita personal income. Source: Bureau of Economic Analysis (BEA).
Overproduction	Residuals from the following cost of production model: $$\frac{PRODUC_{it}}{TA_{it-1}} = \alpha_0 + \frac{\alpha_1}{TA_{it-1}} + \alpha_2 \frac{SALES_{it}}{TA_{it-1}} + \alpha_3 \frac{\Delta SALES_{it}}{TA_{it-1}} + \alpha_4 \frac{\Delta SALES_{it-1}}{TA_{it-1}} + \varepsilon_{it}$$ where $PRODUC =$ cost of goods sold (COGS) + change in inventory ($\Delta INVT$) and $TA =$ total assets. We estimate the above model for each Fama-French 48 industry and year combination with firms in Compustat universe (Cheng et al., 2016; Roychowdhury, 2006). Source: Compustat.
Abnormal discretionary expenditure	Negative residuals from the following discretionary expenditure model:

	$$\frac{DISEX_{it}}{TA_{it-1}} = \alpha_0 + \frac{\alpha_1}{TA_{it-1}} + \alpha_2 \frac{SALES_{it-1}}{TA_{it-1}} + \varepsilon_{it}$$ where $DISEX$ = R&D expenses + advertising expenses + SG&A expenses and TA = total assets. We estimate discretionary expenditure model for each Fama-French 48 industry and year combination with firms in Compustat universe (Cheng et al., 2016; Roychowdhury, 2006). Source: Compustat.
ZSCORE	Modified Altman's (1968) Z-score calculated as: ZSCORE = 3.3 (Net income/Total assets) + 1.0 (Sales/Total assets) + 1.4 (Retained earnings/Total assets) + 1.2 (Working capital/Total assets) + 0.6 [(Stock price ×Outstanding shares)/Total liabilities]. Source: Compustat.
LOSS	A dummy variable with the value of one if a firm has a negative net income before extraordinary items during a year, otherwise zero. Source: Compustat.
SALEGR	Percentage change in annual sales of a firm. Source: Compustat.
EXTRA	A dummy variable with the value of one if a firm reports extraordinary items, otherwise zero. Source: Compustat.
CEOOPT	A CEO's incentive ratio for option holdings following Kim et al. (2011). Source: ExecuComp, CRSP.
CEOSTK	A CEO's incentive ratio for stock holdings following Kim et al. (2011). Source: ExecuComp, CRSP.
CFOOPT	A CFO's incentive ratio for option holdings following Kim et al. (2011). Source: ExecuComp, CRSP.
CFOSTK	A CFO's incentive ratio for stock holdings following Kim et al. (2011). Source: ExecuComp, CRSP.
CG	Takeover index is used as a measure of firm-level corporate governance. Source: Cain et al. (2017).
IG	Internal governance, calculated by adding the standardised values of EHORIZON (65 – average age of non-CEO executives) and EPAYRATIO (average total compensation of non-CEO executives/total compensation of a CEO) (Cheng et al., 2016). Source: ExecuComp.
INSTD	Average standard deviation of the percentage of institutional investors' shareholdings in a firm over five years (20 quarters). Source: Thompson-Reuters Institutional (13f) Holdings.
CSCORE	Conditional conservatism measured following Khan and Watts (2009). Source: Compustat.
POWER	CEO power index (with the value of zero to six) calculated by combining six dummy variables – whether a CEO has pay slice higher than the industry median (Bebchuk et al., 2011), whether a CEO is also the chairman of the board (duality), whether a CEO with duality is also the president of the firm, whether a CEO's total number of titles is higher than the industry median, whether a CEO is the only executive who sits in the board (Adams et al., 2005), whether a CEO's tenure is higher than the industry median (Han et al., 2016). Source: ExecuComp.
CEOFEMALE	A dummy variable with the value of one if a firm has a female CEO. Source: ExecuComp.
CFOFEMALE	A dummy variable with the value of one if a firm has a female CFO. Source: ExecuComp.
CEODUAL	A dummy variable with the value of one if the CEO is also the chair of the board. Source: ExecuComp.
INNOVATION	Natural logarithm of the number of citation-weighted patents. Source: Kogan et al. (2017).
DD	Distance-to-default measured following Bharath and Shumway (2008). Source: Compustat, CRSP.
FLUIDITY	A measure of product market competition constructed by Hoberg et al. (2014). Source: http://hobergphillips.tuck.dartmouth.edu/

PAYGAP	Measured as the natural logarithm of the difference between a CEO's total compensation (TDC1) and non-CEO executives' median total compensation. Source: ExecuComp.
OVERCON	CEO overconfidence, calculated using CEO's options holdings (Malmendier et al., 2011; Humphery-Jenner et al., 2016). First, we calculate a ratio of value per vested option to option's average strike price. If the value of this ratio is 0.67 or more for at least two times during the sample period, we set OVERCON as the value of one from the first time the ratio has a value of 0.67 or higher to the remaining sample period (Kim et al., 2016). Source: ExecuComp, CRSP.
Overinvestment	A dummy variable with the value of one if the residuals from the following model are negative in a specific year, otherwise we set the value to zero: $$INVEST_t = \beta_0 + \beta_1 MB_{t-1} + \beta_2 ROA_{t-1} + \beta_3 CASH_{t-1} + \beta_4 AGE_{t-1} + \beta_5 LEV_{t-1} + \beta_6 LOGASSET_{t-1} + \beta_7 INVEST_{t-1} + YEAR\ FE + INDUSTRY\ FE + \varepsilon_t$$ Source: Compustat.

Appendix A.2

Alternative proxy

This table reports regression estimates using alternative proxies of stock price crash risk propensity. $COUNT_t$ and $EXTRASIG_t$ are the two alternative proxies to measure the propensity of stock price crash risk. $CITI_{t-1}$ is a CEO's industry tournament incentives. Appendix A.1 shows definitions of all variables. Industry dummies capture Fama-French 48 industry group fixed effects. Year dummies capture time fixed effects. Firm FE and CEO FE indicate firm and CEO fixed effects, respectively. Figures with parentheses are standard errors robust to heteroscedasticity. Standard errors in column (5) and (6) are clustered at the CEO level. All other models have standard errors clustered at the firm level. All models include a constant. Superscripts *,**, and, *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

	Industry-Year FE		Firm-Year FE		CEO-Year FE	
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
	$COUNT_t$	$EXTRASIG_t$	$COUNT_t$	$EXTRASIG_t$	$COUNT_t$	$EXTRASIG_t$
$CITI_{t-1}$	-0.0056***	-0.0054**	-0.0060***	-0.0058**	-0.0064***	-0.0048*
	(0.0018)	(0.0023)	(0.0021)	(0.0026)	(0.0023)	(0.0028)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
CEO FE	No	No	No	No	Yes	Yes
R^2	0.0203	0.0375	0.0277	0.0337	0.0371	0.0440
No. of observations	16,763	16,763	16,763	16,763	16,761	16,761