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# Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin



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# Organization capital and stock price crash risk<sup>★</sup>

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#### ARTICLE INFO

JEL classification: G10

G32

Keywords: Organization capital Corporate governance Stock price crash risk

#### ABSTRACT

This study explores the relationship between organization capital and stock price crash risk. Using a sample of publicly traded firms in China between 2010 and 2022, we find that firms with a high level of organization capital have higher future stock price crash risk. This positive relationship is more prominent for firms with low financing constraints, high profit retention ratios, and high levels of risk-taking behavior than for other firms. We also examine the potential mechanisms that moderate this positive relationship. Our results indicate that the positive association is less apparent among non-state-owned enterprises, firms in intensely religious environments, firms in which management holds shares, and firms with strong monitoring vigilance. Further analysis reveals that firms can reduce this positive association by increasing the frequency with which independent directors meet and increasing the diversity of the backgrounds of independent directors. Our findings are robust to various robustness tests, such as the instrumental variable approach, entropy balancing analysis, and alternative measures of organization capital and stock price crash risk.

### 1. Introduction

Intangible assets play increasingly critical roles in the survival and success of modern enterprises, and as a vital intangible asset, organization capital (OC) has drawn widespread attention from researchers in recent years (Corrado et al., 2009; Peters and Taylor, 2017). OC is the collection of knowledge, business practices, corporate culture, and systems built over time that facilitates the efficient interaction of human capital and tangible capital to improve corporate production efficiency (Lev et al., 2009; Carlin et al., 2012). As OC is embedded in the organization and key talents, such as corporate executives and line managers, it is rooted in the routine operations of the enterprise and is difficult to imitate or replace (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013). Anecdotal news reports indicate that firms with substantial OC experience a rapid decline in their stock prices after the unexpected release of negative information. This phenomenon raises an important question: Do key talents in firms with substantial OC tend to hoard

<sup>★</sup> This work was supported by the Shenzhen Technology University

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<sup>&</sup>lt;sup>1</sup> For example, Facebook has substantial OC. However, Facebook lost more than \$100 billion of its market value within few days after the scandal broke that Facebook users' profiles were used by Cambridge Analytica without users' consent to design political advertising and sway voter sentiment (Tuttle, 2018). Similarly, Wal-Mart has a high level of OC due to its supply chain and inventory management. However, Wal-Mart's market value decreased more than \$10 billion immediately after the exposure of the Mexican bribery scandal (Barstow, 2013).

negative information, potentially resulting in increased stock price crash risk?

According to agency theory, asymmetric information motivates key talents (i.e., agents) to hide negative information about the firm for their own benefits, including bonuses, promotions, and job opportunities (Healy and Palepu, 2001). Once hoarded bad news is exposed to the public, the firm's equity prices experience a crash (Jin and Myers, 2006; Hutton et al., 2009). Stock price crash risk can be described as the presence of negative skewness in the return distribution of a specific stock, which captures the asymmetric risk of corporate stock prices (Habib et al., 2018).

As a unique corporate characteristic, high levels of OC may escalate the agency problem between shareholders and key talents (Leung et al., 2018). Firms with substantial OC are associated with complex corporate information environments (Kim et al., 2021) that provide ideal opportunities for key talents to conceal bad news. Moreover, firms with substantial OC provide key talents with better outside options than other firms; thus, key talents have strong incentives to suppress bad news to maintain their outside options for their own benefit (Eisfeldt and Papanikolaou, 2013). The accumulation of this bad news continues until it reaches the threshold at which the news is leaked, leading to stock price crashes (Jin and Myers, 2006). Hence, firms with substantial OC may have increased future stock price crash risk.

OC is also connected to advanced business practices and superior management ability (Eisfeldt and Papanikolaou, 2013). Firms with substantial OC have a high level of social capital and thus have comprehensive access to and exchange of information (Subramaniam and Youndt, 2005). Conversely, an efficient operating environment reduces the likelihood of key talents suppressing negative information. Moreover, firms with substantial OC are more noticeable to a broad range of stakeholders (Brynjolfsson et al., 2002), meaning that key talents are likely to suffer high reputational costs once opportunistic behaviors are detected. Such employees may thus have few chances and little willingness to pursue self-interested activities or conceal negative information (He and Ren, 2022). In other words, firms with substantial OC may also have a reduced risk of future stock price crashes relative to firms with low levels of OC. Given these competing arguments, we examine whether high levels of OC increase or decrease firms' future stock price crash risk.

Financing constraints substantially affect corporate survival and growth (Clementi and Hopenhayn, 2006). Firms with financing constraints are often subject to strict external monitoring, which limits the ability of key talents to conceal negative information. In contrast, in firms with few financing constraints, key talents are more likely to raise extra funds to build OC to suit their own interests. Therefore, we examine whether the effects of OC on stock price crash risk are different for firms with different degrees of financial constraints. Similarly, key talents in firms with high profit retention ratios have more funds and a better chance of building OC in their own interests than talents in firms with lower profit retention ratios. Thus, we also examine whether the effects of OC on stock price crash risk differ with the corporate retention ratio.

Hasan and Cheung (2023) find that firms with substantial OC are often associated with high total risk and idiosyncratic risk. Kim et al. (2011b) find that key talents in firms displaying greater risk-taking behavior are more likely to withhold bad news than talents in firms displaying less risky behavior and thus have greater stock price crash risk. Cao et al. (2022) further find that firms with greater idiosyncratic risk often have increased stock price crash risk. Thus, our last task is to investigate whether the effects of OC on stock price crash risk are also induced by corporate risk-taking behavior.

The Chinese stock market provides a suitable context for determining the essential role of OC in future stock price crash risk. Despite rapid development over the last 40 years, the Chinese stock market remains underdeveloped compared with mature stock markets in terms of its legal and governance systems (Allen et al., 2005). A high level of information opaqueness and severe agency problems are prevalent in Chinese listed firms (Li and Cai, 2016), making stock price crashes more frequent (Piotroski and Wong, 2012). Moreover, more than 95 % of firms in China are small and medium-sized enterprises (SMEs) (Cheng et al., 2022). As the influence of OC is more obvious in developing enterprises than in established firms (Eisfeldt and Papanikolaou, 2013), the effects of OC on stock price crash risk are predicted to be stronger in the Chinese market than in mature markets.

We perform the following tests. First, we collect accounting and firm characteristics data on publicly traded firms from the China Stock Market and Accounting Research (CSMAR) database for the 2010–2022 period. We then estimate corporate OC using the model of Eisfeldt and Papanikolaou (2013) and the model of Peters and Taylor (2017) as an alternative measure. Following previous studies (Kim et al., 2011a; Lei and Song, 2022), in our baseline analyses, we calculate the negative coefficient of skewness (*Ncskew*) of corporate weekly returns as a proxy for stock price crash risk. We then replace *Ncskew* with down-to-up volatility (*Duvol*) as an alternative proxy. Our baseline analyses suggest that firms with substantial OC experience increased future stock price crash risk. We also find that a one standard deviation increase in the corporate OC ratio leads to an economically significant increase of approximately 4.3 % to 4.6 % in future stock price crash risk relative to its average value.

Second, we split our full sample into two sub-samples based on the degree of financing constraints, profit retention ratios, and corporate risk-taking behavior. Our findings indicate that firms with low financing constraints, high retention ratios, and high levels of risk-taking behavior are prone to increased future stock price crash risk. Third, we carry out three additional robustness tests of our main results using the instrumental variable (IV) approach and entropy balancing analysis to address potential endogeneity problems and the multivariate crash risk measure as an alternative proxy for crash risk. The results of the robustness tests support all of the baseline results. Finally, we explore the moderating effect of corporate ownership structures, cultural factors, and reduced corporate agency–principal conflicts on the positive association between OC and future stock price crash risk. Our findings indicate that the positive association is less pronounced for non-state-owned enterprises (non-SOEs) and firms headquartered in intensely religious environments with more Buddhist temples. The positive association is also moderated by strong internal and external monitoring and the granting of shares to management. Further analysis reveals that firms can reduce this positive association by increasing the frequency at which independent directors meet and diversifying the background of their independent directors.

