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Gambling Preferences and Stock Price Crash Risk: Evidence from China

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Gambling Preferences and Stock Price Crash Risk: Evidence from China

ABSTRACT

This paper investigates whether attitudes towards gambling help explain the occurrence of stock price crashes in China. By using a province's per capita welfare lottery sales as a proxy for local gambling preference, we find that firms in regions with stronger gambling preference experience greater stock price crash risk. This result is robust to a battery of sensitivity tests after addressing possible endogeneity issues by using an instrumental variable approach and propensity score matching. Furthermore, we find that the impact of local gambling attitudes on stock price crash risk is mitigated by higher quality internal monitoring and more stringent external monitoring. Lastly, we identify two channels through which gambling preferences intensify stock price crash risk: aggressive corporate strategies and speculative accounting practices. Overall, these findings suggest that local gambling preferences influence firms' stock price crash risk.

JEL classification: G12, M40, Z10

Keywords: Gambling preference; Stock price crash risk; Culture;

1. Introduction

Corporations interact with their local environment and the local environment where a company is located impacts financial market outcomes (Hilary and Hui 2009; Kumar et al. 2011; Chen et al. 2014; Callen and Fang 2015). Given the potential significance of the local environment on company outcomes, we investigate whether local gambling preferences affect the likelihood future stock price crashes. In regions where gambling is more socially acceptable, companies tend to take on more speculative and risky projects (Chen et al., 2014), which renders a negative shock to company stock prices if these projects fail. In addition, managers in gambling-prone areas are more likely to accumulate bad company news for an extended period and optimistically expect the situation will turn around. Once the amount of accumulated bad news reaches a tipping point, the bad news has to be released, which leads to stock price crashes (Hutton et al., 2009; Jin and Myers, 2006; Kim et al., 2016b)¹.

Recent literature has identified numerous factors that influence crash risk, including opaque financial reports (Kim and Zhang, 2014), CEO overconfidence (Kim et al., 2016b), stock liquidity (Chang et al., 2017), accounting conservatism (Kim and Zhang, 2016), information transparency (Jin and Myers, 2006), corporate tax avoidance (Kim et al., 2011a), and crackdowns on corruption (Chen et al., 2018). However, whether the gambling preferences of the local environment affect stock price crash risk is not examined. In this study, we aim to fill this void by investigating the effect of local

¹ Luckin Coffee Inc. (Nasdaq code: LK), a Nasdaq listed Chinese firm, recently admitted fabricated sales of 2.2 billion yuan (US\$310m) on April 2, 2020, which led to a one-day 80% stock price plunge. Although this firm is not in our sample, it indicates how withholding bad news by some Chinese firms over an extended period while hoping for future good performance can lead to stock price crashes.

gambling preference on stock price crash risk using Chinese data.

We focus on the impact of local gambling preferences on the likelihood of future stock price crashes in China for three reasons. First, as reported by Sobrun-Maharaj et al. (2012), Asians are more susceptible to gambling due to their cultural beliefs such as superstition and luck. Among Asians, the most susceptible ethnic group are the Chinese, with gambling seemingly integrated into their culture. Chan et al. (2019) report that gambling has a very long history in China. Figure 5.1 of Chan et al. (2019) examine Chinese gambling from a cultural perspective and indicate that gambling can be explained by a traditional Chinese hierarchical belief system that determines all events in one's life that includes five factors: fate, luck, feng shui (i.e., contextual factors of one's living or work environment), inner virtues, and engaging in useful studies. Second, the Chinese stock market features lower transparency, higher stock price synchronicity and higher stock price crash risk (Morck et al. 2000; Jin and Myers 2006). Morck et al. (2000) propose that differences in protection for investors' property rights could explain the variation of stock price synchronicity across countries. Jin and Myers (2006) provide evidence that opaqueness leads to higher synchronicity and stock price crash risk. In our study, we look at whether another dimension of a region's local environment, gambling preferences, affects their stock price crash risk. Third, vast regional variation in gambling preferences is required to study the influences of gambling preference on crash risk. As shown in Figure 1, there is a wide variation in the gambling preferences across the 31 provinces in China, which allows us to test our hypotheses. The diversity in gambling preferences within China originates from 31 provinces with 56 ethnic groups. We use per capita welfare lottery sales as a proxy for local gambling preference because lottery sales capture the direct gambling propensities of the people in that

region (lotteries are the only legal channel of betting in China). With these three considerations in mind, we investigate whether local gambling preferences influence stock price crash risk using Chinese data.

[Insert Figure 1 about here]

We posit that firms located in regions where gambling is more socially acceptable experience more stock market crashes for several reasons. First, Chen et al. (2014) find that firms in regions influenced by gambling culture are more likely to adopt aggressive strategies and invest more in speculative and risky projects. Firms' stock prices will plunge abruptly once these projects turn out to be unsuccessful investments. Second, as indicated by Christensen et al. (2018), for firms located in places where gambling is more socially acceptable, managers are more inclined to take speculative and risky positions when reporting firm performance and disclosing firm information. One of these risky practices is to withhold bad company information. Once the accumulated bad information reaches a tipping point and is suddenly revealed to the public, the stock price will collapse. We further investigate this question by looking at firms' internal and external monitoring mechanisms. Serving as checks and balances, high-quality internal monitoring could mitigate stock price crashes by restricting firm managers' aggressive strategies and enhancing corporate transparency. Similarly, more stringent outside monitoring could deter firms' deviant behavior. Consequently, we expect that the impacts of local gambling preferences on firms' stock price crash risk will be lower in firms with good internal monitoring and more stringent outside monitoring.

We test our hypotheses using local gambling preference data in China from 2008 to 2017, which is measured by per capita welfare lottery sales. Our results provide

evidence supporting the hypotheses. We find that the local gambling preference is significantly positively related with firm-level stock price crash risk. The results are also economically significant in that a one standard deviation increase in our measure of gambling preference leads to a 3.9 - 5.2% increase in average crash risk. Knack and Keefer (1997) show that the levels of gambling preferences and economic development in a particular region are typically highly correlated. To exclude the potential effect of other regional factors on a firm's crash risk, we control for regional demographic characteristics including GDP per capita, provincial population, and the percentage of the population with at least a college education. We further establish the causal relationship between local gambling preference and stock price risk by addressing possible endogeneity issues using an instrumental variable approach and propensity score matching.

In addition, we find that the impact of gambling preference on crash risk is attenuated by firms' high-quality internal monitoring systems. Furthermore, the impact of gambling preference on stock price crash risk is alleviated by more stringent outside monitoring mechanisms including analysts, institutional investors, media coverage, and auditors. Lastly, we identify two channels for the impact of gambling preference on stock price crash risk. The first channel is that firms in gambling-prone regions take more aggressive strategies in their operation. The second channel is that firms in regions where gambling is more socially acceptable try to engage in more speculative accounting practices.

Our study contributes to the literature in three ways. First, our empirical evidence contributes to the literature on the impact of local culture on corporate behavior and stock market performance. Hilary and Hui (2009) show that religious adherence

influences corporate policy, including risk exposure and investment. Kumar et al. (2011) show that the local gambling preference is associated with market outcomes including investor stock selection, employee compensation plans, and initial public offering (IPO). Chen et al. (2014) find that local gambling preferences are a strong determinant of corporate innovative activities, while Christensen et al. (2018) find that firms in regions when gambling is more socially acceptable engage in more misreporting. We add to the literature by finding that firms in gambling-prone regions experience greater stock price crash risk.

Second, this paper adds to the literature on the determinants of crash risk by finding local gambling preferences affect the likelihood of future stock price crashes. Prior studies have examined several factors related to crash risk, including stock liquidity (Chang et al., 2017), accounting conservatism (Kim and Zhang, 2016), social trust (Li et al., 2017), crackdowns on corruption (Chen et al., 2018), CEO overconfidence (Kim et al., 2016b), and CFO option-based compensation (Kim et al., 2011b). This study is the first to explore the impact of gambling preference on stock price crash risk. One particularly related study is Callen and Fang (2015), who find that firms headquartered in counties with higher levels of religiosity exhibit lower levels of future stock price crash risk using US data. However, our paper is different from their study because religiosity is different from local gambling attitudes, as evidenced by Figure 1 of Kumar et al. (2011).

Finally, our results extend the research in economics that studies the mutual effects between cultural forces and economic behavior (Guiso et al., 2006) using Chinese data. As documented by Sobrun-Maharaj et al. (2012), Asians are more susceptible to gambling due to their cultural beliefs and values such as superstition and luck, with

gambling seemingly integrated into their culture. Our evidence reinforces the relationship between culture and economic behavior.

The rest of the paper is organized as follows. Section 2 reviews the prior literature on gambling preferences in corporate decision making and develops our hypotheses. We describe the sample selection, variable measurement, and research design in Section 3. Empirical results are presented in Section 4. Section 5 further explores the channels of the relationship between gambling preference and crash risk. Section 6 conducts additional analyses and Section 7 concludes.

2. Literature Review and Hypothesis Development

Previous literature documents that managers have incentives to strategically withhold bad news or accelerate the disclosure of good news stemming from compensation, career, or reputation concerns (Ball 2009; Kothari et al. 2009; Bao et al. 2019). When bad news hoarding reaches a tipping point, the large amount of negative information will be suddenly released to the market, leading to an abrupt decline in stock price or stock price crashes (Hutton et al., 2009). Jin and Myers (2006) first propose and confirm that country level opacity predicts firm level crash risk. Similarly, Hutton et al. (2009), using firm-level data, find that opaque firms are more prone to stock price crashes. Recognizing the significantly detrimental effect of stock price crashes on investors, a series of subsequent studies have investigated the determinants of firm level stock price crash risk. Kim et al. (2011a) find that tax avoidance is positively related with stock price crash risk, while Kim et al. (2011b) document a positive relationship between CFO option-based compensation and crash risk. Some other studies investigate the impact of stock liquidity (Chang et al., 2017), accounting conservatism (Kim and Zhang,

2016), CEO overconfidence (Kim et al., 2016b), social trust (Li, et al. 2017) and CEO trustworthiness (Gu et al., 2020) on stock price crash risk. One study closely related to ours is Callen and Fang (2015), who investigate the association between religiosity and future stock price risk. They find robust evidence that firms headquartered in counties with higher levels of religiosity exhibit lower levels of future stock price crash risk. In this study, we aim to extend the stock price crash literature by looking at whether local gambling preference affects future stock price crash risk in China, where gambling seems to be long-embedded in the culture (Chan et al., 2019).

Prior research has found that variations in gambling attitudes are correlated with individual investment decisions and corporate financial outcomes. For example, Kumar et al. (2011) find that in regions with higher gambling preferences, investors exhibit a stronger propensity to hold lottery-type stocks, employee stock option plans are more popular, the initial day return following an initial public offering is higher and the magnitude of the negative lottery-type stock premium is larger. Moreover, Kumar et al. (2016) find that the return co-movement is stronger among lottery-type stocks located in regions where investors exhibit a stronger gambling propensity and that investors with a greater gambling propensity trade lottery-type stocks more actively. Using similar proxies for gambling attitude, Chen et al. (2014) find that firms located in gambling-prone areas tend to undertake riskier projects and spend more on innovation, while Christensen et al. (2018) find that in places where gambling is more socially acceptable, managers will be more likely to take financial reporting risks that increase the likelihood of financial restatements. Consistently, Callen and Fang (2020) find that auditors charge higher fees for firms headquartered in regions with more liberal gambling norms. Taken as a whole, the above literature on gambling attitude indicates

that investors and managers in regions with a higher gambling preference are more speculative and risk-taking in their investment and financial reporting activities.

We extend the literature that explores the relationship between local gambling attitudes and corporate behavior by investigating whether local gambling attitudes affect firms' future stock price crash risk using Chinese data, where gambling is deep-rooted in the culture and the stock market is relatively less transparent compared with other countries. We argue that firms headquartered in regions where gambling is more socially acceptable are more likely to experience stock price crashes. Firms in gambling prone areas tend to take more aggressive strategies in their operations. Chen et al. (2014) indicate that opportunistic managers influenced by gambling preferences are more likely to risk the wealth of investors in pursuit of the high potential gains to the firm and the manager. However, these speculative and risky projects have non-trivial chances of failure. Once these speculative investments fail to meet investor expectations, stock prices will plunge.

Also, as evidenced by Christensen et al. (2018), local gambling preferences could amplify managers' already high-risk tolerance, so that managers in regions where gambling is more socially acceptable are more willing to take risks in financial reporting and disclosure practices. This will be manifested in two ways in financial disclosures. First, in regions where gambling is more socially acceptable, managers will implement more aggressive accounting practices that result in inflated performance figures. Second, these managers will be more likely to hoard bad news, hoping for a future turnaround. However, if the situation does not improve and managers keep accumulating bad news, the stock price will decline abruptly once the accumulated bad news must be released to the market. Both these aggressive accounting and speculative

disclosure practices will finally lead to stock price crashes once the company cannot maintain the inflated performance. Based on these arguments, we derive our first hypothesis as follows:

H1: Firms headquartered in regions with higher levels of gambling preferences are more likely to experience future stock price crashes.

Internal monitoring is an interlocking set of activities to safeguard assets, minimize errors, and ensure that operations are conducted in an approved manner. Ashbaugh-Skaife et al. (2009) find that firms' internal control weakness is associated with both higher idiosyncratic risk and systematic market risk and hence the cost of equity will be higher. In addition, weak internal control will also result in poor accounting quality, poor operating and investment efficiency (Cheng et al. 2013; Harp and Barnes 2018). Previous research also find that independent boards improve the quality of financial reporting and corporate transparency (Aggarwal et al., 2011; Ahmed and Duellman, 2007; Armstrong et al., 2014). On the contrary, if the CEOs are too powerful and dominates a firm's operation and policies, internal monitoring mechanisms will become ineffective, leading to lower firm value and more opportunistic behaviors (Bebchuk et al., 2011; Khanna et al., 2015).

Overall, the extant research implies that good quality internal monitoring will not only enhance a firm's transparency, but also restrains managers from deviant operating and investing activities. Effective internal monitoring is particularly important in gambling-prone regions because it could deter managers from behaving opportunistically and aggressively, hence diminishing future stock price crash risk. In contrast, without the existence of effective internal monitoring, managers would be more likely to engage in

misreporting and risky projects, which will result in more stock price crashes. Hence, we formally present our second hypothesis as follows:

H2: The positive relationship between gambling preference and future crash risk is attenuated by high quality internal monitoring.

Another important mechanism to limit managers' aberrant activities is outside monitoring (Jensen and Meckling, 1976). Stringent monitoring not only prevents managers from pursuing risky and value destroying business activities, but also promotes market transparency by discovering and revealing hidden private information within firms (Dyck et al. 2010; Gul et al. 2010; Chen et al. 2015; Dou et al. 2018). Monitoring mechanisms are particularly important for firms headquartered in regions where gambling is socially acceptable. Shaped by the local gambling preference environment, managers feel emboldened to embark on risky projects and engage in aggressive accounting practices, which will lead to higher stock price crash risk. More stringent outside monitoring could restrain managers from engaging in such deviant behaviors, and, in turn, lower firms' crash risk. Therefore, we conjecture that the positive relationship between gambling preference and future crash risk will be curbed for firms with more stringent external monitoring. Our formal hypothesis is developed as follows:

H3: The impact of gambling preference on future stock price crash risk will be alleviated in firms with more stringent outside monitoring.