Our study contributes to the literature in two ways. First, it enriches research on the factors influencing stock price crash risk. As

crash risk is a key feature of stock return distributions, exploring the determinants of stock price crash risk has critical implications for risk management and investment selection (Habib et al., 2018). Numerous studies identify various factors that are linked to stock price crash risk, such as product market competition (Li and Zhan, 2019), CEO overconfidence (Kim et al., 2016), intangible intensity (Wu and Lai, 2020), and corporate brands (Hasan et al., 2022). In this study, we expand this research and explore the influence of a vital corporate intangible asset, OC, on future stock price crash risk.

Second, this study extends the literature on OC. In recent years, an increasing number of studies have investigated the impact of OC from corporate operational and financial perspectives, for example, focusing on corporate performance (Tronconi and Marzetti, 2011; Boubaker et al., 2022), corporate value (Hasan et al., 2021), the firm life cycle (Hasan and Cheung, 2018), mergers and acquisitions (Li et al., 2018), and cash holdings (Marwick et al., 2020). However, few studies examine the impacts of OC on stock price crash risk. Unlike previous studies that investigate the associations between OC and stock returns or firm risk (Eisfeldt and Papanikolaou, 2013; Hasan and Cheung, 2023), which consider the means and variances of stock returns, we take a different perspective by using agency theory to link OC to stock price crash risk. We believe that this study provides insights for capital market investors. Traditional returns and risk measures cannot distinguish between large stock price plunges over a short period and steady price declines over a long period (Robin and Zhang, 2015). As stock price crash risk is a potent way to capture equity price crashes over a short period (Hutton et al., 2009), our study examines the association between a firm's OC and its stock price fluctuations from a new angle.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and presents the hypotheses. Section 3 presents the data and methodology. Section 4 reports the empirical results. Section 5 presents the robustness tests. Section 6 presents the results of further analysis. Section 7 concludes the paper.

#### 2. Literature review and hypothesis development

Stock return distributions often display greater negative skewness than large positive price movements (Chen et al., 2001; Kim et al., 2014). This financial phenomenon has prompted numerous scholars to investigate the factors that affect these price crashes. One stream of literature focuses on external factors, such as stock returns and trading volume (Chen et al., 2001), institutional investors (An and Zhang, 2013), auditors specializing in a particular industry (Robin and Zhang, 2015), adoption of international accounting standards (DeFond et al., 2015), stock liquidity (Chang et al., 2017), social trust (Li et al., 2017), and economic policy uncertainty (Lei and Song, 2022). Another stream focuses on internal factors, such as opaque financial reports (Hutton et al., 2009), tax planning strategies (Kim et al., 2011a), religion (Callen and Fang, 2015a), equity incentives and short-term compensation (Kim et al., 2011b; Callen and Fang, 2015b), and internal control systems (Chen et al., 2017). However, research on how firm-specific intangible assets affect stock price crash risk remains limited.

The only studies of corporate intangible assets and stock price crash risk of which we are aware are Wu and Lai (2020) and Hasan et al. (2022). Wu and Lai (2020) use intangible assets in financial statements and find that firms with a higher level of intangible assets are subject to a higher risk of crashes than other firms. Hasan et al. (2022) find that firms with a high brand reputation are subject to low crash risk. Our study extends this research and focuses on an important kind of corporate intangible asset, OC, which cannot be directly identified in financial statements. OC plays a critical role in the international capital stock, accounting for more than 40 % of cash flows generated from intangible assets in the United States (Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2014). Therefore, we adopt a new angle and attempt to fill the gap in the literature by investigating the influence of OC on future stock price crash risk.

Key corporate talents can obtain better outside options when working in firms with substantial OC (Hasan and Cheung, 2023). OC produces a corporate competitive advantage in the long run through the link between internal managerial resources and external social networks, which also benefits the career development of key talents (Hasan and Uddin, 2022). Thus, key talents have incentives to build OC to increase their outside options at the expense of shareholders (Eisfeldt and Papanikolaou, 2013). In addition, the corporate information environment is more complex for firms with substantial OC (Kim et al., 2021). Such environments provide an ideal opportunity for key talents to suppress bad news to protect their own interests. This accumulated bad news may then be publicly released abruptly over a short period, leading to stock price crashes (Jin and Myers, 2006). Moreover, substantial OC brings more risk-taking activities to the firms (Hasan and Cheung, 2023), which may also contribute to increasing corporate stock price crash risk.

In contrast, OC is considered to be one of the factors driving exceptional corporate performance. Firms with substantial OC levels are often linked to less cash flow uncertainty, better financial outcomes, and lower interest expenses (Atkeson and Kehoe, 2005; Lev et al., 2009; Attig and Cleary, 2014; Danielova et al., 2022) than firms with less OC. In this sense, OC may actually decrease the likelihood of key talents withholding negative information (Hutton et al., 2009). Moreover, firms with substantial OC may be more visible to analysts and potential investors, reducing the chance for key talents to hoard negative information and lowering future stock price crash risk. To reflect these contrary arguments, we propose two opposite hypotheses on the association between OC and future stock price crash risk, as follows:

Hypothesis 1a. Firms with substantial OC are more likely than firms with less OC to have high future stock price crash risk.

Hypothesis 1b. Firms with substantial OC are less likely than firms with less OC to have high future stock price crash risk.

Financing constraints prevent firms from funding their desired investments (Lamont et al., 2001). Key talents in firms with few financing constraints have abundant resources to build OC to improve their outside options in their own interests. Conversely, due to inadequate cash flow, firms with constrained financing have limited cash to fund necessary investments (He and Ren, 2022). This situation reduces the probability of key talents investing in OC for their own benefit. Moreover, firms with greater financing constraints

are subject to stricter external monitoring and frequent scrutiny, which restrict the opportunities for managers to conceal and accumulate negative news (Kothari et al., 2009). Therefore, we propose our second hypothesis as follows:

**Hypothesis 2.** The impact of OC on future stock price crash risk is more prominent for firms with fewer financing constraints than for firms with greater financing constraints.

OC tends to influence corporate cash holdings (Hasan and Cheung, 2023). Not paying corporate profits out to shareholders motivates key talents to make decisions for their own benefit at the expense of shareholders (Décamps et al., 2011). This problem is particularly severe when firms have high retention ratios (Jensen, 1986). As high retention ratios imply rich internal funds, key talents have more opportunities and incentives to invest in OC in their own interests. Therefore, we propose our third hypothesis as follows:

**Hypothesis 3.** The impact of OC on future stock price crash risk is more prominent for firms with higher retention ratios than for firms with lower retention ratios.

The key talents are more likely to withhold bad news to maintain share prices in firms that engage in more risk-taking activities, because shareholders limit operational decisions once they detect such activities (Li et al., 2017). Kim et al. (2011b) and Cao et al. (2022) find that firms with high total risk and idiosyncratic risk often have high stock price crash risk. All these findings suggest that the crash risk might occur more frequently in firms with more risk-taking activities. As OC also influences corporate risk-taking practices and key talents behavior (Hasan and Cheung, 2023), we therefore propose our final hypothesis as follows:

**Hypothesis 4**. The impact of OC on future stock price crash risk is more prominent for firms engaging in high levels of risk-taking behavior than for firms engaging in low levels of risk-taking behavior.

#### 3. Methodology

#### 3.1. Data and stock price crash risk

We collect accounting and firm characteristics data for publicly traded firms in China's A-share market from the CSMAR database for the 2010–2022 period. We remove firms that were terminated, suspended, or have a listing history of less than 3 years. Financial firms and banks are also excluded. Our final sample consists of 23,314 observations from 3207 listed firms. Following previous studies (Kim et al., 2011a; Lei and Song, 2022), we calculate *Ncskew* and *Duvol* to proxy for stock price crash risk. *Ncskew* for a given firm in a given year can be estimated as follows:

$$Ncskew_{i,t} = -\frac{n(n-1)^{3/2} \sum w_{i,\tau}^3}{(n-1)(n-2) \left(\sum w_{i,\tau}^2\right)^{3/2}}$$
(1)

where *i* represents the firm, *n* is the number of trading weeks in a given year t, and  $w_{i,\tau}$  represents the weekly returns in week  $\tau$ , estimated as the natural logarithm of  $(1 + \varepsilon_{i,\tau})$ .  $\varepsilon_{i,\tau}$  is the error term, which is estimated using the following model:

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

where  $r_{i,\tau}$  is a firm's return and  $r_{m,\tau}$  is the weighted average return of the market value of all stocks listed on the Chinese stock market in week  $\tau$ 

We also calculate *Duvol* as an alternative indicator of corporate stock price crash risk as follows:

$$Duvol_{i,t} = ln \left[ \frac{(n_{up} - 1) \sum_{down} w_{i,\tau}^2}{(n_{down} - 1) \sum_{up} w_{i,\tau}^2} \right]$$
(3)

where  $n_{up}$  and  $n_{down}$  are the number of weeks in which  $w_{i,\tau}$  is above or below, respectively, the annual average of  $w_{i,\tau}$ .

#### 3.2. Regression model

The level of corporate OC is difficult to estimate, partly because OC cannot be directly identified in financial statements. We use Eisfeldt and Papanikolaou's (2013) measure of OC based on sales, general, and administrative (SG&A) expenses to construct the OC measure for Chinese listed firms, as follows:

$$OC_{1,i,t} = (1 - \delta_{OC})OC_{1,i,t-1} + \frac{SG\&A_{i,t}}{CPL}$$
 (4)

The initial OC is estimated as

$$OC_{1,i,0} = \frac{SG\&A_{i,1}}{g + \delta_{OC}}$$
 (5)

where  $OC_{1,i,t}$  represents firm i's OC in year t.  $\delta_{OC}$  is the OC depreciation rate, which is fixed at 0.2, as determined in previous studies

(Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017).  $SG\&A_{i,t}$  includes expenses related to a firm's information technology development, staff training, research and development, consulting, and brand promotion. SG&A expenses are deflated by the consumer price index in year t. g represents the OC growth rate, which is estimated by the average growth rate of firm-specific SG&A expenses.

Following Peters and Taylor (2017), we calculate an alternative OC measure as follows:

$$OC_{2,i,t} = (1 - \delta_{OC})OC_{2,i,t-1} + SG\&A_{i,t} \times \theta_0$$
 (6)

The initial OC is estimated as

$$OC_{2,i,0} = \frac{SG\&A_{i,1} \times \theta_0}{g + \delta_{OC}}$$

$$(7)$$

where  $\theta_0$  is the ratio of SG&A expenses invested in OC, which is set at 0.3 (Peters and Taylor, 2017; Qu and Cheung, 2023). The two OC measures are similar, except that Peters and Taylor (2017) calculate OC by utilizing a portion of SG&A expenses instead of the deflated value of SG&A expenses.

Following previous studies (Kim et al., 2014; Hasan et al., 2022), we employ the following regression to determine the effects of corporate OC on a firm's one-year-ahead stock price crash risk.

Crash 
$$Risk_{i,t+1} = \beta_0 + \beta_1 OCR_{i,t} + \beta_2 Controls + Industry + Year + \varepsilon_{i,t}$$
 (8)

where  $Crash \, Risk \,$  refers to  $Ncskew \,$  or  $Duvol \,$  and is a proxy for the one-year-ahead stock price crash risk of publicly traded firms in China. Using one-year-ahead stock price crash risk can alleviate the potential endogeneity problems that arise from reverse causality concerns. Our key independent variable is the corporate OC ratio (OCR), measured in two ways, i.e.,  $OC_{1,i,t}$  or  $OC_{2,i,t}$ , divided by the book value of a firm's total assets.

We control for variables (*Controls*) that may increase stock price crash risk based on previous studies (Chen et al., 2001; Li and Zhan, 2019). They include proxies for stock price crash risk, firm size (Size), return on assets (ROA), detrended trading volume (DTV), stock returns (Return), stock return volatility (Sigma), price-to-sales ratio (PS), leverage (Leverage), and accrual earnings management (Accrual). We also control for board characteristics that may affect stock price crash risk, including the independent director ratio (Independent) and board size (Board Size). Following Hasan and Cheung (2018) and Boubaker et al. (2022), we also control for industry and year fixed effects and cluster robust standard errors at the firm level. We substitute firm fixed effects for industry fixed effects and obtain similar regression results. The definitions of the primary variables are listed in the appendix. Finally, we winsorize the continuous variables at the 1 % and 99 % levels to mitigate the influence of outliers.  $\varepsilon$  is the residual term.

To test Hypotheses 2, 3, and 4, we divide our full sample into two sub-samples. To test Hypothesis 2, we calculate the corporate financing constraints index following the model presented by Fee et al. (2009). Next, we divide firms into high (low) financing constraints sub-samples according to whether their financing constraints are above (below) the median value of the financing constraints index. Similarly, to test Hypothesis 3, we split the full sample into two sub-samples at the median value of the corporate retention ratio. To test Hypothesis 4, following Li et al. (2017), we calculate the standard deviation of operating income divided by total assets over the current and the previous 2 years as a proxy for corporate risk-taking behavior. We then split the full sample into high (low) risk-taking behavior sub-samples at the median value.

We conduct various robustness tests of our baseline results. First, although we use the one-year-ahead stock price crash risk measures to alleviate the potential reverse causality problem in our baseline regression, our results may suffer from other endogeneity problems, such as omitted unobservable variables or measurement errors. We thus apply the IV approach to address these potential endogeneity concerns. According to Hasan and Cheung (2018), firms operating in the same industry often invest in similar types of OC. That is, firm-level OC in the same industry may demonstrate similarities and strong correlations with industry-level OC. However, it is unlikely that the OC of an individual firm can significantly influence the broader industry-level OC. There seems to be no direct and theoretically sound connection between industry-level OC and firm-level future stock price crash risk. Therefore, we follow Hasan and Cheung (2018) and use the industry average OC each year as an IV to perform a two-stage least squares regression as a robustness check.

Second, we use the entropy balancing approach to address the potential endogeneity problems that arise from regression model design and sample selection bias. The entropy balancing methodology proposed by Hainmueller (2012) improves estimation accuracy without excluding any observations from the treatment and control groups. Following previous studies (Boubaker et al., 2022; Qu and Cheung, 2023), we split our sample into two groups at the median value of OC and then conduct an entropy balancing analysis.

Third, we employ a multivariate crash risk (*MCRASH*) measure recently proposed by Chabi-Yo et al. (2022) as an alternative proxy for stock price crash risk. *MCRASH* captures a stock's sensitivity to crash events based on seven risk factors in an asset pricing model, providing a fresh perspective on assessing stock price crash risk. The seven risk factors include the market (*MKT*), size (*SMB*), value (*HML*), profitability (*RMW*), and investment (*CMA*) factors proposed by Fama and French (2015), the momentum factor proposed by Carhart (1997), and the betting-against-beta factor proposed by Frazzini and Pedersen (2014). Following Chabi-Yo et al. (2022), we construct daily *MCRASH* as follows:

$$MCRASH_i^{\mathbf{X}} := \mathbb{P}\left[r_i \leq Q_p(r_i) \middle| \bigcup_{j=1}^N \left[X_j \leq Q_p(X_j)\right]\right]$$
 (9)

where  $r_i$  represents the daily stock returns of firm i.  $\mathbf{X} = (X_1, ..., X_N)$  represents the daily returns of seven risk factors.  $Q_p(r_i)$  and  $Q_p(X_j)$  represent the upper p-quantile of  $r_i$  and  $X_j$ , respectively. Hence, MCRASH is the conditional probability that an individual stock return  $r_i$  does not exceed its p-quantile given that at least one of the seven priced factors  $X_j$  simultaneously at or below its p-quantile (Chabi-Yo et al., 2022). Following Chabi-Yo et al. (2022), we let p equals 5 % and estimate daily MCRASH using a rolling window of 250 daily returns. Then, we calculate the average daily MCRASH over a year as a proxy for the annual MCRASH of each stock. The higher value of MCRASH suggests a higher level of price crash risk.