3. Research Design

3.1 Sample and Data

Our sample starts with all Chinese A-share listed firms for the period from 2008 to 2017. The sample period starts in 2008 because it is the first year when lottery data are available. Our dependent variables (crash risk measures) lead the independent variables by one year, so the crash risk data is from 2009 to 2018. Financial and stock return data are derived from the China Securities Market and Accounting Research (CSMAR) database. Provincial level lottery data are collected from the Chinese Research Data Services (CNRDS) database. Provincial level demographic data are also collected from CSMAR database. We then exclude: (i) financial services firms because the disclosure requirements and accounting rules are significantly different for this regulated industry; (ii) firms with fewer than 30 trading weeks of stock returns in a fiscal year to ensure the calculation of firm-specific weekly returns; and (iii) firm-year observations with missing information for the necessary financial, stock return, and provincial level variables. Our final sample includes 18,525 firm-year observations (2,895 individual firms).

3.2 Measuring stock price crash risk

Following Chen et al. (2001) and Kim et al. (2011b), we employ two measures of crash risk: negative conditional return skewness (NCSKEW) and the down-to-up volatility of firm-specific weekly returns (DUVOL). Specifically, we define the firm-specific weekly return, denoted by $W_{i,\tau}$, as the natural log of one plus the residual return ($\varepsilon_{i,\tau}$) from the following expanded market model regression:

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

where $r_{i,\tau}$ is the return on stock i in week τ and $r_{m,\tau}$ is the value-weighted market return in week τ . We include the lead and lag terms for the market index return to allow

for nonsynchronous trading (Dimson, 1979). We first obtain the residual return $\varepsilon_{i,\tau}$ from Eq. (1) and then calculate weekly return $W_{i,\tau}$ as the natural log of one plus the residual return; that is, $W_{i,\tau} = \text{Ln}(1 + \varepsilon_{i,\tau})$.

The first measure of crash risk is the negative coefficient of skewness, *NCSKEW*, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, we calculate the *NCSKEW* for each firm i in year t as:

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

where n is the number of observations of the firm-specific weekly returns of firm i during the year t . A higher *NCSKEW* value indicates that the firm is more likely to crash.

The second measure is the down-to-up volatility of firm-specific weekly returns (*DUVOL*). Specifically, we define down weeks as all weeks with $W_{i,\tau}$ below its annual mean and up weeks as all weeks with $W_{i,\tau}$ above its annual mean for a firm i in year t . We calculate the standard deviation for each of the two subsamples separately. Then, the *DUVOL* measure is the log of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks as follows:

$$DUVOL_{i,t} = \text{Ln}[(n_u - 1) \sum_{DOWN} W_{i,\tau}^2 / ((n_d - 1) \sum_{UP} W_{i,\tau}^2)] \quad (3)$$

where n_u and n_d are the numbers of up and down weeks, respectively. Firms with a higher level of *DUVOL* are more likely to crash.

3.3 Measuring gambling preferences

Similar to Christensen et al. (2018), we measure gambling attitudes based on welfare lottery data (the actual gambling activity) of the people in different provinces in China. More specifically, we measure gambling attitude in two ways. First, we use a continuous measure, *GAMBLE*, calculated as total welfare lottery spending in each province where the firm is headquartered in a year scaled by the population in the same province and the same year. Second, we use a dichotomous measure, *GAMBLE_D*, that equals one if the firm is located in a province with per capita welfare lottery spending greater than the median value in a given year, and zero otherwise.

3.3 Empirical Models

To investigate the impact of gambling preference on future stock price crash risk, we estimate the following model:

$$\begin{aligned} CrashRisk_{t+1} = & \beta_0 + \beta_1 GAMBLE_t + \beta_2 CrashRisk_t + \beta_3 DTURN_t + \beta_4 SIGMA_t + \\ & \beta_5 RET_t + \beta_6 SIZE_t + \beta_7 ABACC_t + \beta_8 LEV_t + \beta_9 ROA_t + \beta_{10} TOP1_t + REGION + \\ & YEAR + IND + \varepsilon \end{aligned} \quad (4)$$

where β_1 represents the impacts of gambling preference on crash risk. The dependent variable, *CrashRisk*, is measured by either *NCSKEW* or *DUVOL*. The primary independent variable *GAMBLE* is proxied by per capita welfare lottery spending (*GAMBLE* or *GAMBLE_D*) in our main test. We measure all independent variables in year *t*, which is a one-year lag from the dependent variable, thus allowing us to examine whether gambling preference in year *t* can predict the future crash risk in year *t* + 1.

The control variables are the factors that have been shown in the literature to affect

future crash risk. First, we include the lagged variable of crash risk ($NCSKEW_t$ or $DUVOL_t$) to control for potential serial correlation. Second, we include eight firm-level control variables in the model. We control for the detrended stock trading volume ($DTURN$) because Hong and Stein (2003) suggest that investor opinion heterogeneity is a predictor of crash risk. We include past returns (RET), firm size ($SIZE$), and the market-to-book ratio (MB) because Chen et al. (2001) document that, in addition to trading volume, past returns are related to future crash risk because the bubble built up by past returns is typically followed by a sudden drop in prices. We also include stock volatility ($SIGMA$) since more volatile stocks are more likely to undergo a future price crash. Additional firm-level control variables are financial leverage (LEV), profitability (ROA), and the absolute value of abnormal accruals ($ABACC$), which is a proxy for earnings management (Hutton et al., 2009).

Further, it cannot be neglected that other regional factors can also drive the positive relationship between gambling preference and crash risk. Because some regional characteristics may differ between firms in regions of high gambling preferences and those in regions of low gambling preferences, we include three regional demographic variables in the analysis, thus ensuring that our results are not driven by these factors. We control for the per capita GDP (P_GDP) of a province, which measures provincial economic development, the natural logarithm of the population (POP) of a province, and the percentage of the province's population with at least a college education (EDU). All the above variables are defined in more detail in Appendix A.

Industry fixed effects are included in all regressions because it is very likely that different industries will have observed levels of crash risk that have no direct causal relationship with the level of gambling preference expressed at the province level, but

instead reflect other institutional features of the industry. Year fixed effects are also included to control for common macroeconomic shocks. We winsorize all continuous variables at the 1% and 99% levels to mitigate the effect of outliers. Since our independent variable is at the provincial level, we cluster the standard errors by province to alleviate concerns about potential time-series dependence in the data.

4. Empirical results

4.1 Descriptive statistics

Panel A of Table 1 reports the summary statistics of the variables used in our analysis. The two measures of crash risk, NCSKEW and DUVOL, are similar in distribution. The mean values of NCSKEW and DUVOL are -0.327 and -0.222, with standard deviations of 0.607 and 0.437, respectively. The mean value of the proxy of gambling preference (GAMBLE) is 2.562, which means that, on average, one person spends 2.562 yuan each year in lottery purchases. The mean value of GAMBLE_D is 0.497, which implies that roughly half of the firms are in regions where gambling is more socially acceptable.

[Insert Table 1 about here]

Panel B of Table 1 compares the firms in high gambling preference regions with those in low gambling preference regions. Compared with firms in low gambling preference regions, firms in high gambling preference regions have significantly higher crash risk as indicated by both crash measures, which supports our Hypothesis 1. The two groups also show other significantly different characteristics. For example, the mean value of DTURN for firms with higher gambling preference is -0.10, while it is -0.106 for firms

with lower gambling preference, indicating that average monthly stock turnover is higher for firms in higher gambling preference regions. Firm size is higher, but leverage is lower, for firms headquartered in regions with higher gambling preference. Additionally, regarding province-level characteristics, we observe that lower gambling preference provinces have smaller populations, but better educated people, which is consistent with Kumar (2009) who indicates that less educated people are more likely to purchase lotteries and are more gambling prone.

Table 2 presents the Pearson correlation among all the variables. The results show that the two crash risk measures are significantly positively correlated. More interestingly, both are significantly positively related with our continuous and dichotomous gambling attitude variables. Both the descriptive statistics and correlation analyses indicate that crash risks are higher for firms located in regions where gambling preference is higher, which is consistent with our Hypothesis 1. However, the univariate analyses do not control for other factors that could potentially affect a firm's crash risk. Next, we perform more in-depth analyses on the relationship between gambling attitudes and stock price crash risk using multivariate tests.

[Insert Table 2 about here]

4.2 Baseline regression analysis

Table 3 reports the baseline regression results using Eq. (4). Columns (1) and (2) show the results when we use $NCSKEW_{t+1}$ as the dependent variable, while columns (3) and (4) use $DUVOL_{t+1}$ as the dependent variable. The results suggest that $NCSKEW_{t+1}$ is significantly and positively related with gambling preference as measured by both the continuous gambling preference proxy $GAMBLE$ and the dichotomous gambling

preference proxy GAMBLE_D after controlling for firm-level and province-level determinants of crash risk. Similarly, the results in columns (3) and (4) using $DUVOL_{t+1}$ as the measure for crash risk also show a positively significant relationship between gambling preference and future crash risk for both continuous and binary measures of gambling preference. This positive relationship between crash risk and gambling preference is not only statistically, but also economically, significant. Using the continuous gambling crash measure as an example, the coefficient of GAMBLE (column 1) is 0.028, which means that a one-standard-deviation increase in gambling preference is associated with a 5.20% ($=0.028 \times 0.607 / 0.327$) increase in average crash risk. The increase is 3.94% ($=0.020 \times 0.437 / 0.222$) as shown in column (3) where crash risk is measured by $DUVOL_{t+1}$. For the sake of brevity, we will not tabulate the results using the binary gambling preference measure in subsequent analyses although the results are similar or even better. However, the results using the binary gambling preference measure in the subsequent analyses are available upon request.

[Insert Table 3 about here]

The coefficients of other firm-level control variables are mostly consistent with previous studies (Hutton et al., 2009; Kim et al., 2011b). Firms with a higher past return (RET) and a higher market-to-book ratio (MB) tend to have higher risks of a future crash. However, when the firm is more liquid (DTURN), the future crash risk is lower. Larger firms have lower crash risk as evidenced by the negative coefficient on SIZE. When the firms are opaque (higher ABACC), the crash risk is higher, which is consistent with Hutton et al. (2009). One of the regional factors, POP, is consistently significantly positive in all the four models. One possible explanation for this significantly positive relationship is that provinces with a higher population tend to have

high competition, which induces managers to withhold bad news from the general public, including competitors.

In summary, the results in Table 3 suggest that firms in regions with high gambling preferences tend to have a higher chance of future stock price crashes, which supports our first hypothesis.

4.3 Robustness check

4.3.1 Addressing endogeneity issues: instrumental variable approach

The analysis in the previous sections identifies a significantly positive association between crash risk and gambling preference. However, although we use crash risk measures in year $t + 1$ and gambling preference measures in year t to alleviate the potential reverse causality problem, endogeneity concerns remain. For example, the positive association between gambling preference and firms' crash risk may occur due to unobservable factors related to gambling preferences or because firms with higher crash risks self-select to locate in regions with high gambling preferences.

To address the endogeneity concerns, we perform a two-stage-least-square (2SLS) estimation according to Roberts and Whited (2012), who propose that an appropriate instrument needs to satisfy relevance and exclusion conditions. In view of this, we identify two plausible instruments for our 2SLS estimation. The first instrument is the natural logarithm of the average altitude of each province (ALTITUDE). In China, the high-altitude regions are generally mountain areas with inconvenient traffic, where there are very few entertainment activities available to the local residents. Due to the cultural destitution, gambling becomes one of the few entertainments the local residents

can enjoy, which is gradually evolved into a culture over time. Hence, we expect gambling is more rampant in areas with higher altitude. The second plausible instrument is the natural logarithm of one plus the number of pawnshops (PAWN) in each province in year 1911. We use the number of pawnshops in 1911 since the regulations to ban illegal gambling were not strictly enforced then. The number of pawnshops in each province is expected to be positively correlated with the local gambling preferences, since pawnbroking could supply funds for gambling. For both of these instrumental variables, we have no reason to believe that they would directly affect the crash risk of the firms in our sample period except through the channel of influencing the gambling culture of that region. The results are presented in Table 4. Columns (1) and (2) report the first stage with the dependent variable being GAMBLE. As expected, both instrumental variables are significantly positively related with gambling preference. Further, the F-statistic from a Kleibergen-Paap weak identification test is 799, significantly higher than the Stock and Yogo (2005) critical value of 19.93 for a 10% maximal bias of the instrumental variable estimator relative to OLS, which rejects the null that the ALTITUDE and PAWN are weak instruments. The Hansen's J-statistics for overidentifying restrictions fail to reject the null hypothesis that our instruments are uncorrelated with the error term, further giving us confidence that our instruments are appropriate. Columns (3) and (4) report our second-stage regression results, with $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as crash risk measures, respectively. The results show that, after controlling for possible endogeneity, gambling preference continues to be positively correlated with crash risk.

[Insert Table 4 about here]

4.3.2 Addressing endogeneity issues: Propensity score matching

We are also concerned that firms in gambling-prone areas systematically differ from their counterparts in regions with lower gambling preferences. To more directly compare observably similar firms facing different levels of gambling preferences, we re-examine our results using propensity score matching method. We define treatment (control) firm-years as those in the top (bottom) quartile of gambling preference every year. We then calculate the probability of belonging to each group using a Probit model. The covariates include firm-year control variables used in Table 3, except the lagged crash risk measures ($NCSKEW_{t-1}$ and $DUVOL_{t-1}$) and industry and year dummies. We use one-to-one matching algorithm with caliper equals 0.05 to find one control firm-year observation for each treatment firm-year observation in the same industry and the same year. We match without replacement to achieve better covariate balance between our groups, although results are similar with replacement. We finally use the matched sample to re-run Eq. (4). Table 5 report the regression results using the matched sample from propensity score matching. The results show that, after propensity score matching, gambling preference continues to be positively correlated with crash risk.

[Insert Table 5 about here]

Taken together, the regression results using an instrument variable approach and the propensity score matched sample both indicate the unlikelihood that omitted variables drive the relationship between gambling preference and stock price crash risk.

4.3.3 Excluding the three biggest provinces in terms of population

In this subsection, we exclude firms headquartered in the three biggest provinces in

terms of population² to alleviate the possible bias caused by the size of the population. Columns (1) and (2) in Table 6 present results on the relationship between gambling preference and crash risk using the reduced sample, with $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ as the crash risk measures. The results are consistent with Table 3, which further indicates that firms located in gambling-prone areas tend to experience greater crash risk.

[Insert Table 6 about here]

4.3.4 Alternative measures of crash risk

In this subsection, we calculate our crash risk measures in alternative ways. First, following Hutton et al. (2009), we measure the firm-specific weekly returns (W) as the natural logarithm of one plus the residual return from the model below, adjusting for not only market returns, but also industry returns.

$$r_{i,z} = \alpha_i + \beta_1 r_{m,z-1} + \beta_2 r_{i,z-1} + \beta_3 r_{m,z} + \beta_4 r_{i,z} + \beta_5 r_{m,z+1} + \beta_6 r_{i,z+1} + \varepsilon_{i,z} \quad (1a)$$

where $r_{i,t}$ is the weekly return for stock i in week z and $r_{m,z}$ and $r_{i,z}$ are the value-weighted average weekly market return and industry return, respectively. Following Dimson (1979), we include the lag and lead terms of the market returns and industry returns to mitigate the non-synchronized trading problem. We then use models (2) and (3) to calculate the two alternative measures of firm-specific future crash risk, $NCSKEW_A$ and $DUVOL_A$, respectively.

Second, following Hutton et al. (2009) and Callen and Fang (2015), we construct a

² The three provinces with the biggest populations are Guangdong, Shandong, and Henan.

measure of the likelihood of crashes, CRASH_COUNT, based on the number of firm-specific daily returns exceeding 3.09 standard deviations above and below the mean firm specific daily return over the fiscal year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution. CRASH_COUNT is measured as the difference between the frequencies of negative extreme daily returns and the frequencies of positive extreme daily returns. A higher value of CRASH_COUNT corresponds to a higher frequency of crashes.

Columns (3) and (4) in Table 6 present the regression results of Eq. (4) using the alternative measures of crash risk adjusted by both market and industry returns, NCSKEW_At+1 and DUVOL_At+1. Column (5) reports the results using CRASH_COUNTt+1, an alternative measure of crash risk. Consistent with Table 3, the association between gambling preference and crash risk remains positive and statistically significant using these alternative crash risk measures.

4.4 Cross sectional analyses

4.4.1 The effect of internal monitoring

Hypothesis 2 predicts that the positive association between gambling preference and future crash risk is more prominent (more positive) for firms with weaker internal monitoring. We examine the impact of several internal monitoring mechanisms on the relation between local gambling preference and firm crash risk. The first one we investigate is internal control quality (IC). We measure IC based on the DIB internal control index, with a higher index indicating a better quality internal control system. The index is constructed by Shenzhen DIB Enterprise Risk Management Technology

Ltd.³ DIB's internal control index is a composite index based on the listed firm's internal control disclosure, internal control assessment, internal control weaknesses, and auditing/assurance reports. This index is consistent with the ideas of Doyle et al. (2007) but has more advantages since it was constructed by an independent professional rating agency with great independence, high data reliability, and strong objectivity.

The second internal monitoring mechanism is board independence, which is deemed as one important mechanism to monitor managers. Using Chinese data, Jiang et al. (2016) find that independent directors can help improve corporate governance and market transparency through their voting. The third internal monitoring mechanism we are going to examine is the number of board committees following Singh et al. (2018). Board committees derive their monitoring power from the authority delegated to them by the board. For example, the audit committee is responsible for monitoring the internal audit function and the finance committee is responsible for reviewing the firm's financial policies and procedures. Therefore, we conjecture that more board committees will help better curb managerial misbehavior induced by local gambling preferences.

To test Hypothesis 2, we first split the full sample into two groups along the median value of these internal monitoring mechanisms (i.e., internal control index, proportion of independent directors, and number of board committees). We then estimate Eq. (4) for the high-quality and low-quality internal monitoring subsamples separately.

In addition, a powerful CEO will make a firm's internal monitoring less effective (Bebchuk et al., 2011; Khanna et al., 2015). Following Bebchuk et al. (2011), we

³ This is translated based on the Chinese description of DIB's products. See the link below for more details: (<http://www.dibdata.cn/#/product/1/ic>)

measure a CEO's power using his or her pay slice, where a higher pay slice implies that the CEO is more powerful. We calculate a CEO's pay slice (*Pay_slice*) as the fraction of the CEO compensation to the average compensation of top executives (including the CEO). We conjecture that a higher pay slice will stimulate managerial misbehavior induced by local gambling preferences, and hence leads to higher crash risk.

Panel A of Table 7 reports the results of the effects of internal controls on the relationship between gambling preference and stock price crash risk. When we use *NCSKEW* as the crash risk measure, the coefficient of *GAMBLE* in column (1) is positive but insignificant for the groups with high-quality internal control. In contrast, the coefficient on *GAMBLE* is positive and significant at the 1% level for the group of firms with lower-quality internal control. The F-test indicates that the difference in the coefficients of *GAMBLE* of these two columns is statistically significant at the 8% level. Columns (3) and (4) report the results using *DUVOL* as the crash risk measure. The results are similar to those in columns (1) and (2), albeit the difference of the coefficients on *GAMBLE* is not statistically significant between the two groups of firms.

Panel B reports the results when we use board independence to split the sample, while Panel C splits the sample based on number of board committees. The results are similar for these two internal control mechanisms, that is, the impact of local gambling preferences on crash risk are more pronounced for firms with less effective internal monitoring. Panel D shows the results when we use CEO's pay slice to partition the whole sample. Again, the impact of local gambling preferences on crash risk is only statistically significant for firms with weak internal monitoring, that is, firms with higher pay slice.

Taken as a whole, the results in Table 7 support Hypothesis 2 that the impact of local gambling preferences on crash risk is more pronounced when the internal monitoring is less effective.

[Insert Table 7 about here]

4.4.2 The effect of external monitoring

As documented in Section 2, external monitoring can help curb managers' deviant behavior. Managers in regions with higher gambling preferences are more likely to invest in risky projects or engage in misreporting. Hence, we expect the role of external monitors to curb managers' misbehavior will be more pronounced for firms located in regions with higher gambling preferences. In this section, we explore the effects of several outside monitoring mechanisms on the relationship between gambling preference and crash risk. More specifically, we look at four types of external monitors well recognized in the literature: analysts, media, institutional shareholders, and auditors.

First, analysts play a role as information intermediaries between firm management and market participants to improve the informational efficiency of stock markets. Further, financial analysts may act as monitors by preventing managers from pursuing suboptimal or value-destroying business activities. Chen et al. (2015) find that when a firm experiences an exogenous decrease in analyst coverage, shareholders value internal cash holdings less, its CEO receives higher excess compensation, its management is more likely to make value-destroying acquisitions, and its managers are more likely to engage in earnings management activities. By uncovering and disseminating information to the market, analysts help investors detect and curb

managerial misbehaviors. Therefore, we conjecture that analyst coverage will help curb managerial misbehavior induced by local gambling preferences.

Secondly, Chen et al. (2007) find that independent institutional investors that have maintained large stakes in a firm for at least one year (long-term) will engage in monitoring activities. Furthermore, Dou et al. (2018) find that institutional shareholders with more than a 5% stake exert governance through the threat of exit. As a result, managers are expected to have fewer incentives to conceal their activities and are less likely to manage earnings. Hence, both direct monitoring and the threat of exit by institutional investors will impede managerial misconduct in both investing and reporting activities.

We next examine whether media help mitigate the impact of local gambling preference on crash risk. Zingales (2000) first proposed that media can play a role in the capital market. Dyck and Zingales (2002) further find that managers are sensitive to the way in which the media report and comment upon their decisions since it could affect their reputations. Consistent with Dyck and Zingales (2002) and Liu and McConnell (2013) report that value-reducing takeover attempts are more likely to be abandoned the more negative the tone and the broader the media coverage of such proposed takeovers. Dyck et al. (2010) further find that the media act to unveil fraud, such as misreporting behavior, which may expose managers to higher reputational damages and litigation risks. Given the significant role played by media in impeding managers' deviant behavior, we investigate whether media is effective at alleviating the impact of local gambling preference on crash risk.

Lastly, Khurana and Raman (2004) and Watts and Zimmerman (1983) show that high

quality auditors are able to uncover bad news and reduce agency costs through their monitoring role. Furthermore, high-quality auditors reduce financial market risks (Francis, 2011). Using Chinese data, Gul et al. (2010) provide evidence that high-quality audits enhance corporate transparency.

Similar to the analyses in section 4.4.1, we split the whole sample into two groups based along the quality of external monitoring mechanisms⁴. The results are reported in Table 8. Similar to the results of internal control quality, the impact of gambling preference on stock price crash risk is mitigated for firms under more stringent external monitoring (firms with more analysts following, firms with higher institutional ownership, firms with more media coverage, and firms audited by a top ten auditors as ranked by the Chinese Institute of Certified Public Accountants (CICPA)). The estimated coefficient on GAMBLE is statistically positive at the 5% level or better in all columns where external monitoring is weak, but not significant for most of the columns where external monitoring is stronger. The difference in the coefficients on GAMBLE between the group of firms with more monitoring and those with less monitoring is mostly statistically significant at conventional levels. The only exception is for institutional investors when the crash risk is measured by DUVOL, with the coefficients of GAMBLE significant in both groups and the difference in the coefficients on GAMBLE between the two groups significant only at the 15% level. Taken as a whole, the

⁴ With respect to analysts, we partition our sample along the median number of analysts following a firm. Presumably, firms with more analyst following them are under more stringent monitoring. Likewise, we partition the whole sample into two groups along the median value of institutional shareholder ownership and the median value of the number of media covering a firm. We assume that firms with more institutional shareholding (more media coverage) will have tighter external monitoring. Lastly, following DeFond et al. (1999), we treat the top ten auditors in China as high-quality auditors that have more capabilities and incentives to monitor their clients. The ranking of auditors is published by CICPA every year. For example, the link for the ranking in 2016 is http://www.cicpa.org.cn/news/201610/t20161021_49236.html.

evidence presented in Table 8 indicates that external monitoring will help curb the negative impact of gambling preference on stock price crash risk, which is consistent with Hypothesis 3.

[Insert Table 8 about here]

5. Channel analyses

Our results so far indicate that firms in regions of high gambling preferences are more likely to have future crash risks. However, it is still not clear what are the underlying mechanisms for the impact of gambling preferences on stock price crash risk. In this section, we explore possible channels. Studies show that greater social acceptance of gambling significantly affects corporate decisions and financial markets (Kumar et al., 2016), and firms in areas with higher gambling preferences appear to take on more speculative and risky projects, resulting in a higher probability of failure (Chen et al., 2014), and are more likely to engage in misreporting (Christensen et al., 2018). This indicates that local gambling preferences intensify manager's aggressiveness to formulate aggressive strategies and accounting policies, thereby leading to future crash risk. Motivated by these studies, we propose two channels for the impact of gambling preference on stock price crash risk: aggressive corporate strategies and speculative accounting practices.

Specifically, we utilize the two-step regression approach following (Kim et al., 2016a). In the first step, we examine the relationship between gambling preference and firm behavior. In the second step, we examine the association between firm behavior and crash risk. If gambling preferences increase future crashes by increasing strategic aggressiveness, adopting aggressive accounting practices, or engaging in opportunistic

disclosing activities, we expect a positive correlation in the first step regression and a positive correlation in the second step regression.

5.1 Corporate strategy channel

We use two variables to proxy for a firm's corporate strategy aggressiveness. First, following Bentley et al. (2013), we employ strategy aggressiveness (STRA) score⁵ to explore whether strategy aggressiveness is a channel for the impact of gambling preference on crash risk. Second, we use a firm's earnings volatility (*EARNINGS_VOL*)⁶ as an alternative proxy for strategy aggressiveness. If the managers are more aggressive in corporate strategies, the earnings will be more volatile (Callen and Fang, 2015; John et al., 2008).

The results are presented in Panel A of Table 9. Columns (1) to (3) of Panel A report the results for STRA. Column (1) shows the first step regression results. The coefficient of GAMBLE on strategic aggressiveness is significantly positive (0.167 with t-value = 2.62), indicating that gambling preferences urge firms to formulate a more aggressive corporate strategy as a whole. Columns (2) and (3) report the regression results of the second step model. As shown in columns (2) and (3), the coefficients on STRA are significantly positive, suggesting a positive relationship between strategic aggressiveness and future crash risk.

[Insert Table 9 about here]

Columns (4) to (6) of Panel A report the results when we use *EARNINGS_VOL* as a

⁵ See Appendix A for detailed definition of strategy aggressiveness (STRA).

⁶ See Appendix A for detailed definition of earnings volatility (*EARNINGS_VOL*).

proxy for strategy aggressiveness. Column (4) shows the first step regression results. The coefficient of GAMBLE on *EARNINGS_VOL* is significantly positive (0.012 with t -value = 3.50), indicating that gambling preferences urge firms to be more risk-taking as a whole. In columns (5) and (6), the coefficients on *EARNINGS_VOL* are significantly positive, suggesting a positive relationship between corporate risk-taking and future crash risk.

Taken together, the results in Panel A of Table 9 demonstrate that gambling preference increases strategic aggressiveness and increased strategic aggressiveness results in a higher level of future crash risk. Therefore, the above findings support our expectation that gambling preference increases future crash risk through the channel of increasing a company's strategic aggressiveness.

5.2 Accounting practice channels

In the next two subsections, we look at three dimensions of accounting practices—two mandatory reporting practices (including accounting conservatism and upward earnings management), and voluntary information disclosure.

5.2.1 Accounting conservatism

Kim and Zhang (2016) document that conditional conservatism reduces crash risk effectively because it restricts managers' incentive and ability to overstate performance and hide bad news from investors. Xu et al. (2014) show that conditional conservatism lessens the impact of bad news hoarding. We measure firm-year conditional conservatism (*C_SCORE*) according to Khan and Watts (2009) as detailed in Appendix B. Due to missing accounting information for calculating *C_SCORE*, we are left with

12,089 firm-year observations to examine the impact of gambling preference on conservatism.

The results are presented in Panel B of Table 9. Column (1) shows the first step regression results. The coefficients of GAMBLE on conditional conservatism is significantly negative (-0.004 with t-value = -9.60), indicating that firms in regions with higher gambling preferences engage in more aggressive accounting practices. The coefficients on C_SCORE in Columns (2) and (3) are significantly negative, suggesting a negative relationship between conditional conservatism and future crash risk. Taken together, the results indicate that gambling preferences increase firm level crash risk through the channel of aggressive accounting policies.

5.2.2 Earnings management

Hutton et al. (2009) show that managers use earnings management to hoard bad news, which, in turn, leads to stock price crashes. Therefore, in this subsection, we investigate whether gambling preference increases crash risk through the channel of upward earnings management. The results are presented in Panel B of Table 9. The dependent variable is signed abnormal accrual (ACCRUAL) estimated from the modified Jones model (Dechow et al., 1995). Column (4) shows that the coefficient of GAMBLE on signed abnormal accrual is significantly positive, indicating that gambling preferences stimulate managers to manage earnings upwards. The coefficients on ACCRUAL in Columns (5) and (6) are significantly positive, suggesting a positive relationship between upward earnings management and future crash risk.