#### 4. Empirical analyses

#### 4.1. Summary and correlation statistics

Table 1 summarizes the descriptive statistics and pairwise correlation values. Panel A shows that the mean (median) value of Ncskew is -0.4395 (-0.3921). This figure is reasonable, as the stock return distribution often implies stock price crash risk (Chen et al., 2001; Kim et al., 2014). Ncskew has a minimum value of -2.6670 and a maximum value of 1.6839, suggesting substantial differences in stock price crash risk across Chinese listed firms. The findings for Duvol further support this result; the mean (median) value of Duvol is -0.3064 (-0.3067), and it ranges from -1.4794, the lowest value, to 0.9501, the highest value.

The average OC, the key independent variable, of Chinese listed firms accounts for approximately 29 % of total assets based on Eisfeldt and Papanikolaou's (2013) OC measure ( $OCR_1$ ) and approximately 9 % of total assets based on Peters and Taylor's (2017) measure ( $OCR_2$ ). These values are comparable to those of previous studies on the Chinese stock market (Qu and Cheung, 2023). Additionally, the lowest and highest values of  $OCR_1$  ( $OCR_2$ ) are 0.0169 (0.0051) and 1.3503 (0.4071), respectively, suggesting large differences in OC across Chinese listed firms.

In terms of the control variables, the average weekly return (*Return*) of stocks in the Chinese stock market is approximately 0.31 %, with a volatility (*Sigma*) of 6.19 % during our sample period. The mean value of *Accrual* is 6.05 %, suggesting that some Chinese listed firms actively engage in earnings management. The minimum value of the independent director ratio (*Independent*) is 33.33, which is consistent with the requirement of the guidelines issued by the China Securities Regulatory Commission that at least one third of board members in Chinese listed firms be independent.

The results in Panel B indicate that most of the variables have strong pairwise correlations.  $OCR_1$  is positively correlated with one-year ahead Nsckew, which suggests that firms with higher levels of OC may be more prone to increased future stock price crash risk. Panel B reports only the correlation results for  $OCR_1$  for brevity, but we obtain similar correlation results when we substitute  $OCR_1$  for  $OCR_2$ .

# 4.2. Effects of OC on stock price crash risk

Table 2 displays our baseline empirical results for the effects of OC on future stock price crash risk. As shown in Column (1), the estimated coefficient of  $OCR_1$  (0.0771) is significantly and positively related to one-year ahead Nsckew at the 1 % level, implying that firms with higher levels of OC are subject to greater future stock price crash risk than firms with lower levels of OC. This coefficient implies that a one standard deviation increase in  $OCR_1$  leads to an economically significant increase of 4.26 % in future stock price crash risk relative to its average value. As the average value of Nsckew is negative, and economic significance focuses on the magnitude of the effect, we follow Mitton (2024) and take the absolute value to measure the coefficient's economic significance.

We repeat our analysis in Column (2) by substituting  $OCR_1$  for  $OCR_2$ , which is estimated based on Peters and Taylor's (2017) OC measure. The coefficient of  $OCR_2$  (0.2568) remains positive and significant at the 1 % level. Similar to the results for  $OCR_1$ , the coefficient of  $OCR_2$  implies that a one standard deviation increase in  $OCR_2$  leads to an economically significant increase of 4.27 % in future stock price crash risk relative to its average value. Thus, the results in Columns (1) and (2) support Hypothesis 1a that firms with higher levels of OC are subject to higher future stock price crash risk than firms with lower levels of OC.

To ensure the robustness of our baseline conclusions, we substitute Nsckew for Duvol as an alternative indicator of stock price crash risk. As shown in Columns (3) and (4), the estimated coefficients of  $OCR_1$  and  $OCR_2$  remain positive and significant at the 1 % level, suggesting that a one standard deviation increase in  $OCR_1$  and  $OCR_2$  leads to an economically significant increase of 4.58 % and 4.61 %, respectively, in future stock price crash risk relative to its average value. These results further support Hypothesis 1a. Given these results, we can conclude that a one standard deviation increase in corporate OCR leads to an economically significant increase of approximately 4.3 % to 4.6 % in future stock price crash risk relative to its average value.

The coefficients for the control variables align with both previous research and our expectations. For example, large (*Size*) and growth (*PS*) firms with high stock returns (*Returns*) and profitability (*ROA*) (Li and Zhan, 2019; Hasan et al., 2022) and firms with more earnings management (*Accrual*) (Hutton et al., 2009) have higher future stock price crash risk. Moreover, due to potentially stricter monitoring, firms with greater financial leverage (*Leverage*) and larger board sizes (*Board Size*) have lower future stock price crash risk (Hunjra et al., 2020).

Table 3 shows the regression results for Hypotheses 2, 3, and 4. For brevity, we omit the estimated coefficients for the control variables, although these variables are included in all of the regression models. As shown in Columns (1) and (2) of Panel A, the estimated coefficient of  $OCR_I$  for firms with low financing constraints is positive and significant at the 1 % level, whereas the estimated coefficient for firms with high financing constraints is not significant. The differences in the coefficients are significant at the 1 % level. These findings indicate that the positive effects of OC on future stock price crash risk are less prominent when firms face financing

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**Table 1** Descriptive statistics and correlations.

Panel A. Descript	ive statistics												
Variables		Obs		Mean		Median		STD		M	Iin		Max
(a) Dependent va	riables												
Ncskew		23,314		-0.4395		-0.392	1	0.74	96	_	2.6670		1.6839
Duvol		23,314 -0.3064		-0.306	7	0.48	19	_	1.4794		0.9501		
(b) Independent v	variables												
OCR <sub>1</sub>		23,314		0.2887		0.2237		0.24	26	0.	.0169		1.3503
OCR <sub>2</sub>		23,314		0.0872		0.0676		0.07	32	0.	.0051		0.4071
(c) Control variab	oles												
Size	23,314		22.9974		22.8163	3	1.09	91	20	0.8335		26.4220	
ROA		23,314		0.0340		0.0333		0.06	05	_	0.2389		0.1958
DTV		23,314		0.1127		0.0293		2.71	90	_	7.3238		8.6083
Return		23,314		0.0031		0.0021		0.00	89	_	0.0149		0.0315
Sigma		23,314		0.0619		0.0572		0.02	35	0.	.0254		0.1429
PS		23,314		4.4294		2.5699		5.63	54	0.	.1832		36.1557
Leverage		23,314		0.4504		0.4477		0.19	93	0.	.0563		0.8784
Accrual		23,314		0.0605		0.0490		0.04	34	0.	.0077		0.2361
Independent		23,314		0.3751		0.3571		0.05	36	0.	.3333		0.5714
Board Size		23,314		2.2510		2.3026		0.17	69	1.	.7918		2.7726
Panel B. Correlati													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Ncskew <sub>t+1</sub>	1.0000												
(2) OCR <sub>1,t</sub>	0.0163**	1.0000											
(3) Ncskew <sub>t</sub>	0.0536***	0.0263***	1.0000										
(4) Size <sub>t</sub>	0.0700***	-0.2008***	0.0282***	1.0000									
(5) ROA <sub>t</sub>	0.0754***	0.0528***	0.0528***	0.1598***	1.0000								
(6) DTV <sub>t</sub>	-0.0484***	0.0152**	-0.0843***	0.0264***	-0.0445***	1.0000							
(7) Return <sub>t</sub>	0.0589***	0.0018	-0.1785***	0.1011***	0.1428***	0.4777***	1.0000						
(8) Sigma <sub>t</sub>	-0.0261***	0.0044	-0.1644***	-0.0807***	-0.0904***	0.4934***	0.5673***	1.0000					
(9) PS <sub>t</sub>	0.0600***	-0.0346***	0.0119*	-0.1284***	0.0309***	0.0698***	0.2693***	0.2999***	1.0000				
(10) Leverage <sub>t</sub>	-0.0345***	-0.1878***	-0.0382***	0.3634***	-0.3272***	-0.0097	-0.0555***	-0.0445***	-0.3807***	1.0000			
(11) Accrual <sub>t</sub>	0.0120*	-0.0549***	0.0149**	-0.0573***	-0.1195***	-0.0341***	-0.0556***	0.0816***	0.0777***	0.1254***	1.0000		
(12)	0.0070	0.0057	0.0114*	0.0362***	-0.0252***	0.0129**	0.0094	0.0312***	0.0573***	-0.0100	0.0335***	1.0000	
$Independent_t$													
(13) Board Size <sub>t</sub>	-0.0127*	-0.0600***	-0.0100	0.2217***	0.0400***	-0.0300***	-0.0430***	-0.1171***	-0.1363***	0.1478***	-0.0795***	-0.5195***	1.0000

Panel A reports the descriptive statistics of key variables during the sample period. Panel B reports the pairwise Pearson cross-correlations of the variables. \* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01.