Taken together, Panel B of Table 9 demonstrates that gambling preferences induce managers to manage earnings upwards with the inflated earnings resulting in a higher

level of future crash risk. Therefore, the above findings support our conjecture that gambling preference increases future crash risk through the channel of upwardly managing earnings.

5.2.3 Information hoarding

In this section, we test the effects of local gambling preferences on information hoarding, that is, the delay of bad news management forecasts relative to that of good news management forecasts⁷. According to Kothari et al. (2009), if managers tend to hoard bad news for a period but release good news immediately, we should expect a stronger negative stock price reaction to bad news than the positive stock price reaction to good news. In a similar spirit to Baginski et al. (2018), we examine the delay of bad news management forecasts relative to good news management forecasts in the following models (5) and (6):

$$CAR = \alpha + \beta_0 BadNews + \beta_1 MFNews + \beta_2 BadNews \times MFNews + \beta_3 EarnSurp + \beta_4 EarnSurp \times BadNews + \varepsilon \quad (5)$$

$$CAR = \alpha + \beta_0 ADJBadNews + \beta_1 ADJMFNews + \beta_2 BadNews \times ADJMFNews + \varepsilon \quad (6)$$

where CAR equals the cumulative abnormal returns above value-weighted market returns for seven trading days surrounding the management earnings forecast announcement date; $MFNews$ is the news included in the management forecast, which is equal to the management forecasted earnings subtracting the most recent analyst

⁷ Kothari et al. (2009) also investigate a sample of dividend changes. We focus on management forecasts for the similar reason as Baginski et al. (2018) that dividend changes are less common and most of the dividend changes are upward revisions.

consensus forecast, scaled by the analyst consensus forecast; *BadNews* equals to 1 if *MFNews* is less than 0, and 0 otherwise; and *EarnSurp* is the earnings surprise in a concurrent earnings announcement relative to the most recent analyst consensus forecast. *ADJBadNews* and *ADJMFNews* are the adjusted *BadNews* and *MFNews*, respectively, following the method of Rogers and Van Buskirk (2013).

Columns (1) and (3) in panel C of Table 9 presents our findings. Consistent with Kothari et al. (2009) and Baginski et al. (2018), the magnitude of the market reaction to bad news (i.e., $|\alpha + \beta_0|$) is significantly larger than the magnitude of the market reaction to good news (i.e., $|\alpha|$) for both models. The F-tests examining the significance of the difference between $|\alpha + \beta_0|$ and $|\alpha|$ are presented at the bottom of columns (1) and (3). As indicated by the F-tests, the absolute magnitude of the stock price reaction to bad news is significantly greater than that to good news by 0.011 and 0.015 in the two model specifications, respectively. This evidence supports the delay of bad news disclosure relative to good news disclosure in general.

We then employ the following models (7) and (8) to investigate whether the local gambling preferences affects the delay of bad news disclosure relative to good news disclosure:

$$\begin{aligned} CAR = & \alpha + \beta_0 BadNews + \beta_1 GAMBLE + \beta_2 BadNews \times GAMBLE + \\ & \beta_3 MFNews + \beta_4 BadNews \times MFNews + \beta_5 EarnSurp + \beta_6 EarnSurp \times \\ & BadNews + \beta_i Controls + \varepsilon \end{aligned} \quad (7)$$

$$\begin{aligned} CAR = & \alpha + \beta_0 ADJBadNews + \beta_1 GAMBLE + \beta_2 ADJBadNews \times GAMBLE + \\ & \beta_3 ADJMFNews + \beta_4 BadNews \times ADJMFNews + \beta_i Controls + \varepsilon \end{aligned} \quad (8)$$

As we conjecture that high gambling preferences escalates management bad news

hoarding, we expect greater differential market reaction to bad news versus good news when gambling preference is high (i.e., $|\alpha + \beta_0 + \beta_1 + \beta_2| - |\alpha + \beta_1| > |\alpha + \beta_0| - |\alpha|$). Columns (2) and (4) in panel C of Table 9 present our findings, with the F-tests presented at the bottom of columns (2) and (4), respectively. Consistent with our conjecture, when the local gambling preference is high, the differential market reactions between good and bad news are, on average, 2.3% and 2.8%, respectively, whereas this differential reactions are, on average, 1.1% and 1.2% when the local gambling preference is low. The differences between the two differential market reactions (i.e., $1.2\% = 2.3\% - 1.1\%$, and $1.6\% = 2.8\% - 1.2\%$) are statistically significant at conventional levels. Overall, the evidence in panel C of Table 9 supports the notion that managers are more likely to delay the disclosure of bad news relative to good news when the local gambling preferences are high, indicating that bad news hoarding is another channel through which local gambling preferences exacerbate stock price crash risk.

6. Additional analyses

6.1 Does welfare lottery sales represent philanthropic behavior of local people?

In this study, we use welfare lottery sales to proxy for gambling preferences. However, a natural question may arise is whether this lottery spending measures local people's gambling attitude or simply reflects local people's support to social welfare. To exclude the second possibility, we next look at whether a firm's social welfare behavior is correlated with the lottery spending. Particularly, we look at two types of social welfare activities, i.e., corporate social responsibility (CSR) and corporate donation. If the lottery spending reflects local people's attitude towards social welfare, we expect the

lottery spending will be positively associated with the firms' CSR and donation.

The CSR⁸ data are collected from Hexun CSR report database, which is an independent professional CSR rating agency for listed firms. The donation data are collected from the Chinese Research Data Services (CNRDS) database. To make it comparable across firms, the donation amount is scaled by total assets.

We control for other firm level characteristics that might affect CSR score and corporate donation in multivariate regressions. The control variables are the factors that have been shown in the literature to affect CSR following Khan et al. (2013), including the percentage of outstanding shares owned by the largest shareholder at the fiscal year end (TOP1), profitability (ROA), financial leverage (LEV), board independence (BOARD_IND), CEO duality (DUALITY), firm size (SIZE), and whether the firm is an state-owned enterprise or not (SOE). Table 10 presents the results. The coefficients on GAMBLE for both CSR (CSR_SCORE) and corporate donation (DONATION) are insignificant. The results, although limited, indicate that high lottery spending per capita does not indicate that the local people are more supportive to social welfare or have charity preferences.

6.2 The influence of local investors

The above analyses show that local gambling preferences influence corporate crash risk through making managers more risk taking. However, as discussed by Adhikari and Agrawal (2016), gambling preferences also affect the risk attitudes of local

⁸ The CSR scores range from 0 to 100 and are calculated by conducting a comprehensive evaluation of CSR from five aspects: 1) shareholder responsibility; 2) employee responsibility; 3) supplier and customer rights and interests; 4) environmental responsibility, and 5) social responsibility.

investors. To cater to these investors, firms employ aggressive corporate strategies and accounting practices, which might result in higher crash risk. If local investors matter for corporate crash risk, we expect firms with more local investors in regions with higher gambling spending will experience more crash risks. To explore this possibility, following Adhikari and Agrawal (2016), we add two variables that represent the local investors' involvement in capital market into our regressions.

First, as argued by Hong et al. (2008), a firm is likely to get a larger share of local investment if it is located in provinces with fewer investment opportunities due to local bias. Therefore, we create a variable BE/PI , which equals the aggregate book equity of all the public companies headquartered in a province in a given year divided by the aggregate disposable income of urban residents in the province during the year⁹. In the analysis, we use the variable Low_BE/PI , which is a dummy variable that equals one if the BE/PI associated with a firm is below the median BE/PI of all sample firms in a given year, and zero otherwise. Second, Bailey et al. (2011) suggest that individual investors have a higher tendency to behavioral biases such as gambling preferences than institutional investors. Therefore, local gambling preferences will matter more for firms with larger fractions of individual shareholdings if the crash risk reflects local investors' gambling attitude. Hence, we create a $High_Indiv$ indicator, which is equal to one if a firm has an above-median fraction of individual shareholdings in a year (approximated by below-median fraction of institutional shareholdings), and zero otherwise.

Based on these two indicators of the importance of local investors to a firm, we

⁹ We calculate the aggregate disposable income of urban residents by multiply the per capita urban disposable income by the number of population in the province in a given year. The data of disposable income of urban residents are from the National Bureau of Statistics of China.

examine whether the influence of local gambling preferences on crash risk is driven by firms for which local investors are likely to be more important. Accordingly, we re-estimate our regression in Table 3 after adding an indicator variable for the importance of local investors (i.e., *Low_BE/PI* or *High_Indiv*) and its interaction with GAMBLE. A positive and significant coefficient on the interaction terms would indicate that crash risk is more sensitive to local investors' preference for gambling.

Table 11 presents these results. Columns (1) and (3) show the results of the regression using GAMBLE and its interaction with the first indicator variable, *Low BE/PI*. The point estimate of the interaction terms, which measure the incremental effects of gambling preferences in small firms, are negative and insignificant. Columns (2) and (4) show the results when we use *High_Indiv* to measure the importance of local investors. The incremental effect of GAMBLE on crash risk among firms with more individual investors is also insignificant as manifested by insignificant coefficient on the interaction term *GAMBLE * High_Indiv*. More importantly, after controlling for the influence of local investors, the influence of GAMBLE on crash risks remains.

Overall, we find that the effect of gambling preferences on crash risk is not driven the attitude of local investors who are also potentially affected by local gambling preferences. These findings reinforce our argument that local gambling preferences affect corporate crash risk by influencing managers' aggressiveness in corporate strategies, disclosure policies, and accounting practices.

6. Conclusion

This study examines the impact of one aspect of the local environment, gambling preference, on a firm's future stock price crash risk using data from China, where

gambling is deeply rooted in the culture. Using a sample of Chinese listed firms over the 2008–2017 period, we find that firms located in gambling-prone provinces are more likely to have future crash risk. This positive relationship between gambling preference and crash risk remains robust after controlling for various firm- and province-level characteristics. We employ the two-stage least squares (2SLS) approach and propensity score matching method to account for possible endogeneity issues and the results are robust. Moreover, we find that this positive and significant relationship between gambling preference and crash risk is attenuated in firms with better quality internal control and stronger external monitoring.

Lastly, we explore potential channels through which gambling preference affects crash risk. Consistent with the argument that local gambling preferences will stimulate managers' speculative behavior, we find that firms in regions where gambling is more socially acceptable adopt more aggressive strategies and engage in more speculative accounting practices, which leads to a higher likelihood of stock price crashes over an extended period.

This study has important implications for the crash risk literature. Extant studies examine the determinants of crash risk based on manager- and firm-specific characteristics. We go beyond the current literature by examining the impact of the local environment on crash risk. Our results indicate that regional gambling preferences are an important determinant for firm level stock price crash risk.

References

- Adhikari, B.K., Agrawal, A., 2016. Religion, gambling attitudes and corporate innovation. *Journal of Corporate Finance* 37, 229–248.
- Aggarwal, R., Erel, I., Ferreira, M., Matos, P., 2011. Does Governance Travel Around the World? Evidence from Institutional Investors. *Journal of Financial Economics* 99, 154–181.
- Ahmed, A.S., Duellman, S., 2007. Accounting conservatism and board of director characteristics: An empirical analysis. *Journal of accounting and economics* 43, 411–437.
- Armstrong, C.S., Core, J.E., Guay, W.R., 2014. Do independent directors cause improvements in firm transparency? *Journal of financial economics* 113, 383–403.
- Ashbaugh-Skaife, H., Collins, D.W., Kinney Jr, W.R., LaFond, R., 2009. The effect of SOX internal control deficiencies on firm risk and cost of equity. *Journal of Accounting research* 47, 1–43.
- Baginski, S.P., Campbell, J.L., Hinson, L.A., Koo, D.S., 2018. Do career concerns affect the delay of bad news disclosure? *The Accounting Review* 93, 61–95.
- Bailey, W., Kumar, A., Ng, D., 2011. Behavioral biases of mutual fund investors. *Journal of Financial Economics* 102, 1–27.
- Ball, R., 2009. Market and political regulatory perspectives on the recent accounting scandals. *Journal of Accounting Research* 47, 277–323.
- Bao, D., Kim, Y., Mian, G.M., Su, L., 2019. Do managers disclose or withhold bad news? Evidence from short interest. *The Accounting Review* 94, 1–26.
- Basu, S., 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting & Economics* 24, 3–37.
- Bebchuk, L.A., Cremers, K.J.M., Peyer, U.C., 2011. The CEO pay slice. *Journal of Financial Economics* 102, 199–221.
- Bentley, K.A., Omer, T.C., Sharp, N.Y., 2013. Business strategy, financial reporting irregularities, and audit effort. *Contemporary Accounting Research* 30, 780–817.
- Callen, J.L., Fang, X., 2020. Local Gambling Norms and Audit Pricing. *Journal of Business Ethics* 164, 151–173.
- Callen, J.L., Fang, X., 2015. Religion and Stock Price Crash Risk. *Journal of Financial and Quantitative Analysis* 50, 169–195.
- Chan, C.C., Li, W.W.L., Chiu, A.S.L., 2019. *The psychology of Chinese gambling*. Springer Singapore.
- Chang, X., Chen, Y., Zolotoy, L., 2017. Stock Liquidity and Stock Price Crash Risk. *Journal of Financial and Quantitative Analysis* 52, 1605–1637.
- Chen, J., Hong, H., Stein, J., 2001. Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics* 61, 345–381.
- Chen, T., Harford, J., Lin, C., 2015. Do analysts matter for governance? Evidence from natural experiments. *Journal of financial Economics* 115, 383–410.

- Chen, X., Harford, J., Li, K., 2007. Monitoring: Which Institutions Matter? *Journal of Financial Economics* 86, 279–305.
- Chen, Y., Podolski, E.J., Rhee, S.G., Veeraraghavan, M., 2014. Local gambling preferences and corporate innovative success. *Journal of Financial and Quantitative Analysis* 49, 77–106.
- Chen, Y., Xie, Y., You, H., Zhang, Y., 2018. Does crackdown on corruption reduce stock price crash risk? Evidence from China. *Journal of Corporate Finance* 51, 125–141.
- Cheng, M., Dhaliwal, D., Zhang, Y., 2013. Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting? *Journal of Accounting and Economics* 56, 1–18.
- Christensen, D.M., Jones, K.L., Kenchington, D.G., 2018. Gambling Attitudes and Financial Misreporting. *Contemporary Accounting Research* 35, 1229–1261.
- Dechow, P.M., Sloan, R.G., Sweeney, A.P., 1995. Detecting earnings management. *Accounting review* 70, 193–225.
- DeFond, M.L., Wong, T.J., Li, S., 1999. The impact of improved auditor independence on audit market concentration in China. *Journal of accounting and economics* 28, 269–305.
- Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7, 197–226.
- Dou, Y., Hope, O.K., Thomas, W.B., Zou, Y., 2018. Blockholder exit threats and financial reporting quality. *Contemporary Accounting Research* 35, 1004–1028.
- Doyle, J.T., Ge, W., McVay, S., 2007. Accruals quality and internal control over financial reporting. *The accounting review* 82, 1141–1170.
- Dyck, A., Morse, A., Zingales, L., 2010. Who blows the whistle on corporate fraud? *Journal of Finance* 65, 2213–2253.
- Dyck, A., Zingales, L., 2002. The corporate governance role of the media, in: *The Right to Tell: The Role of Mass Media in Economic Development*. The World Bank, Washington, pp. 107–140.
- Francis, J.R., 2011. A framework for understanding and researching audit quality. *AUDITING: A Journal of Practice & Theory* 30, 125–52.
- Gu, L., Liu, J., Peng, Y., 2020. Locality Stereotype, CEO Trustworthiness and Stock Price Crash Risk: Evidence from China. *Journal of Business Ethics* 1–25.
- Guiso, L., Sapienza, P., Zingales, L., 2006. Does culture affect economic outcomes? *Journal of Economic Perspectives* 20, 23–48.
- Gul, F.A., Kim, J.B., Qiu, A.A., 2010. Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China. *Journal of Financial Economics* 95, 425–442.
- Harp, N.L., Barnes, B.G., 2018. Internal control weaknesses and acquisition performance. *The Accounting Review* 93, 235–258.
- Hilary, G., Hui, K.W., 2009. Does religion matter in corporate decision making in America? *Journal of Financial Economics* 93, 455–473.

- Hong, H., Kubik, J.D., Jeremy, C.S., 2008. The only game in town: Stock-Price Consequences of Local Bias. *Journal of Financial Economics* 90, 20–37.
- Hong, H., Stein, J.C., 2003. Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies* 16, 487–525.
- Hutton, A.P., Marcus, A.J., Tehranian, H., 2009. Opaque financial reports, R2, and crash risk. *Journal of Financial Economics* 94, 67–86.
- Jensen, M.C., Meckling, W.H., 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* 3, 305–360.
- Jiang, W., Wan, H., Zhao, S., 2016. Reputation concerns of independent directors: Evidence from individual director voting. *The Review of Financial Studies* 29, 655–696.
- Jin, L., Myers, S.C., 2006. R2 around the world: New theory and new tests. *Journal of Financial Economics* 79, 257–292.
- John, K., Litov, L., Yeung, B., 2008. Corporate governance and risk-taking. *The journal of finance* 63, 1679–1728.
- Khan, A., Muttakin, M.B., Siddiqui, J., 2013. Corporate governance and corporate social responsibility disclosures: Evidence from an emerging economy. *Journal of business ethics* 114, 207–223.
- Khan, M., Watts., R.L., 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48, 132–150.
- Khanna, V., Kim, E.H., Lu, Y., 2015. CEO Connectedness and Corporate Fraud. *Journal of Finance* 70, 1203–1252.
- Khurana, I.K., Raman, K.K., 2004. Litigation risk and the financial reporting credibility of big 4 versus non-big 4 audits: Evidence from Anglo-American countries. *The Accounting Review* 79, 473–95.
- Kim, J.B., Li, Y., Zhang, L., 2011a. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics* 100, 639–662.
- Kim, J.B., Li, Y., Zhang, L., 2011b. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics* 101, 713–730.
- Kim, J.B., Luo, L., Xie, H., 2016a. Dividend Payments and Stock Price Crash Risk. *SSRN Electronic Journal*.
- Kim, J.B., Wang, Z., Zhang, L., 2016b. CEO Overconfidence and Stock Price Crash Risk. *Contemporary Accounting Research* 33, 1720–1749.
- Kim, J.B., Zhang, L., 2016. Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence. *Contemporary Accounting Research* 33, 412–441.
- Kim, J.B., Zhang, L., 2014. Financial reporting opacity and expected crash risk: Evidence from implied volatility smirks. *Contemporary Accounting Research* 31, 851–875.
- Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. *Quarterly Journal of Economics* 112, 1251–1288.

- Kothari, S.P., Shu, S., Wysocki, P.D., 2009. Do managers withhold bad news? *Journal of Accounting research* 47, 241–276.
- Kumar, A., 2009. Who gambles in the stock market? *Journal of Finance* 64, 1889–1933.
- Kumar, A., Page, J.K., Spalt, O.G., 2016. Gambling and Comovement. *Journal of Financial and Quantitative Analysis* 51, 85–111.
- Kumar, A., Page, J.K., Spalt, O.G., 2011. Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics* 102, 671–708.
- Li, X., Wang, S.S., Wang, X., 2017. Trust and stock price crash risk: Evidence from China. *Journal of Banking and Finance*.
- Liu, B., McConnell, J.J., 2013. The role of the media in corporate governance: Do the media influence managers' capital allocation decisions? *Journal of Financial Economics* 110, 1–17.
- Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215–260.
- Roberts, M., Whited, T., 2012. Endogeneity in empirical corporate finance, in: Constantinides, G., Harris, M., Stulz, R. (Eds.), *Handbook of the Economics of Finance*. Amsterdam, North Holland.
- Rogers, J.L., Van Buskirk, A., 2013. Bundled forecasts in empirical accounting research. *Journal of Accounting and Economics* 55, 43–65.
- Singh, S., Tabassum, N., Darwish, T.K., Batsakis, G., 2018. Corporate governance and Tobin's Q as a measure of organizational performance. *British Journal of Management* 29, 171–190.
- Sobrun-Maharaj, A., Rossen, F. V, Wong, A.S.K., 2012. The impact of gambling and problem gambling on Asian families and communities in New Zealand (final report). Auckland UniServices Ltd.
- Stock, J.H., Yogo, M., 2005. Testing for weak instruments in Linear IV regression, in: Andrews, DWK and Stock, J.H. (Ed.), *Identification and Inference for Econometric Models*. New York: Cambridge University Press, pp. 80–108.
- Watts, R., Zimmerman, J., 1983. Agency problems, auditing and the theory of the firm, some evidence. *Journal of Law and Economics* 26, 613–33.
- Xu, N., Li, X., Yuan, Q., Chan, K.C., 2014. Excess perks and stock price crash risk: Evidence from China. *Journal of Corporate Finance* 25, 419–434.
- Zingales, L., 2000. In search of new foundations. *The journal of Finance* 55, 1623–1653.

Figure 1 Lottery sales across regions in China

Figure 1 depicts the per capita welfare lottery sales for each of the 31 provinces in China using the data from 2017.

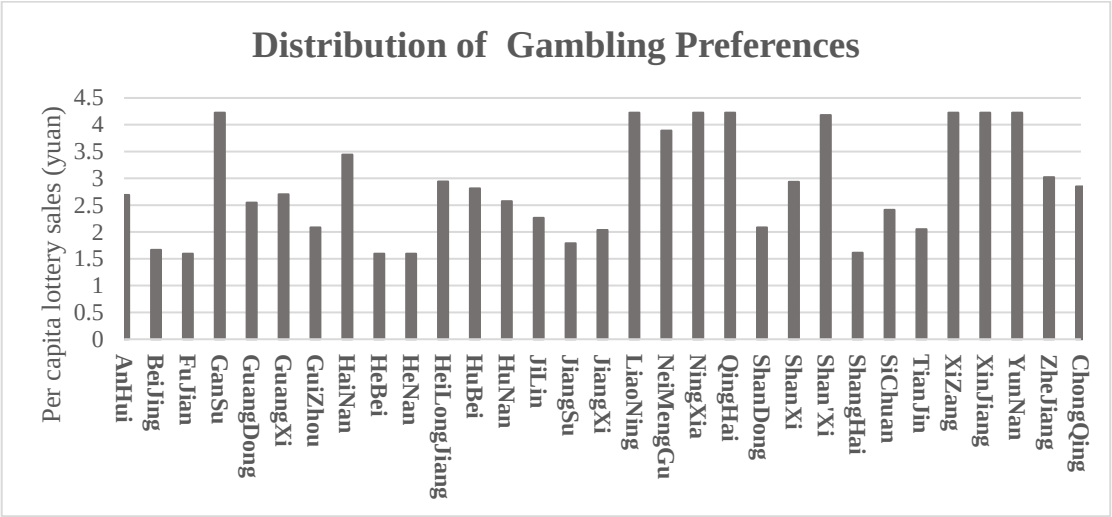


Table 1 Descriptive statistics

This table reports the descriptive statistics of the variables for the Chinese A-share listed firms from 2008 to 2017. Panel A reports the descriptive statistics for all the firm-years included in this study and Panel B compares the means and medians between firms located in regions with high gambling propensity versus low gambling propensity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

Panel A: Descriptive statistics for full sample

Variable	Obs.	Mean	Median	SD	25%	75%
NCSKEW	18525	-0.327	-0.273	0.607	-0.695	0.108
DUVOL	18525	-0.222	-0.212	0.437	-0.527	0.102
GAMBLE	18525	2.562	2.493	0.700	1.975	2.982
GAMBLE_D	18525	0.497	0	0.500	0	1
DTURN	18525	-0.103	-0.082	0.390	-0.327	0.110
RET	18525	0.036	0.020	0.127	-0.054	0.116
STD	18525	0.066	0.060	0.024	0.048	0.079
SIZE	18525	22.044	21.872	1.166	21.112	22.787
LEV	18525	0.441	0.445	0.204	0.278	0.610
MB	18525	2.451	2.018	1.392	1.422	3.089
ABACC	18525	0.057	0.041	0.053	0.018	0.080
ROA	18525	0.040	0.036	0.040	0.014	0.065
TOP1	18525	0.354	0.337	0.143	0.234	0.462
POP	18525	3.929	0.586	1.722	2.923	4.024
P_GDP	18525	10.879	0.466	2.220	9.930	10.938
EDU	18525	0.139	0.113	0.081	0.084	0.151

Panel B: Comparison of means and medians between firms located in regions with high gambling preference versus low gambling preference. The firms are classified into the high (low) gambling propensity sample if the province in which a firm is headquartered has a GAMBLE value above (below) the sample median. See Appendix A for detailed variable definitions.

Variable	High gambling preference sample (N=9217)		Low gambling preference sample (N=9308)		Difference in Mean	Difference in Median
	Mean	Median	Mean	Median	(High-Low)	(High-Low)
NCSKEW	-0.321	-0.268	-0.333	-0.279	0.012**	0.011**
DUVOL	-0.218	-0.210	-0.225	-0.213	0.007**	0.003**
GAMBLE	3.109	2.982	1.995	1.988	1.114***	0.994***
DTURN	-0.100	-0.068	-0.106	-0.098	0.006	0.03***
RET	0.041	0.026	0.032	0.013	0.009***	0.013***
STD	0.064	0.058	0.068	0.062	-0.004***	-0.004***
SIZE	22.074	21.905	22.012	21.848	0.062***	0.057***
LEV	0.435	0.435	0.446	0.456	-0.011***	-0.021***
MB	2.497	2.043	2.402	1.993	0.095***	0.050**
ABACC	0.056	0.04	0.059	0.042	-0.003***	-0.002***
ROA	0.040	0.036	0.041	0.036	-0.001	0.000
TOP1	0.354	0.337	0.354	0.337	0.000	0.000
POP	3.935	4.196	3.923	4.009	0.012	0.187***
P_GDP	10.857	10.924	10.900	10.962	-0.043***	-0.038
EDU	0.135	0.114	0.144	0.105	-0.009***	0.009***

Table 2 Pearson Correlation Matrix

This table presents correlations for the variables in our tests. Bold correlations are those significant at the 5% level or better. See Appendix A for detailed variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)NCSKEW	1															
(2)DUVOL	0.88	1														
(3)GAMBLE	0.11	0.13	1													
(4)GAMBLE_D	0.01	0.01	0.80	1												
(5)DTURN	-0.12	-0.13	0.06	0.02	1											
(6)RET	-0.17	-0.19	0.09	0.03	0.56	1										
(7)STD	-0.09	-0.09	-0.08	-0.07	0.25	0.39	1									
(8)SIZE	-0.09	-0.11	0.02	0.02	0.10	-0.04	-0.22	1								
(9)LEV	-0.08	-0.09	0.00	-0.03	0.10	0.00	0.00	0.48	1							
(10)MB	0.05	0.03	0.02	0.02	0.06	0.38	0.33	-0.50	-0.41	1						
(11)ABACC	0.02	0.01	-0.02	-0.02	0.02	0.03	0.09	-0.05	0.12	0.05	1					
(12)ROA	0.06	0.04	-0.05	-0.02	-0.05	0.07	-0.09	-0.04	-0.43	0.31	0.00	1				
(13)TOP1	-0.05	-0.05	-0.01	-0.00	-0.01	-0.01	-0.04	0.22	0.07	-0.10	-0.01	0.10	1			
(14)POP	0.03	0.03	-0.06	0.00	-0.03	0.01	-0.02	-0.09	-0.06	0.02	-0.03	0.03	-0.08	1		
(15)P_GDP	-0.01	-0.01	-0.21	-0.04	-0.02	0.03	-0.09	0.12	-0.13	0.11	-0.04	0.10	0.02	-0.16	1	
(16)EDU	-0.01	-0.01	-0.18	-0.02	0.00	0.01	-0.03	0.12	-0.07	0.07	-0.02	0.06	0.06	-0.58	0.70	1

Table 3 Gambling attitude and stock price crash risk

This table presents the estimates of regressions of gambling preference on crash risk. The first measure of crash risk is NCSKEW, which is the negative coefficient of skewness. The second measure is DUVOL, which is the down-to-up volatility. All independent variables are lagged by one year. The t-statistics reported in parentheses are based on the standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

	Dependent Variables			
	NCSKEW _{t+1}		DUVOL _{t+1}	
	(1)	(2)	(3)	(4)
GAMBLE	0.028*** (2.71)		0.020*** (2.83)	
GAMBLE_D		0.035** (2.56)		0.024** (2.44)
NCSKEW	0.090*** (8.05)	0.088*** (8.43)		
DUVOL			0.078*** (9.36)	0.073*** (10.39)
DTURN	-0.061*** (-5.51)	-0.060*** (-4.91)	-0.039*** (-5.00)	-0.037*** (-4.34)
RET	0.969*** (12.75)	0.954*** (12.27)	0.700*** (13.99)	0.690*** (13.70)
STD	-1.346*** (-4.48)	-1.342*** (-3.85)	-1.151*** (-5.35)	-1.153*** (-4.71)
SIZE	-0.013** (-2.29)	-0.010* (-1.75)	-0.019*** (-4.50)	-0.016*** (-3.84)
LEV	-0.011 (-0.46)	-0.013 (-0.51)	-0.021 (-1.24)	-0.026 (-1.48)
MB	0.028*** (4.60)	0.030*** (4.82)	0.016*** (3.69)	0.017*** (3.98)
ABACC	0.195** (2.56)	0.149** (2.00)	0.107* (1.90)	0.068 (1.21)
ROA	0.687*** (3.38)	0.651*** (3.25)	0.431*** (3.52)	0.415*** (3.45)
TOP1	-0.115** (-2.48)	-0.117*** (-2.72)	-0.075** (-2.40)	-0.079** (-2.53)
POP	0.453*** (3.16)	0.312** (2.32)	0.324*** (3.50)	0.213** (2.49)
P_GDP	0.091 (0.61)	0.023 (0.10)	0.064 (0.61)	0.014 (0.09)
EDU	0.184** (2.03)	0.107 (1.37)	0.149** (2.49)	0.086 (1.53)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	18,525	18,525	18,525	18,525
Adj. R-squared	0.075	0.072	0.075	0.071