Table 2
Organization capital and stock price crash risk.

	Ncskew		Duvol	
	(1)	(2)	(3)	(4)
OCR <sub>1</sub>	0.0771***		0.0579***	
	(3.67)		(4.13)	
OCR <sub>2</sub>		0.2568***		0.1930***
		(3.69)		(4.15)
Ncskew	0.0687***	0.0687***		
	(9.68)	(9.68)		
Duvol			0.0679***	0.0679***
			(9.70)	(9.70)
Size	0.0534***	0.0535***	0.0280***	0.0281***
	(9.55)	(9.55)	(7.63)	(7.63)
ROA	0.1853*	0.1851*	0.0715	0.0713
	(1.89)	(1.89)	(1.14)	(1.13)
DTV	-0.0082***	-0.0082***	-0.0038**	-0.0038**
	(-3.45)	(-3.45)	(-2.53)	(-2.53)
Return	0.1440***	0.1440***	0.0945***	0.0945***
	(17.08)	(17.08)	(17.01)	(17.01)
Sigma	-0.6208*	-0.6211*	-0.7888***	-0.7890***
	(-1.79)	(-1.79)	(-3.56)	(-3.56)
PS	0.0046***	0.0046***	0.0034***	0.0034***
	(4.03)	(4.03)	(4.51)	(4.52)
Leverage	-0.0803**	-0.0803**	-0.0555***	-0.0555***
, and the second	(-2.39)	(-2.38)	(-2.59)	(-2.59)
Accrual	0.3071***	0.3071***	0.1597**	0.1596**
	(2.61)	(2.61)	(2.16)	(2.16)
Independent	-0.1016	-0.1016	-0.0176	-0.0176
-	(-0.90)	(-0.90)	(-0.24)	(-0.24)
Board Size	-0.0933***	-0.0933***	-0.0600***	-0.0600***
	(-2.63)	(-2.63)	(-2.62)	(-2.62)
Constant	-1.3291***	-1.3293***	-0.7332***	-0.7334***
	(-8.74)	(-8.74)	(-7.32)	(-7.32)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	23,314	23,314	23,314	23,314
Adj. R <sup>2</sup>	0.0542	0.0542	0.0561	0.0561

This table shows the regression results for analyzing the effect of organization capital on corporate future stock price crash risk. The dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.05; \*\* p < 0.05; \*\*\* p < 0.01.

constraints, which is consistent with Hypothesis 2. As shown in Columns (3) and (4), this result remains robust to the different OC measures. In addition, as shown in Columns (5) to (8), we obtain similar results after replacing *Ncskew* with *Duvol*.

A possible explanation for this finding is that firms with financing constraints are often subject to strict monitoring and scrutiny of their activities, limiting the ability of key talents to conceal negative information. However, for less constrained firms, key talents have more opportunities to invest in OC and conceal negative information to improve their outside options in their own interests. Thus, the positive relationship between OC and future stock price crash risk is more prominent for firms with lower financing constraints.

As shown in Columns (1) to (4) in Panel B, the coefficients of both OC measures for firms with low profit retention ratios are not significant, whereas the coefficients for firms with high retention ratios are all significant and positive. These findings suggest that OC clearly increases future stock price crash risk for firms with high retention ratios but has limited effects on firms with low retention ratios. The differences in the coefficients are also significant. These results support Hypothesis 3. Our results again remain robust when Ncskew is replaced with Duvol, as shown in Columns (5) to (8). The potential reason for these findings is that substantial retention ratios imply rich internal funds; key talents in firms with substantial cash holdings have more opportunities and incentives to invest in OC and conceal bad news in their own interests.

Panel C displays the impact of OC on future stock price crash risk for firms with different risk-taking behaviors. As shown in Columns (1) to (4), the coefficients of the OC measures for firms with a high level of risk-taking behavior are all significant and positive, whereas those for firms with a low level of risk-taking behavior are not significant. These results suggest that the positive effect of OC on future stock price crash risk is more pronounced for firms that engage in more corporate risk-taking activities, which supports Hypothesis 4. The differences in the coefficients are also significant. As shown in Columns (5) to (8), our results remain robust when *Ncskew* is replaced with *Duvol*. The potential reason for these findings is that firms with substantial OC often display greater risk-taking behavior (Hasan and Cheung, 2023) relative to firms with less OC. Thus, the positive effect of OC on future stock price crash risk may be stronger for firms in high risk-taking behavior sub-samples. In other words, as OC is positively correlated with corporate risk-taking activities, this association may also contribute to those firms' future stock price crash risk.

**Table 3**Impact of financing constraints, profit retention and risk-taking

Panel A Financ	cing constraints							
	Ncskew				Duvol			
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OCR <sub>1</sub>	0.1502***	-0.0112			0.1065***	-0.0028		
OCD	(5.64)	(-0.35)	0.4991***	-0.0364	(5.99)	(-0.13)	0.3540***	-0.0086
OCR <sub>2</sub>			(5.66)	-0.0364 (-0.34			(6.01)	-0.0086 $(-0.12)$
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	(-0.12) Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,136	10,178	13,136	10,178	13,136	10,178	13,136	10,178
Adi. R <sup>2</sup>	0.0736	0.0383	0.0737	0.0383	0.0787	0.0356	0.0787	0.0356
Difference	0.0000***		0.0010***		0.0000***		0.0000***	
Panel B Retent	ion ratio							
-	Ncskew				Duvol			
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OCR <sub>1</sub>	0.0765**	0.0296			0.0600***	0.0257		
	(2.51)	(0.96)			(2.86)	(1.30)		
OCR <sub>2</sub>			0.2555**	0.0987			0.1999***	0.0856
			(2.53)	(0.97)			(2.88)	(1.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,455	9859	13,455	9859	13,455	9859	13,455	9859
Adj. R <sup>2</sup>	0.0463	0.0738	0.0463	0.0738	0.0481	0.0759	0.0481	0.0759
Difference	0.0700*		0.0900*		0.0800*		0.0400**	
Panel C Risk-ta	aking behavior							
	Ncskew				Duvol			
	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OCR_1$	0.0878***	0.0038			0.0541***	0.0199		
0.00	(3.07)	(0.12)	0.0005111	0.610=	(2.77)	(0.97)	0.1001	
OCR <sub>2</sub>			0.2926***	0.0137			0.1801***	0.0667
Gt1-	W	W	(3.09)	(0.13)	W	¥7	(2.78)	(0.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. Adj. R <sup>2</sup>	10,977	12,337	10,977	12,337	10,977	12,337	10,977	12,337
	0.0492	0.0644	0.0493	0.0644	0.0513	0.0666	0.0513	0.0666
Difference	0.0300**		0.0200**		0.0800*		0.0100**	

This table shows the regression results for analyzing the effect of organization capital on corporate future stock price crash risk after considering corporate financing constraints, retention ratios and risk-taking behavior. The dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.05; \*\*\* p < 0.05; \*\*\* p < 0.01.

#### 5. Robustness tests

We perform a series of additional tests to assess the robustness of our baseline conclusions. Panel A of Table 4 shows the results of the IV estimation. As can be seen from the first-stage results, the coefficients of the IV, i.e., *IV\_OCR*, are all positive and significant at the 1 % level. These results indicate that *IV\_OCR* satisfies the relevance condition for both OC measures. The results from the second-stage regression indicate a significant positive effect of the instrumented OC measures on future stock price crash risk. Moreover, the first-stage F statistics suggest that *IV\_OCR* is not a weak instrument (Staiger and Stock, 1997). The Cragg–Donald Wald F statistics significantly exceed the critical threshold at the 10 % significance level, indicating that our IV is a strongly valid instrument. The Kleibergen–Paap rank LM and Hansen J statistics are significant at the 1 % level, implying that our regression is well identified. To summarize, the results of the IV approach support our baseline finding that firms with higher OC levels are subject to higher future

stock price crash risk than firms with lower OC levels.