Table 4 Addressing endogeneity issues

This table presents the two-stage-least-square (2sls) tests for gambling preference and crash risk. We use two instrumental variables: (1) the logarithm of the average altitude (in meter) of each province (ALTITUDE) and (2) the logarithm of one plus the number of pawnshops in each province in year 1911 (PAWN). Columns (1) and (2) report the results for the first-stage regression. Column (3) and Column (4) report the results of crash risk on the instrumented gambling variables derived from Column (1) and Column (2), respectively. Year and industry fixed effects are controlled in the regression. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

Variables	Dependent Variables			
	(1)	(2)	(3)	(4)
	1 st stage		2 nd stage	
	GAMBLE	GAMBLE	NCSKEW _{t+1}	DUVOL _{t+1}
Instrumented GAMBLE			0.127*** (3.69)	0.089*** (3.65)
ALTITUDE	0.183*** (29.47)	0.183*** (29.46)		
PAWN	0.252*** (34.11)	0.252*** (34.10)		
NCSKEW	0.002 (0.38)		0.056*** (7.33)	
DUVOL		0.004 (0.50)		0.040*** (5.27)
DTURN	0.004 (0.40)	0.004 (0.40)	-0.105*** (-7.30)	-0.071*** (-6.86)
RET	0.261*** (6.59)	0.263*** (6.60)	0.594*** (11.82)	0.405*** (11.26)
STD	-2.199*** (-12.21)	-2.199*** (-12.78)	-3.314*** (-14.20)	-2.548*** (-15.45)
SIZE	0.023*** (5.42)	0.024*** (5.43)	-0.018*** (-3.39)	-0.020*** (-5.09)
LEV	-0.161 (0.02)	-0.161*** (-6.81)	0.038 (1.25)	0.004 (0.20)
MB	0.012*** (3.41)	0.012*** (3.42)	0.039*** (8.67)	0.026*** (7.88)
ABACC	-0.031 (-0.46)	-0.045 (-0.67)	0.242*** (2.85)	0.127** (2.09)
ROA	-0.543*** (-5.03)	-0.543*** (-5.03)	0.829*** (5.99)	0.528*** (5.36)
TOP1	0.012	0.012	-0.133***	-0.094***

	(0.50)	(0.50)	(-4.07)	(-4.05)
POP	-0.123***	-0.123***	0.024*	0.017*
	(-11.90)	(-11.90)	(1.91)	(1.92)
P_GDP	0.070	0.070***	0.011	0.013
	(4.40)	(4.39)	(0.65)	(1.03)
EDU	-0.641***	-0.641***	0.020	0.036
	(-6.41)	(-6.41)	(0.16)	(0.40)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	17,983	17,983	17,983	17,983
R-squared	0.102	0.102	0.044	0.048
<i>Weak identification test</i>				
Kleibergen-Paap Wald F statistic	798.97	798.89		
<i>Test of overidentifying restrictions</i>				
Hansen J-statistic			1.416	0.809
p-Value			0.234	0.363

Table 5 Propensity score matching analysis

This table presents the propensity score matching tests for gambling preference and crash risk. Column (1) and (2) present the regression results after propensity score matching. Year and industry fixed effects are controlled in the regression. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

Variables	Dependent variables	
	(1) NCSKEW _{t+1}	(2) DUVOL _{t+1}
GAMBLE	0.042*** (3.25)	0.032*** (3.83)
NCSKEW	0.071*** (3.95)	
DUVOL		0.044*** (3.34)
DTURN	-0.072** (-2.45)	-0.032 (-1.34)
RET	0.837*** (4.33)	0.579*** (4.89)
STD	-1.935* (-1.94)	-1.775** (-2.39)
SIZE	-0.010 (-0.56)	-0.013 (-1.09)
LEV	-0.125** (-2.17)	-0.117*** (-2.64)
MB	0.043*** (3.21)	0.027*** (3.58)
ABACC	0.031 (0.24)	0.012 (0.14)
ROA	0.213 (0.70)	0.125 (0.66)
TOP1	-0.075 (-0.91)	-0.071 (-1.16)
POP	0.018 (0.51)	0.008 (0.37)
P_GDP	0.000 (0.01)	-0.017 (-0.85)
EDU	0.007 (0.03)	0.066 (0.40)
Year	Yes	Yes
Industry	Yes	Yes
Observations	3,986	3,986
R-squared	0.093	0.092

Table 6 Additional analysis

This table presents the robustness check on the relationship between gambling preference and crash risk. In columns (1) and (2), the dependent variables are the crash risk variables but we exclude firms headquartered in the three biggest provinces in terms of population to alleviate the possible bias caused by the size of the population. In columns (3), (4) and (5), we use alternative measures of crash risk as described in section 4.3.4. Year and industry fixed effects are included. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Excl. three biggest provinces		Alternative crash risk Measures		
	NCSKEW _{t+1}	DUVOL _{t+1}	NCSKEW _{A,t+1}	DUVOL _{A,t+1}	CRASH COUNT _{t+1}
GAMBLE	0.029*** (2.61)	0.022*** (2.76)	0.025** (2.06)	0.016* (1.77)	0.016* (1.95)
NCSKEW	0.089*** (6.27)		0.103*** (8.47)		
DUVOL		0.079*** (7.89)		0.088*** (7.29)	
CRASH_COUNT					0.041*** (5.35)
DTURN	-0.066*** (-5.28)	-0.043*** (-4.86)	-0.078*** (-3.38)	-0.046*** (-2.79)	-0.038** (-2.39)
RET	0.955*** (11.47)	0.690*** (13.40)	0.809*** (10.99)	0.454*** (10.32)	0.642*** (8.63)
STD	-1.543*** (-4.29)	-1.363*** (-5.89)	-1.603*** (-2.91)	-1.325*** (-3.34)	-1.277*** (-3.54)
SIZE	-0.015** (-1.98)	-0.022*** (-4.03)	-0.000 (-0.05)	-0.011* (-1.74)	-0.007 (-1.08)
LEV	-0.010 (-0.35)	-0.011 (-0.61)	0.007 (0.15)	0.028 (0.79)	0.015 (0.47)
MB	0.032*** (4.56)	0.018*** (4.05)	0.029*** (3.52)	0.020*** (3.36)	0.023*** (4.67)
ABACC	0.217** (2.46)	0.139** (2.28)	0.134 (0.94)	0.078 (0.78)	0.218** (2.42)
ROA	0.587** (2.29)	0.391** (2.55)	0.781*** (3.36)	0.459*** (2.73)	0.670*** (4.65)
TOP1	-0.139*** (-2.77)	-0.083** (-2.37)	-0.073 (-1.45)	-0.064* (-1.80)	-0.124*** (-3.64)
POP	0.601*** (3.39)	0.334*** (2.94)	0.395** (2.34)	0.253** (2.09)	0.019 (1.52)
P_GDP	0.175 (1.10)	0.134 (1.62)	0.257 (0.93)	0.156 (0.77)	0.013 (0.66)
EDU	0.196** (1.99)	0.134** (2.07)	-0.015 (-0.10)	0.023 (0.22)	0.043 (0.35)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Observations	14,202	14,202	18,525	18,525	18,525
R-squared	0.071	0.071	0.073	0.073	0.074

Table 7 Differential effect of gambling preference on future stock price crash risk conditional on internal monitoring

This table presents the effects of internal monitoring on the relationship between gambling preference and crash risk. The dependent variables are the two crash risk variables. In Panel A and B, we partition the entire sample along the median value of the DIB internal control index (IC) and the median value of board independence, respectively. Panel C partition the entire sample based on the median value of the number of board committees. In Panel D, the entire sample is partitioned based on the industry median value of Pay_slice. All independent variables are lagged by one year. Year and industry fixed effects are included. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. F-test is used to test the difference in the coefficients on GAMBLE for the two groups. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

	Panel A: DIB internal control index				Panel B: Board independence			
	NCSKEWt+1		DUVOLt+1		NCSKEWt+1		DUVOLt+1	
	(1) High	(2) Low	(3) High	(4) Low	(1) High	(2) Low	(3) High	(4) Low
GAMBLE	0.011 (0.83)	0.042*** (3.49)	0.014* (1.78)	0.023*** (3.05)	0.009 (0.43)	0.032*** (2.88)	0.011 (0.74)	0.040** (2.56)
<i>F-test for the coefficients of GAMBLING between more and less internal monitoring:</i>								
Chi2	3.04*		2.13		5.41**		4.23**	
P-value	0.08		0.14		0.02		0.04	
NCSKEW	0.087*** (7.79)	0.089*** (6.04)			0.063*** (2.82)	0.084*** (7.38)		
DUVOL			0.078*** (7.03)	0.073*** (6.79)			0.050** (2.34)	0.068*** (6.00)
DTURN	-0.067*** (-3.77)	-0.065*** (-5.27)	-0.048*** (-3.10)	-0.037*** (-2.65)	-0.069 (-1.61)	-0.057*** (-2.60)	-0.037 (-1.26)	-0.033** (-2.12)
RET	0.930*** (9.04)	1.022*** (10.36)	0.631*** (8.27)	0.768*** (11.23)	1.275*** (6.49)	0.979*** (9.52)	0.876*** (6.37)	0.681*** (9.27)
STD	-0.520	-1.650***	-0.501	-1.390***	-3.075***	-1.620***	-2.737***	-1.324***

	(-0.95)	(-3.86)	(-1.40)	(-4.20)	(-3.06)	(-3.16)	(-3.92)	(-3.64)
SIZE	-0.025***	-0.013*	-0.030***	-0.018***	0.050**	-0.013	0.014	-0.015**
	(-2.91)	(-1.80)	(-4.54)	(-3.25)	(2.52)	(-1.49)	(0.98)	(-2.47)
LEV	0.048	-0.063	0.013	-0.042	0.028	0.015	0.091	-0.027
	(1.24)	(-1.59)	(0.36)	(-1.32)	(0.30)	(0.33)	(1.38)	(-0.84)
MB	0.021***	0.026***	0.0084*	0.015***	0.040***	0.024***	0.030***	0.016***
	(2.77)	(3.63)	(1.67)	(3.20)	(2.69)	(3.44)	(2.86)	(3.11)
ABACC	0.202	0.183*	0.103	0.113	0.321	0.154	0.248	0.089
	(1.61)	(1.70)	(1.06)	(1.34)	(1.16)	(1.21)	(1.29)	(0.99)
ROA	0.343	1.027***	0.172	0.668***	-0.181	0.707***	-0.042	0.481***
	(1.23)	(3.28)	(1.26)	(4.25)	(-0.43)	(3.46)	(-0.14)	(3.31)
TOP1	-0.140***	-0.098*	-0.087**	-0.064**	-0.099	-0.056	-0.108	-0.044
	(-2.67)	(-1.72)	(-2.55)	(-2.06)	(-0.99)	(-1.15)	(-1.56)	(-1.27)
POP	0.135	0.834***	0.111	0.523***	-0.012	0.010	-0.015	0.008
	(0.40)	(4.49)	(0.70)	(4.91)	(-0.31)	(0.56)	(-0.54)	(0.63)
P_GDP	0.032	0.123	-0.013	0.112	0.030	0.065**	0.035	0.026
	(0.14)	(0.57)	(-0.02)	(0.56)	(0.54)	(2.29)	(0.87)	(1.27)
EDU	-0.012	0.389***	0.062	0.241**	-0.465	-0.181	-0.376	-0.042
	(-0.17)	(3.56)	(0.53)	(2.38)	(-1.29)	(-1.05)	(-1.49)	(-0.34)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,564	8,961	9,564	8,961	10,056	8,469	10,056	8,469
R-squared	0.09	0.07	0.07	0.09	0.080	0.081	0.080	0.081

	Panel C: Number of board committees				Panel D: Pay_slice			
	NCSKEWt+1		DUVOLt+1		NCSKEWt+1		DUVOLt+1	
	(1) High	(2) Low	(3) High	(4) Low	(1) High	(2) Low	(3) High	(4) Low
GAMBLE	0.019 (0.75)	0.025*** (3.09)	0.002 (0.14)	0.019*** (3.36)	0.027*** (2.98)	0.002 (1.53)	0.020*** (3.10)	0.005 (1.41)
<i>F-test for the coefficients of GAMBLING between more and less internal monitoring:</i>								
<i>Chi2</i>	2.55		4.76**		3.81*		2.78*	
<i>P-value</i>	0.11		0.03		0.05		0.09	
NCSKEW	0.114*** (4.63)	0.076*** (9.37)			0.083*** (9.12)	0.068*** (4.77)		
DUVOL			0.088*** (3.62)	0.063*** (7.84)			0.067*** (7.41)	0.057*** (4.07)
DTURN	-0.006 (-0.13)	-0.062*** (-3.97)	-0.018 (-0.50)	-0.038*** (-3.40)	-0.036** (-2.02)	-0.108*** (-3.96)	-0.024* (-1.88)	-0.065*** (-3.33)
RET	0.622*** (2.76)	0.983*** (13.18)	0.462*** (2.86)	0.711*** (13.37)	0.938*** (11.05)	0.992*** (7.68)	0.696*** (11.55)	0.675*** (7.30)
STD	-1.003 (-0.89)	-1.369*** (-3.70)	-1.510* (-1.88)	-1.128*** (-4.31)	-1.317*** (-3.13)	-1.563** (-2.41)	-1.131*** (-3.82)	-1.334*** (-2.90)
SIZE	0.002 (0.08)	0.000 (0.03)	-0.015 (-1.15)	-0.009** (-1.98)	-0.006 (-0.86)	0.015 (1.28)	-0.012** (-2.47)	-0.004 (-0.51)
LEV	-0.104 (-1.05)	-0.000 (-0.01)	-0.095 (-1.35)	-0.014 (-0.60)	0.001 (0.02)	-0.053 (-0.91)	-0.021 (-0.84)	-0.039 (-0.93)
MB	0.016 (1.04)	0.027*** (5.19)	0.007 (0.66)	0.016*** (4.37)	0.020*** (3.53)	0.038*** (4.14)	0.012*** (2.88)	0.022*** (3.35)
ABACC	-0.498* (-1.88)	0.158* (1.53)	-0.257 (-1.04)	0.067 (0.28)	0.108 (0.45)	0.123 (0.51)	0.056 (0.23)	0.027 (0.11)