Panel B of Table 4 shows the results of the entropy balancing method. The coefficients of OCR in Columns (1) and (2) are significant and positive at the 1 % level, which aligns with our baseline results in Table 2. These results remain robust when *Ncskew* is replaced with *Duvol* in Columns (3) and (4). Therefore, the model results in Panels A and B demonstrate that our baseline conclusions remain robust after we consider the potential endogeneity problem arising from regression model design and sample selection bias. Panel C of Table 4 reports the regression results using an alternative crash risk measure – *MCARSH*, proposed by Chabi-Yo et al. (2022). As shown in Panel C, the coefficients of the OC measures remain significantly positive at the 1 % level after substituting *MCRASH* for *Ncskew* or

Table 4
Robustness results.

		Ncskew			Duvol	
		(1)		(2)	(3)	(4)
First-stage OLS regression						
IV_OCR <sub>1</sub>		0.8788***			0.8784***	
		(25.24)			(25.26)	
IV_OCR <sub>2</sub>				0.8791***		0.8787***
				(25.28)		(25.30)
Second-stage OLS regression						
OCR <sub>1</sub>		0.1951***			0.1271***	
		(4.35)			(4.25)	
OCR <sub>2</sub>				0.6464***		0.4210***
				(4.35)		(4.25)
Controls		Yes		Yes	Yes	Yes
FE		Yes		Yes	Yes	Yes
Obs.		23,314		23,314	23,314	23,314
Adj. R <sup>2</sup>		0.0529		0.0529	0.0551	0.0551
First-stage F statistic		637.01***		638.93***	638.10***	640.03***
Cragg-Donald Wald F statistic		7516.73		7539.53	7511.40	7534.20
Kleibergen-Paap rank LM statist	tic	295.69***		296.65***	295.59***	296.56***
Hansen J statistic p value		0.000		0.000	0.000	0.000
Panel B Entropy balancing analy					p1	
Panel B Entropy balancing analy	Ncskew		(0)		Duvol	(0)
	Ncskew (1)		(2)		(3)	(4)
	Ncskew (1) 0.0581***		(2)		(3) 0.0488***	(4)
$OCR_1$	Ncskew (1)				(3)	
OCR <sub>1</sub>	Ncskew (1) 0.0581***		0.1926***		(3) 0.0488***	0.1611***
OCR <sub>1</sub>	Ncskew (1) 0.0581*** (2.60)		0.1926*** (2.60)		(3) 0.0488*** (3.28)	0.1611*** (3.27)
${ m OCR}_1$ ${ m OCR}_2$ ${ m Controls}$	Ncskew (1) 0.0581*** (2.60) Yes		0.1926*** (2.60) Yes		(3) 0.0488*** (3.28) Yes	0.1611*** (3.27) Yes
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ ${ m FE}$	Ncskew (1) 0.0581*** (2.60) Yes Yes		0.1926*** (2.60) Yes Yes		(3) 0.0488*** (3.28) Yes Yes	0.1611*** (3.27) Yes Yes
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ FE Obs.	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314		0.1926*** (2.60) Yes Yes 23,314		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ ${ m FE}$	Ncskew (1) 0.0581*** (2.60) Yes Yes		0.1926*** (2.60) Yes Yes		(3) 0.0488*** (3.28) Yes Yes	0.1611*** (3.27) Yes Yes
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ FE Obs.	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ ${ m FE}$ ${ m Obs.}$ ${ m Adj.}$ ${ m R}^2$	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611**** (3.27) Yes Yes 23,314
${ m OCR_1}$ ${ m OCR_2}$ ${ m Controls}$ ${ m FE}$ ${ m Obs.}$ ${ m Adj.}$ ${ m R}^2$	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611**** (3.27) Yes Yes 23,314
OCR <sub>1</sub> OCR <sub>2</sub> Controls FE Obs. Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487  MCRASH (1) 0.0025***		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492
OCR <sub>1</sub> OCR <sub>2</sub> Controls  FE  Obs.  Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487 MCRASH		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492
OCR <sub>1</sub> OCR <sub>2</sub> Controls FE Obs. Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487  MCRASH (1) 0.0025*** (3.10)		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492 (2)
OCR <sub>1</sub> OCR <sub>2</sub> Controls FE Obs. Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487  MCRASH (1) 0.0025*** (3.10)		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492 (2) (2)
OCR <sub>1</sub> OCR <sub>2</sub> Controls FE Obs. Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487  MCRASH (1) 0.0025*** (3.10)  Yes Yes		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492  (2)  0.0085*** (3.11) Yes Yes
OCR <sub>1</sub> OCR <sub>2</sub> Controls FE Obs. Adj. R <sup>2</sup> Panel C Multivariate crash risk i	Ncskew (1) 0.0581*** (2.60)  Yes Yes 23,314 0.0487		0.1926*** (2.60) Yes Yes 23,314 0.0487  MCRASH (1) 0.0025*** (3.10)		(3) 0.0488*** (3.28) Yes Yes 23,314	0.1611*** (3.27) Yes Yes 23,314 0.0492 (2) (2)

This table shows the results of robustness tests during the sample period. Panels A and B show the instrumental variable approach and entropy balancing technique estimation results, respectively. In Panels A and B, the dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. In Panel C, the dependent variable is the multivariate crash risk (MCRASH) measure. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01.

Duvol, which further supports our baseline results in Table 2.

#### 6. Further analysis

To further investigate the potential mechanisms by which key talents withhold negative information in firms with substantial OC, we conduct two additional analyses focusing on corporate ownership structures and cultural factors. SOEs dominate the Chinese stock market. Previous studies suggest that the key talents of SOEs are more likely to hide bad information, which often increases stock price crash risk. For example, Bushman and Piotroski (2006) find that the opaque reporting practices of SOEs and political pressure motivate key talents to hide negative information for their own career development, thus leading to greater stock price crash risk in SOEs. Xu et al. (2014) find that executives have stronger incentives to hide bad news to pursue excess perks in SOEs, thus leading to higher stock price crash risk. Therefore, we expect the positive effect of OC on future stock price crash risk to be more pronounced for SOEs than for non-SOEs. As shown in Panel A of Table 5, the coefficients of the OC measures are more significant for SOEs than those of non-SOEs. The differences in the coefficients are significant at the 1 % level. These results align with our expectations, suggesting that corporate ownership structure influences the relationship between OC and stock price crash risk. This positive relationship is stronger for SOEs, whose key talents are more likely to withhold bad news.

Religion, a cultural phenomenon, greatly affects individuals' behavior and decision-making (Williamson, 2000). Key talents with religious beliefs often limit their greed and desires and pursue public welfare, which deters opportunistic behavior and reduces their willingness to hide negative corporate information (Zoeram et al., 2022). Li and Cai (2016) find that firms in intensely religious environments often face lower stock price crash risk. Buddhism was introduced to China approximately 2000 years ago and has had a pervasive and strong influence on the daily lives of Chinese people (Yang, 1970). Following Li and Cai (2016), we employ the number of Buddhist temples within a 300 km radius of the firm's registered area as a proxy for the intensity of religion influencing key talents. We then divide the full sample into high- and low-intensity religious environment sub-samples based on the median number of temples near the corporate headquarters.