	(-1.79)	(1.73)	(-1.29)	(1.03)	(1.05)	(0.78)	(0.77)	(0.24)
ROA	0.466	0.628***	0.100	0.421***	0.580***	0.741***	0.341***	0.557***
	(1.09)	(4.32)	(0.33)	(4.09)	(3.60)	(2.79)	(2.98)	(2.93)
TOP1	-0.106	-0.070**	-0.073	-0.053**	-0.051	-0.156**	-0.027	-0.134***
	(-1.09)	(-2.01)	(-1.06)	(-2.13)	(-1.30)	(-2.51)	(-0.96)	(-3.03)
POP	-0.014	0.038***	-0.001	0.026***	0.034**	0.035	0.021**	0.031*
	(-0.39)	(3.10)	(-0.03)	(2.95)	(2.48)	(1.59)	(2.13)	(1.93)
P_GDP	0.026	-0.002	-0.002	-0.003	-0.006	0.022	-0.007	0.014
	(0.39)	(-0.11)	(-0.04)	(-0.20)	(-0.25)	(0.63)	(-0.45)	(0.55)
EDU	-0.080	0.111	-0.003	0.113	0.148	-0.006	0.116	0.087
	(-0.22)	(0.89)	(-0.01)	(1.27)	(1.04)	(-0.03)	(1.16)	(0.57)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,889	10,636	7,889	10,636	13,008	5,450	13,008	5,450
R-squared	0.127	0.077	0.127	0.076	0.076	0.097	0.077	0.093

Table 8 Differential effect of gambling preference on future stock price crash risk conditional on external monitoring

This table presents the effects of external monitoring on the relationship between gambling preference and crash risk. The dependent variables are the two crash risk measures. In Panel A we partition the entire sample along the median value of the number of analysts following a firm. Panel B and Panel C partition the entire sample based on the median value of institutional shareholder ownership and the number of media reports, respectively. In Panel D, the entire sample is partitioned based on whether a firm's auditor is a top ten auditor in China based on the rankings by the Chinese Institute of Certified Public Accountants. All independent variables are lagged by one year. Year and industry fixed effects are included. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. F-test is used to test the difference in the coefficients on GAMBLE for the two groups. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

	Panel A: Analysts coverage				Panel B: Institutional investors			
	NCSKEWt+1		DUVOLt+1		NCSKEWt+1		DUVOLt+1	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	High	Low	High	Low	High	Low	High	Low
GAMBLE	0.002 (1.34)	0.038*** (3.28)	0.010 (1.46)	0.037*** (3.18)	0.013 (1.32)	0.030** (2.38)	0.020** (2.46)	0.021** (2.52)
<i>F-test for the coefficients of GAMBLING between more and less external monitoring:</i>								
Chi2	2.85*		2.87*		3.12*		2.05	
P-value	0.09		0.09		0.07		0.15	
NCSKEW	0.080*** (4.81)	0.084*** (7.56)			0.071*** (5.49)	0.079*** (6.45)		
DUVOL			0.0681*** (3.99)	0.0702*** (6.32)			0.059*** (5.63)	0.070*** (6.54)
DTURN	-0.108*** (-5.16)	-0.034** (-2.36)	-0.0745*** (-4.34)	-0.02 (-1.63)	-0.057*** (-2.87)	-0.061*** (-3.36)	-0.038*** (-2.89)	-0.040*** (-3.29)
RET	0.828*** (6.06)	1.090*** (13.96)	0.581*** (6.67)	0.802*** (15.19)	0.991*** (12.72)	0.600*** (4.68)	0.444*** (5.47)	0.727*** (12.32)

STD	-0.951 (-1.52)	-1.442*** (-3.81)	-0.765* (-1.91)	-1.345*** (-5.62)	-1.425*** (-3.02)	0.173 (0.45)	0.021 (0.09)	-1.412*** (-4.22)
SIZE	-0.056*** (-4.50)	-0.012 (-1.07)	-0.0501*** (-6.52)	-0.0158*** (-3.18)	-0.015** (-2.02)	-0.052*** (-5.71)	-0.042*** (-6.08)	-0.022*** (-3.66)
LEV	0.004 (0.07)	-0.012 (-0.33)	0.01 (0.20)	-0.03 (-1.32)	-0.004 (-0.13)	0.035 (-0.69)	-0.041 (-1.49)	-0.013 (-0.38)
MB	-0.003 (-0.09)	0.0317*** (3.94)	-0.00 (-0.40)	0.0170*** (3.00)	0.030*** (3.56)	0.003 (0.01)	-0.001 (-0.24)	0.0153*** (2.37)
ABACC	-0.022 (-0.16)	0.270*** (3.78)	-0.01 (-0.07)	0.130** (2.40)	0.053 (0.50)	0.333*** (2.87)	0.122 (1.50)	0.083 (1.26)
ROA	0.303 (1.09)	0.749*** (3.13)	0.14 (0.77)	0.493*** (3.58)	0.794*** (3.42)	0.144 (0.55)	0.031 (0.15)	0.529*** (3.18)
TOP1	-0.113 (-1.49)	-0.077* (-1.86)	-0.07 (-1.59)	-0.0555* (-1.73)	-0.082 (-1.63)	-0.044 (-0.50)	-0.024 (-0.36)	-0.064 (-1.61)
POP	0.332* (1.69)	0.384*** (2.59)	0.201 (1.44)	0.279*** (2.76)	0.412** (2.53)	0.454*** (3.33)	0.302*** (4.01)	0.264** (2.46)
P_GDP	0.215 (0.75)	0.021 (0.04)	0.100 (0.47)	0.100 (0.62)	0.230 (0.75)	0.231 (0.95)	0.034 (0.10)	0.210 (1.20)
EDU	0.034 (0.20)	0.195** (2.03)	0.03 (0.32)	0.154** (2.44)	0.121 (1.33)	0.211 (1.58)	0.199** (2.34)	0.072 (1.11)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6694	10497	6694	10497	9593	8301	9593	8301
R-squared	0.07	0.09	0.07	0.09	0.06	0.09	0.06	0.09

	Panel C: Media coverage				Panel D: Auditors			
	NCSKEW _{t+1}		DUVOL _{t+1}		NCSKEW _{t+1}		DUVOL _{t+1}	
	(1) High	(2) Low	(3) High	(4) Low	(1) Top 10	(2) Non-Top10	(3) Top10	(4) Non-Top10
GAMBLE	0.006 (1.40)	0.031** (2.15)	0.009 (1.12)	0.029** (2.12)	0.002 (0.79)	0.039*** (3.82)	0.003 (1.28)	0.024*** (3.03)
<i>F-test for the coefficients of GAMBLING between more and less external monitoring:</i>								
Chi2	3.88**		3.55*		3.96**		3.12*	
P-value	0.04		0.06		0.04		0.07	
NCSKEW	0.094*** (7.89)	0.086*** (6.51)			0.091*** (7.62)	0.089*** (6.23)		
DUVOL			0.082*** (7.65)	0.074*** (6.20)			0.068*** (6.67)	0.084*** (8.97)
DTURN	-0.035* (-1.82)	-0.077*** (-4.90)	-0.023 (-1.54)	-0.046*** (-4.49)	-0.093*** (-6.73)	-0.043* (-1.67)	-0.055*** (-4.37)	-0.027** (-1.96)
RET	0.919*** (9.79)	0.993*** (10.88)	0.696*** (8.77)	0.673*** (11.62)	0.913*** (8.25)	0.974*** (9.91)	0.621*** (8.06)	0.732*** (11.94)
STD	-1.099*** (-2.68)	-1.429*** (-3.51)	-1.039*** (-4.90)	-1.141*** (-3.94)	-0.991* (-1.84)	-1.547*** (-4.17)	-0.820** (-2.41)	-1.355*** (-5.30)
SIZE	-0.002 (-0.59)	-0.030** (-2.23)	-0.014 (-1.63)	-0.035*** (-3.98)	-0.011 (-0.54)	-0.015** (-2.50)	-0.014** (-2.34)	-0.020*** (-3.93)
LEV	-0.071 (-1.64)	0.042 (0.87)	-0.066** (-2.19)	0.025 (0.64)	-0.022 (-0.47)	-0.031 (-0.93)	-0.023 (-0.90)	-0.041 (-1.44)
MB	0.033*** (4.54)	0.019* (1.91)	0.018*** (3.43)	0.016 (1.43)	0.037*** (4.76)	0.021** (2.22)	0.023*** (4.43)	0.012 (1.56)

ABACC	0.144 (1.16)	0.257** (2.10)	0.125 (1.54)	0.074 (0.83)	0.228** (1.96)	0.173 (1.48)	0.082 (0.77)	0.155* (1.76)
ROA	0.539** (2.10)	0.833*** (3.16)	0.306 (1.59)	0.581*** (3.37)	0.705*** (2.75)	0.723** (2.50)	0.432*** (2.62)	0.433** (2.53)
TOP1	-0.083 (-1.25)	-0.183*** (-3.92)	-0.063 (-1.32)	-0.105*** (-4.16)	-0.159** (-2.32)	-0.084 (-1.61)	-0.103** (-2.36)	-0.053 (-1.54)
POP	0.443*** (2.78)	0.412*** (2.61)	0.296*** (2.79)	0.301*** (2.84)	0.394** (2.26)	0.543*** (3.32)	0.334*** (3.04)	0.333*** (2.92)
P_GDP	0.312 (1.58)	-0.234 (-0.83)	0.213 (1.26)	-0.171 (-0.91)	-0.323 (-1.40)	0.432*** (2.62)	-0.214 (-1.03)	0.211* (1.90)
EDU	0.172 (1.21)	0.150* (1.78)	0.153 (1.40)	0.129** (2.17)	0.392*** (3.05)	0.092 (0.95)	0.297*** (3.71)	0.092 (1.18)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8556	8429	8556	8429	7878	9847	7878	9847
R-squared	0.08	0.06	0.08	0.06	0.07	0.08	0.07	0.08

Table 9 Channel analysis

This table presents the channels through which gambling preference impacts crash risk. Year and industry fixed effects are included. The t-statistics reported in parentheses are based on standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

Panel A Strategy Aggressiveness

This table reports the results for channel analysis on strategy aggressiveness. *STRA* is a firm's strategy aggressiveness score and *EARNINGS_VOL* is a firm's earnings volatility in past five years. See Appendix A for more detailed definition.

	STRA			EARNINGS VOL		
	(1) STRA	(2) NCSKEW _{t+1}	(3) DUVOL _{t+1}	(4) VOL	(5) NCSKEW _{t+1}	(6) DUVOL _{t+1}
GAMBLE	0.167*** (2.62)			0.012*** (3.50)		
STRA		0.004*** (2.78)	0.003*** (2.83)			
EARNINGS VOL					0.060*** (2.78)	0.040*** (2.66)
NCSKEW		0.070*** (5.74)			0.056*** (5.43)	
DUVOL			0.054*** (5.43)			0.040*** (5.93)
SIZE	-0.081 (-1.62)	-0.030*** (-3.86)	-0.023*** (-4.13)	0.054*** (19.52)	-0.019*** (-3.45)	-0.020*** (-4.81)
LEV	0.542* (1.93)	0.176*** (4.52)	0.103*** (3.81)	0.115*** (7.58)	0.012 (0.42)	-0.014 (-0.70)
MB	0.528*** (12.58)	0.037*** (4.61)	0.024*** (4.50)	0.033*** (14.38)	0.040*** (6.57)	0.026*** (5.89)
ROA	17.056*** (13.42)	0.683*** (2.63)	0.401*** (2.59)	0.248*** (3.58)	0.730*** (3.33)	0.454*** (3.47)
SOE	-0.960*** (-9.68)					
BOARD SIZE	-0.558** (-2.17)					
BOARD IND	0.859 (0.94)					
DUALITY	0.201 (1.53)					
DTURN		-0.104*** (-4.31)	-0.069*** (-3.77)	0.029*** (3.83)	-0.102*** (-8.71)	-0.070*** (-8.24)
RET		0.840*** (11.88)	0.571*** (11.06)	-0.195*** (-7.60)	0.629*** (13.47)	0.430*** (15.10)
STD		-3.152*** (-10.57)	-2.414*** (-11.40)	0.409*** (3.57)	-3.620*** (-16.16)	-2.763*** (-16.40)
ABACC		0.056 (0.54)	0.024 (0.33)	0.585*** (13.23)	0.188** (2.31)	0.099* (1.65)
TOP1		0.012 (0.24)	0.024 (0.69)	0.021 (1.26)	-0.145*** (-3.36)	-0.101*** (-3.20)
POP		-0.145 (-0.87)	-0.153 (-1.53)	0.011* (1.77)	0.026 (1.25)	0.018 (1.36)
P GDP		-0.874*** (-3.57)	-0.574*** (-3.68)	-0.027*** (-3.16)	0.004 (0.12)	0.007 (0.37)
EDU		-0.046 (-0.24)	-0.048 (-0.40)	-0.070 (-1.15)	0.045 (0.26)	0.053 (0.48)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,578	7,578	7,578	18,525	18,525	18,525
R-squared	0.096	0.056	0.053	0.053	0.048	0.048

Panel B Accounting practice: Mandatory disclosure

This table reports the results for channel analysis on accounting practice aggressiveness. *C_SCORE* measures a firm's conditional conservatism, while *ACCRUAL* is the signed abnormal accrual of a firm. See Appendix A and B for more detailed discussion on these variables.

	C SCORE			ACCRUAL		
	(1) C_SCORE	(2) NCSKEW _{t+1}	(3) DUVOL _{t+1}	(4) ACCRUAL	(5) NCSKEW _{t+1}	(6) DUVOL _{t+1}
GAMBLE	-0.004*** (-9.60)			0.003** (2.07)		
C_SCORE		-0.572** (-2.45)	-0.384** (-2.19)			
ACCRUAL					0.106*** (3.83)	0.054*** (2.68)
NCSKEW		0.075*** (6.55)			0.071*** (7.06)	
DUVOL			0.057*** (6.75)			0.051*** (7.96)
SIZE	0.014*** (40.65)	-0.042*** (-6.30)	-0.035*** (-6.94)	0.006*** (3.82)	-0.053*** (-10.14)	-0.042*** (-10.54)
LEV	0.011*** (5.65)	0.115*** (3.57)	0.057*** (2.78)	-0.010 (-1.12)	0.086** (2.41)	0.026 (1.15)
MB	-0.001** (-2.13)	0.026*** (4.17)	0.016*** (3.24)	-0.006*** (-5.23)	0.022*** (3.63)	0.013** (2.53)
ROA	0.005 (0.62)	1.029*** (3.73)	0.682*** (4.03)	0.531*** (13.22)	0.986*** (4.00)	0.669*** (4.26)
SOE	-0.002*** (-3.58)			-0.005* (-1.71)		
BOARD_SIZ	-0.001 (-0.56)			0.005 (0.57)		
BOARD_IN	0.010* (1.66)			0.072** (2.52)		
DUALITY	0.002** (2.40)			0.004 (1.23)		
DTURN		-0.088*** (-4.12)	-0.054*** (-3.15)		-0.084*** (-5.79)	-0.055*** (-4.71)
RET		0.757*** (10.69)	0.527*** (9.99)		0.714*** (11.04)	0.500*** (11.86)
STD		-3.638*** (-14.57)	-2.821*** (-14.24)		-3.380*** (-15.65)	-2.665*** (-17.03)
ABACC		0.195* (1.83)	0.110 (1.42)			
TOP1		-0.071 (-1.59)	-0.045 (-1.33)		-0.087** (-2.06)	-0.053* (-1.66)
POP		0.153 (0.94)	0.090 (0.92)		0.063 (0.39)	0.043 (0.42)
P_GDP		-0.564** (-2.50)	-0.354*** (-2.65)		-0.554** (-2.42)	-0.360*** (-2.60)
EDU		0.140 (0.73)	0.101 (0.85)		0.107 (0.58)	0.099 (0.86)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,089	12,089	12,089	13,514	13,514	13,514
R-squared	0.220	0.059	0.058	0.022	0.055	0.056

Panel C Accounting practice: Voluntary disclosure

This table reports the results for channel analysis on bad news hoarding. The dependent variable is *CAR*, which is the cumulative abnormal returns above value-weighted market returns for seven trading days surrounding the management earnings forecast announcement date. The independent variables include: *MFNews* is the news included in the management forecast, which is equal to the management forecasted earnings subtracting the most recent analyst consensus forecast, scaled by the analyst consensus forecast;; *BadNews*, which equals 1 if *MFNews* is less than 0, and 0 otherwise; and *EarnSurp*, which is the earnings surprise in a concurrent earnings announcement relative to the most recent analyst consensus forecast. *ADJBadNews* and *ADJMFNews* are the adjusted *BadNews* and *MFNews*, respectively, following the Rogers and Van Buskirk (2013) method. See section 5.2.3 for more detailed discussion on these variables.

^aThe differential market reaction for “Base model” and “Low gamble” is $|\alpha + \beta_0| - |\alpha|$, and the F-test tests: $|\alpha + \beta_0| < -1 \times \alpha$.

^bThe differential market reaction for “High gamble” is $|\alpha + \beta_0 + \beta_1 + \beta_2| - |\alpha + \beta_1|$, and the F-test tests: $|\alpha + \beta_0 + \beta_1 + \beta_2| < -1 \times (\alpha + \beta_1)$

^cThe difference of market reactions between “High gamble” differential and “Low gamble” differential is $(|\alpha + \beta_0 + \beta_1 + \beta_2| - |\alpha + \beta_1|) - (|\alpha + \beta_0| - |\alpha|)$, and the F-test tests: $(|\alpha + \beta_0 + \beta_1 + \beta_2| - |\alpha + \beta_1|) > (|\alpha + \beta_0| - |\alpha|)$.

	Dependent Variables			
	Kothari et al (2009) method		Rogers and Van Buskirk (2013) method	
	(1)	(2)	(3)	(4)
	CAR	CAR	CAR	CAR
Intercept	0.002*** (9.36)	0.001*** (9.30)	Intercept	0.002*** (9.62) 0.002*** (9.49)
BadNews	-0.016*** (-12.13)	-0.013*** (-11.69)	ADJBadNews	-0.019*** (-11.91) -0.016*** (-11.77)
GAMBLE		0.001** (2.20)	GAMBLE	0.001** (2.12)
BadNews*GAMBLE		-0.014* (-1.74)	ADJBadNews*GAMBLE	-0.019* (-1.91)
MFNews	0.004* (1.72)	0.003* (1.69)	ADJMFNews	0.005* (1.69) 0.006* (1.91)

MFNews*BadNews	0.004 (0.41)	0.004 (0.39)	ADJMFNews*BadNews	0.009 (1.42)	0.006* (1.73)
EarnSurp	0.001 (0.27)	0.000 (0.26)			
EarnSurp* BadNews	0.007** (2.22)	0.006** (2.19)			
Year	Yes	Yes	Year	Yes	
Industry	Yes	Yes	Industry	Yes	
Observations	4,221	4,221	Observations	3,207	
R-squared	0.073	0.073	R-squared	0.075	
Difference between High Gamble Differential Market Reaction and Low Gamble Differential Market Reaction and F-test Significance:					
Base model ^a	0.012***		Base model	0.015***	
Low gamble ^a		0.011***	Low gamble		0.012***
High gamble ^b		0.023***	High gamble		0.028***
Difference ^c		0.012*	Difference		0.016**

Table 10 Lottery sales and charity attitudes

This table presents the estimates of regressions of lottery sales and charity attitudes. The first measure of charity attitude is CSR_SCORE, which is the corporate social responsibility score. The second measure is DONATION, which is the amount of donation scaled by total assets. The control variables are: the percentage of outstanding shares owned by the largest shareholder at the fiscal year end (TOP1), profitability (ROA), financial leverage (LEV), board independence (BOARD_IND), DUALITY, firm size (SIZE), and firm background (SOE). The t-statistics reported in parentheses are based on the standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

	Dependent variables	
	CSR_SCORE	DONATION
	(1)	(2)
GAMBLE	-0.010 (-1.03)	0.008 (1.64)
TOP1	-0.019 (-0.97)	-0.017 (-1.03)
ROA	1.728*** (37.41)	0.500*** (6.87)
LEV	-0.080*** (-5.11)	-0.013 (-0.77)
BOARD_IND	0.065 (1.23)	0.047 (1.14)
DUALITY	-0.003 (-0.69)	0.010 (1.39)
SOE	0.024** (2.32)	-0.022*** (-3.31)
SIZE	0.071*** (15.73)	0.036*** (8.38)
Year	Yes	Yes
Industry	Yes	Yes
Observations	11,011	3,053
Adj. R-squared	0.354	0.233

Table 11 The influence of local investors

This table presents the role of local investors in the estimates of regressions of gambling preference on crash risk. *Low BE/PI* equals one if the BE/PI associated with a firm is below the median BE/PI of all sample firms in a given year, and zero otherwise. BE/PI equals the total book equity of all public companies headquartered in a province during a year divided by the aggregate disposable income of urban residents in the province during the year. *High Indiv* equals one if a firm has an above-median fraction of individual shareholdings in a year (approximated by below-median fraction of institutional shareholdings), and zero otherwise. All independent variables are lagged by one year. The t-statistics reported in parentheses are based on the standard errors clustered by province. Intercepts are not reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. See Appendix A for detailed variable definitions.

	Dependent Variables			
	NCSKEW _{t+1}		DUVOL _{t+1}	
	(1)	(2)	(3)	(4)
GAMBLE	0.049** (2.55)	0.019* (1.78)	0.031** (2.29)	0.014* (1.79)
GAMBLE * Low BE/PI	-0.028 (-1.47)		-0.015 (-1.29)	
GAMBLE * High Indiv		0.013 (1.44)		0.010 (1.45)
Low BE/PI	0.100* (1.83)		0.054 (1.50)	
High Indiv		-0.156*** (-5.77)		-0.106*** (-6.29)
NCSKEW	0.088*** (8.74)	0.077*** (8.08)		
DUVOL			0.073*** (10.79)	0.063*** (9.47)
DTURN	-0.060*** (-5.02)	-0.056*** (-4.68)	-0.038*** (-4.45)	-0.035*** (-4.02)
RET	0.954*** (12.26)	0.840*** (11.65)	0.691*** (13.62)	0.613*** (13.25)
STD	-1.299*** (-3.78)	-0.974** (-2.74)	-1.134*** (-4.62)	-0.898*** (-3.56)
SIZE	-0.009 (-1.57)	-0.023*** (-4.14)	-0.015*** (-3.75)	-0.025*** (-6.20)
LEV	-0.014 (-0.56)	-0.019 (-0.74)	-0.027 (-1.51)	-0.031* (-1.72)
MB	0.030*** (4.89)	0.022*** (3.79)	0.018*** (4.04)	0.012*** (2.89)
ABACC	0.152** (1.99)	0.146* (1.90)	0.070 (1.23)	0.065 (1.13)
ROA	0.657*** (3.29)	0.482** (2.38)	0.421*** (3.52)	0.302** (2.51)
TOP1	-0.119*** (-2.73)	-0.070 (-1.54)	-0.080*** (-2.58)	-0.047 (-1.47)
POP	0.041** (2.45)	0.034* (2.04)	0.028** (2.55)	0.023** (2.22)
P GDP	0.020 (1.02)	0.009 (0.50)	0.007 (0.68)	0.003 (0.29)
EDU	0.256 (1.66)	0.135 (1.05)	0.195* (1.91)	0.122 (1.45)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	18,525	18,525	18,525	18,525
Adj. R-squared	0.072	0.080	0.071	0.079

Appendix A Variable Definitions

Variables	Definitions
<i>Dependent variables</i>	
$NCSKEW_{t+1}$	The negative coefficient of skewness, calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. See Eq. (2) for more details.
$DUVOL_{t+1}$	The down-to-up volatility. For any stock i in year t , we separate all the weeks with firm-specific weekly returns below the annual mean (down weeks) from those with firm-specific weekly returns above the annual mean (up weeks) and compute the standard deviation for each of these subsamples separately. We then take the log of the ratio of the standard deviation of the down weeks to the standard deviation of the up weeks. See Eq. (3) more for details.
<i>Independent variables</i>	
$GAMBLE$	Welfare lottery sales per capita over the fiscal year
$GAMBLE_D$	Indicator variable that equals 1 if the $GAMBLE$ is greater than the median value in year t , and 0 otherwise.
<i>Control variables</i>	
$DTURN_t$	Detrended average monthly stock turnover in a year, calculated as the average monthly share turnover in the year minus the average monthly share turnover in the previous year
RET_t	The mean of firm-specific weekly returns over the fiscal year
STD_t	The standard deviation of firm-specific weekly returns over the fiscal year
$SIZE_t$	The natural logarithm of the book value of total assets at the fiscal year end
LEV_t	The ratio of total debts to total assets at the fiscal year end
MB_t	The ratio of market value of equity to book value of equity at the fiscal year end
$ABACC_t$	The absolute value of discretionary accruals estimated from the adjusted Jones model over the fiscal year
ROA_t	The ratio of net income to total assets
$TOP1_t$	The percentage of outstanding shares owned by the largest shareholder at the fiscal year end
POP	The natural logarithm of the population (in million) of province over the fiscal year
P_GDP	The natural logarithm of per capita GDP (in RMB) in the province over the fiscal year
EDU	The ratio of population with high school degree or above to the total population in the province over the fiscal year

Variables	Definitions
<i>Economic mechanisms</i>	
$STRA_t$	Strategic aggressiveness (STRA) is measured following Bentley et al. (2013) by using the aggregate ranking score of the following six variables over the past five years: the ratio of R&D expenditure to sales revenue, the ratio of employees to sales revenue, the growth rate of sales revenue, the ratio of the sum of sales expenses and management expenses to sales revenue, the volatility of headcount, and the proportion of fixed assets to total assets. Each of the six variables is computed using a rolling average over the prior five years and ranked by forming quintiles based on industry-year grouping. For the first five variables above, the observations are assigned a rank of 4 (0) to the quintile with highest (lowest) value for each variable. In contrast, for the sixth variable (i.e., the proportion of fixed assets to total assets), we invert the order so that the quintile with largest (smallest) value is assigned a rank of 0 (4). Then for each observation, we aggregate the rank scores for all the six variables. As a result, a company could receive a maximum score of 24 and a minimum score of 0, with higher scores indicating more strategic aggressiveness.
$EARNINGS_VOL_t$	Earnings volatility (<i>EARNINGS_VOL</i>) is calculated following John et al. (2008): we first compute the deviation of firm's ROA (Return on Assets, EBITDA/total assets) from the industry average for the corresponding year. Then, we calculate the standard deviation of this measure for each firm over the last five years. Formulas are as follows: $Risk_{it} = std(ROA)_{it} = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (AdjROA_{ijt} - \frac{1}{T} \sum_{t=1}^T AdjROA_{ijt})^2} T = 5$ where $AdjROA_{ijt} = ROA_{ijt} - \frac{1}{N_{jt}} \sum_{k=1}^{N_{jt}} ROA_{kjt}$. N_{jt} is the number of firms within industry j and year t, and ROA is winsorized at the 1% and 99% levels.
C_SCORE_t	The conservatism score estimated following Khan and Watts (2009). See Appendix B for a more detailed explanation.
$ACCRUAL_t$	The signed value of discretionary accrual estimated from the modified Jones model (Dechow et al., 1995)
CAR_t	The seven-day cumulative abnormal return (CAR) around each announcement date for management earnings forecast, where abnormal returns are defined as a firm's stock return minus the corresponding Shanghai and Shenzhen Composite Index return. See section 5.3 for more detailed discussion on this variable.

Appendix B Calculation of Conditional Conservation (C_SCORE)

We measure firm-year conditional conservation (C_SCORE) according to Khan and Watts (2009). The estimation begins with the Basu (1997) model:

$$X_{jt} = \beta_{1t} + \beta_{2t}D_{jt} + \beta_{3jt}R_{jt} + \beta_{4jt}D_{jt} \times R_{jt} + \varepsilon_{jt} \quad (A1)$$

Then, the coefficients β_{3jt} and β_{4jt} are expressed as linear functions of firm-year-specific characteristics that are correlated with the timeliness of good news and conservatism, respectively:

$$G_{SCORE} = \beta_{3jt} = \mu_{1t} + \mu_{2t}MKV_{jt} + \mu_{3t}MB_{jt} + \mu_{4t}LEV_{jt} \quad (A2)$$

$$C_{SCORE} = \beta_{4jt} = \gamma_{1t} + \gamma_{2t}MKV_{jt} + \gamma_{3t}MB_{jt} + \gamma_{4t}LEV_{jt} \quad (A3)$$

where MKV is the natural log of the market value, MB is the market-to-book equity ratio, and LEV is the debt-to-equity ratio, all of which are measured at the beginning of the year. Replacing β_{3jt} and β_{4jt} in Eq. (A1) by Eq. (A2) and Eq. (A3), respectively, yields the following empirical model:

$$\begin{aligned} X_{jt} = & \beta_{1t} + \beta_{2t}D_{jt} + R_{jt}(\mu_{1t} + \mu_{2t}MKV_{jt} + \mu_{3t}MB_{jt} + \mu_{4t}LEV_{jt}) + \\ & D_{jt} \times R_{jt}(\gamma_{1t} + \gamma_{2t}MKV_{jt} + \gamma_{3t}MB_{jt} + \gamma_{4t}LEV_{jt}) + (\delta_{1t}MKV_{jt} + \delta_{2t}MB_{jt} + \\ & \delta_{3t}LEV_{jt} + \delta_{4t}D_{jt}MKV_{jt} + \delta_{5t}D_{jt}MB_{jt} + \delta_{6t}D_{jt}LEV_{jt}) + \varepsilon_{jt} \end{aligned} \quad (A4)$$

We then estimate Eq. (A4) using five-year rolling panel regressions and calculate C_SCORE using Eq. (A3) with the estimated coefficients γ_{1t} , γ_{2t} , γ_{3t} , and γ_{4t} from Eq. (A4). In this case, firms with a higher C_SCORE are considered more conservative.