The key talents of firms in more intensely religious environments are more likely to participate in religious activities than the talents of firms in less intensely religious environments. These religious activities may influence the talents' behavior and reduce their

**Table 5**Ownership structures and religion.

	Ncskew				Duvol			
	SOE	Non-SOE	(3)	Non-SOE	SOE	Non-SOE	SOE (7)	Non-SOE (8)
	(1)	(2)		(4)	(5)	(6)		
OCR <sub>1</sub>	0.1384***	0.0321			0.0986***	0.0294*		
	(3.95)	(1.22)			(4.16)	(1.68)		
OCR <sub>2</sub>			0.4603***	0.1074			0.3278***	0.0982*
			(3.96)	(1.23)			(4.17)	(1.70)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9739	13,575	9739	13,575	9739	13,575	9739	13,575
Adj. R <sup>2</sup>	0.0604	0.0529	0.0604	0.0529	0.0643	0.0528	0.0644	0.0528
Difference	0.0090***		0.0060***		0.0040***		0.0040***	

Panel B Religio	on							
	Ncskew				Duvol			
	High	Low	High	Low	High	Low	High (7)	Low (8)
	(1)	(2)	(3)	(4)	(5)	(6)		
OCR <sub>1</sub>	0.0431	0.1088***			0.0347*	0.0804***		
	(1.44)	(3.71)			(1.72)	(4.19)		
OCR <sub>2</sub>			0.1442	0.3618***			0.1161*	0.2673***
			(1.46)	(3.72)			(1.73)	(4.21)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	11,947	11,367	11,947	11,367	11,947	11,367	11,947	11,367
Adj. R <sup>2</sup>	0.0548	0.0543	0.0548	0.0543	0.0584	0.0551	0.0584	0.0551
Difference	0.0580*		0.0560*		0.0490**		0.0390**	

This table shows the estimated regression results for analyzing the moderate effects regarding the positive impact of organization capital on corporate future stock price crash risk from ownership structures and religion perspectives. The dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.05; \*\*\* p < 0.05; \*\*\* p < 0.05.

tendency to hoard negative information. Thus, we expect the positive relationship between OC and stock price crash risk to be less pronounced for firms headquartered in regions with a high number of temples. As shown in Panel B of Table 5, the coefficients of the OC measures are all positive and significant at the 1 % level for firms located in areas with few temples. In contrast, the coefficients of the OC measures are less significant for firms in areas with a high number of temples. The differences in the coefficients are also significant. These results align with our expectations and imply that cultural factors also influence the relationship between OC and stock price crash risk, and the key talents in more intensely religious environments are less likely to withhold bad news for their own benefits

Effective corporate governance plays a positive role in restraining opportunistic managerial behaviors and can ensure prompt information disclosure (Bhojraj and Sengupta, 2003; Xie et al., 2003). In contrast, weak corporate governance provides key talents with more opportunities and incentives to hide bad news in their own interests at the expense of shareholders (Bae et al., 2006).

**Table 6**Agency–principal conflicts.

Panel A Shareh	noldings							
	Ncskew				Duvol			
	Not hold	Hold	Not hold	Hold	Not hold	Hold	Not hold	Hold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OCR <sub>1</sub>	0.1474***	-0.0064			0.1020***	0.0060		
OCR	(5.21)	(-0.21)	0.4898***	-0.0204	(5.28)	(0.30)	0.3392***	0.0202
OCR <sub>2</sub>			(5.22)	-0.0204 (-0.20)				(0.30)
Controls	Yes	Yes	Yes	(-0.20) Yes	Yes	Yes	(5.29) Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,664	10,650	12,664	10,650	12,664	10,650	12,664	10,65
Adj. R <sup>2</sup>	0.0564	0.0550	0.0564	0.0550	0.0587	0.0545	0.0588	0.054
Difference	0.0000***	0.0550	0.0000***	0.0550	0.0000***	0.0343	0.0000***	0.054
Panel B Indepe	endent director ratio							
	Ncskew				Duvol	4		
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OCR_1$	0.1101***	0.0429			0.0811***	0.0351*		
	(3.87)	(1.41)			(4.14)	(1.75)		
OCR <sub>2</sub>			0.3667***	0.1433			0.2698***	0.1172
			(3.89)	(1.42)			(4.16)	(1.77)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	11,693	11,621	11,693	11,621	11,693	11,621	11,693	11,621
Adj. R <sup>2</sup>	0.0536	0.0551	0.0536	0.0551	0.0512	0.0612	0.0512	0.0612
Difference	0.0600*		0.0560*		0.0410**		0.0480**	
Panel C Corpor	rate site visits							
	Ncskew				Duvol			
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OCR <sub>1</sub>	0.0802***	0.0654*			0.0789***	0.0386		
OCD	(3.11)	(1.91)	0.0670***	0.0177*	(4.81)	(1.64)	0.0055***	0.100
OCR <sub>2</sub>			0.2673***	0.2177*			0.2255***	0.128
Comtuolo	Vac	Vee	(3.12)	(1.92)	Voc	Vac	(3.94)	(1.64)
Controls FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs. Adj. R <sup>2</sup>	14,266	9048	14,266	9048	14,266	9048	14,266	9048
	0.0525	0.0595	0.0525	0.0595	0.0505	0.0598	0.0547	0.059
Difference	0.0010***		0.0010***		0.0290**		0.0280**	

This table shows the estimated regression results for analyzing the moderate effects regarding the positive impact of organization capital on corporate future stock price crash risk from the perspective of reducing corporate agency–principal conflicts. The dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01.

Therefore, we further investigate the moderating effect of effective corporate governance, particularly a reduction in corporate agency–principal conflicts, on the positive association between OC and future stock price crash risk.

The agency problem can be alleviated by granting shares to managers because managers who hold corporate shares make decisions as corporate owners rather than agents. That is, they are less likely to overinvest in OC and hoard bad news in their own interests. Thus, we explore whether managerial equity incentives moderate the positive association between OC and future stock price crash risk. We expect the positive relationship to be less pronounced for firms whose managers hold shares than for firms in which managers are not shareholders. As shown in Panel A of Table 6, the coefficients of the OC measures are not significant for firms whose managers hold shares. In contrast, the coefficients for firms whose managers do not hold shares are all positive and significant at the 1 % level. The differences in the coefficients are also significant at the 1 % level. These results align with our initial expectations.

Moreover, as a main feature of effective corporate governance, strong monitoring vigilance by stakeholders may restrict key talents from withholding negative information in firms with substantial OC and then moderate the positive association between OC and future stock price crash risk. To test this conjecture, we consider corporate governance monitoring from internal and external perspectives. We use the proportion of independent board directors to indicate the effectiveness of the internal monitoring of corporate governance. Numerous studies demonstrate that independent directors often act on behalf of shareholders to provide objective opinions on managerial decisions and constrain opportunistic managerial behavior (Nguyen and Nielsen, 2010). Independent directors can also reduce the possibility of corporate bad news hoarding (Xie et al., 2003). Thus, we split the full sample into two sub-samples at the median value of the independent director ratio. Internal monitoring should be stronger for firms with higher independent director ratios than for firms with lower ratios, and the positive effect of OC on future stock price crash risk is expected to be less prominent for those firms. As shown in Panel B of Table 6, the estimated coefficients for the OC measures align with our expectation that the positive association is weaker for firms with an above-median independent director ratio. Moreover, the differences in the coefficients are all significant at least at the 10 % level.

In addition to the internal monitoring role played by independent directors, we consider the external monitoring role of firms in inhibiting managerial hoarding of negative information. We use analysts' corporate site visits as a proxy for corporate external monitoring. As before, we split the full sample into two sub-samples at the median value of the number of corporate site visits. As shown in Panel C, the estimated coefficients of the OC measures are significant and positive for firms with a below-median number of corporate site visits. The differences in the coefficients are also significant. These findings are also consistent with our expectation that

**Table 7**Further analysis – monitoring vigilance.

	Ncskew				Duvol			
	Fewer	More	Fewer (3)	More	Fewer	More	(7)	More (8)
	(1)	(2)		(4)	(5)	(6)		
OCR <sub>1</sub>	0.0769***	0.0407			0.0614***	0.0300		
	(2.87)	(1.20)			(3.34)	(1.32)		
OCR <sub>2</sub>			0.2559***	0.1369			0.2042***	0.1007
			(2.88)	(1.21)			(3.36)	(1.34)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,101	10,213	13,101	10,213	13,101	10,213	13,101	10,213
Adj. R <sup>2</sup>	0.0534	0.0624	0.0534	0.0625	0.0553	0.0653	0.0553	0.0653
Difference	0.0900*		0.0000***		0.0400**		0.0800*	

Panel B Background diversity									
	Ncskew				Duvol				
	Low (1)	Low	High	Low	High	Low	High	Low	High
		(1) (2)	(3)	(4)	(5)	(6)	(7)	(8)	
OCR <sub>1</sub>	0.1068***	0.0306			0.0649***	0.0356*			
	(3.09)	(1.13)			(2.77)	(0.054)			
OCR <sub>2</sub>			0.3549***	0.1032			0.2159***	0.1190*	
			(3.10)	(1.15)			(2.78)	(1.95)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Obs.	10,171	13,143	10,171	13,143	10,171	13,143	10,171	13,143	
Adj. R <sup>2</sup>	0.0489	0.0629	0.0489	0.0629	0.0520	0.0652	0.0520	0.0652	
Difference	0.0000***		0.0000***		0.0470**		0.0640*		

This table shows the estimated regression results for analyzing the constitutions of monitoring vigilance. The dependent variable is the one-year ahead negative skewness (Ncskew) of firms' weekly returns. Ncskew is substituted for down-to-up volatility (Duvol) as an alternative proxy for stock price crash risk. Fixed effects for industry and year are set as controls. Robust t statistics reported in brackets are based on the standard errors that are clustered at the firm level. \* p < 0.10; \*\* p < 0.05; \*\*\* p < 0.01.

effective corporate governance monitoring moderates the positive association between OC and future stock price crash risk.

To delve deeper into the potential constitutes of monitoring vigilance, we examine whether the number of times that independent directors meet and their background diversity affect the positive association between OC and future stock price crash risk. Specifically, we divide the full sample into two sub-samples based on the median number of independent director meetings. Studies suggest that independent directors who meet more frequently are more likely to perform their monitoring duties well (Conger et al., 1998; Vafeas, 1999). Thus, we expect firms with more frequent independent director meetings to have lower stock price crash risk induced by OC than firms with infrequent meetings. As shown in Panel A of Table 7, the coefficients of the OC measures are significant and positive for firms with fewer independent director meetings, whereas the coefficients are not significant for firms with more frequent independent director meetings. The differences in the coefficients are also significant. These findings are consistent with our expectation that the frequency of independent director meetings strengthens monitoring and moderates the positive association between OC and future stock price crash risk.

The experience and knowledge that independent directors previously possessed have a great influence on board monitoring effectiveness (Wang et al., 2015; Li and Wahid, 2018). We therefore explore whether a higher diversity of backgrounds among independent directors affects the positive influence of OC on future stock price crash risk. We define a dummy variable that equals 1 if an independent director has financial experience and 0 otherwise. We define another dummy variable that equals 1 if an independent director has overseas experience and 0 otherwise. We sum these dummy variables and then divide them by the number of independent directors for each firm. If the average ratio is higher than the median value across all firms, we classify the board as having a high diversity of backgrounds among its independent directors. We expect that having a high diversity of backgrounds among independent directors may limit the positive influence of OC on future stock price crash risk.

As shown in Panel B, the coefficients of the OC measures are more significant and positive for firms with a low diversity of independent directors' backgrounds. The differences in the coefficients are also significant. These findings are consistent with our expectation that independent directors' background diversity moderates the positive association between OC and future stock price crash risk. In summary, the results in Table 7 imply that independent directors who meet frequently and have diverse backgrounds demonstrate effective governance practices and constrain the harmful impact of OC on future stock price crash risk.

#### 7. Conclusions

Using a unique dataset of Chinese publicly traded firms for the 2010–2022 period, we find that firms with higher levels of OC have increased future stock price crash risk compared with firms with lower levels of OC. In the sub-sample analysis, our main findings become more salient for firms with low financing constraints, high profit retention ratios, and for those that engage in more risk-taking activities. Further analysis shows that the positive effects of OC on stock price crash risk are moderated for non-SOEs, firms in a more intensely religious environment, firms that grant shares to management, and firms that face stronger monitoring vigilance. The frequency of independent directors' meetings and their background diversity reduce the effects of substantial OC on future stock price crash risk. Our main results survive various robustness tests, including IV analysis, the entropy balancing approach, and alternative measures of OC and stock price crash risk.

Our results have important practical implications for investors. Investors should be aware that firms with substantial OC may be more likely to experience extreme negative stock price fluctuations in the stock market, especially for firms with low financing constraints, high profit retention ratios, and high levels of risk-taking behavior. As portfolio diversification does not alleviate stock price crash risk (Habib et al., 2018), investors should exercise great caution when selecting firms with high levels of OC and should assess the crash risk of the firms in their portfolios.

#### CRediT authorship contribution statement

**Leqin Chen:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Adrian C.H. Lei:** Conceptualization, Methodology, Software, Writing – review & editing. **Chen Song:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

# Declaration of competing interest

None.

#### Data availability

The data that support the findings of this study are available from CSMAR. Data are available from the authors with the permission of CSMAR.

#### **Appendix**

**Table A**Descriptions of the variables.

** * 11	
Variables	Descriptions
Dependent variables	
Ncskew	Negative skewness of firm-specific weekly returns. See Section 3.1 for detailed calculation.
Duvol	Down-to-up volatility, which is calculated as the natural logarithm of the ratio of the standard deviation of firm-specific weekly returns in
MCRASH	the "down" weeks to the "up" weeks. See Section 3.1 for detailed calculation.  Multivariate crash risk measure. See Section 3.2 for detailed calculation.
MCKASH	Multivariate crash risk measure. See Section 3.2 for detailed calculation.
Vov. Indones dest sociel	lan
Key Independent variab OCR <sub>1</sub>	The organization capital estimated using Eisfeldt and Papanikolaou (2013)'s method divided by corporate total assets. See Section 3.2 for
OGIC	detailed calculation.
OCR <sub>2</sub>	The organization capital estimated using Peters and Taylor (2017)'s method divided by corporate total assets. See Section 3.2 for detailed
5 51.2	calculation.
Control variables	
Size	The natural logarithm of a firm's market value.
Return on assets (ROA)	Net income divided by total assets.
DTV	Detrended trading volume, which is the difference between share turnover in year t and t-1.
Return	The firm-specific average weekly returns over the year.
Sigma	The standard deviation of firm-specific weekly return over the year.
PS	The share price divided by sales per share.
Leverage	Total liabilities divided by total assets.
Accrual	The average three-year moving sum of the discretionary accruals estimated from the modified Jones model (Dechow et al., 1995).
Independent	Independent directors divided by total directors.
Board Size	The natural logarithm of director number.
Instrumental variables	
IV_OCR <sub>1</sub>	The industry average OCR estimated using Eisfeldt and Papanikolaou (2013)'s method.
IV_OCR <sub>2</sub>	The industry average OCR estimated using Peters and Taylor (2017)'s method.
11_0 0112	The meanity artifage out committee and receive and rayor (2017) of meaning
Other variables	
Financing constraints	High financing constraints sub-sample includes the firms with financing constraints index greater than the median value, and low
	financing constraints sub-sample otherwise. The financing constraints index is estimated as per Fee et al. (2009).
Retention ratios	Retained earnings divided by net income.
Independent	High independent directors sub-sample includes the firms with independent director ratio greater than the median value, and low
directors	independent directors sub-sample otherwise.
Risk-taking behavior	High risk-taking behavior sub-sample includes the firms with risk-taking behavior proxy greater than the median value, and low risk-
	taking behavior sub-sample otherwise. The risk-taking behavior proxy is calculated as the standard deviation of operating income divided
	by total assets over the current and prior 2 years.
SOE	A dummy variable that equals 1 for SOE and 0 otherwise.
Religion	High- and low-intensity religious environment sub-groups based on the median number of temples within a 300 km radius of the firm's registered area.
Shareholdings	Hold shares sub-sample includes the firms whose management hold shares, and non-hold shares sub-sample otherwise.
Corporate site visits	High corporate site visits sub-sample includes the firms with corporate site visits greater than the median value, and low corporate site
	visits sub-sample otherwise.
This table museumts o d	acceptation of the main variables

This table presents a description of the main variables.

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