1. INTRODUCTION

A board of directors refers to a group of people appointed to jointly oversee and advise the top management of a firm on behalf of shareholders, thereby reducing potential agency problems (Jensen, 1993). This raises the question of who on a board are the most effective monitors. Prior empirical studies have tended to employ a traditional measure of board effectiveness, *independence*, defined as the proportion of independent directors on a board, to investigate the disciplinary roles of such directors. However, these studies provide mixed and weak findings (Coles, Daniel, & Naveen, 2014), indicating the importance of identifying substantive monitors on a board. Coles et al. (2014) propose *co-option* as a possible solution to this problem. Co-option is measured as the proportion of board members appointed after a CEO assumes office. The rationale behind this measure is that co-opted directors are more likely to be loyal to the CEO, thus increasing *board friendliness*. Consistent with this view, they find that co-opted directors exert a weaker monitoring role, regardless of whether they are classified as independent directors.

Recent corporate governance literature shows that governance mechanisms are important determinants of stock price crash risk. Callen and Fang (2013) find that strong monitoring, measured by institutional investor stability, alleviates such risks. Rather than focusing on an individual monitoring mechanism, Andreou, Antoniou, Horton, and Louca (2016) investigate broad dimensions of monitoring mechanisms, such as ownership structure, accounting opacity, board structure, and managerial incentives, and find that strong board monitoring mechanisms mitigate crash risk. However, no studies have examined the relation between crash risk and *board friendliness*, which has drawn considerable interest in recent corporate governance research and might be related to management's willingness to withhold negative information. This study attempts to fill this gap in the literature by investigating the impact of co-opted boards on the firm's future stock price crash risk.

Managers have an incentive to conceal information on their bad performance from shareholders to prevent a potential loss in wealth (Ball, 2009). Prior studies document that factors that contribute to managers' incentives to withhold negative information include formal compensation contracts and career concerns (Kothari, Shu, & Wysocki, 2009; LaFond & Watts, 2008), managerial opportunism (Kim, Li, & Zhang, 2011a), and the value of option portfolios (Kim, Li, & Zhang, 2011b). If managers withhold negative information for an extended period, negative information accumulates within the firm. However, once this level reaches a certain threshold, the accumulated negative information is released to the stock market all at once, resulting in a stock price crash (Jin & Myers, 2006). We conjecture that board friendliness[1], measured by co-option, facilitates managerial activities related to withholding negative information, leading to a stock price crash.

Following Coles et al. (2014), we use two measures of co-option. First, *CO-OPTION* is a standard measure of board co-option and is defined as the ratio of the number of captured directors to the size of the board. Second, *TW CO-OPTION* is a tenure-weighted measure of co-option, defined as the ratio of the sum of the tenures of co-opted directors to the sum of the tenures of all board members. This measure reflects that the level of co-option might increase as co-opted directors work with the CEO over an extended period. Higher values for both measures indicate a greater degree of board capture. We expect that both measures are positively associated with a one-year-ahead stock price crash risk.

Following prior studies (Chen, Hong, & Stein, 2001; Kim et al., 2011a, 2011b), we measure a firm-specific stock price crash risk as the negative skewness of firm-specific weekly returns (*NCSKEW*) and the down-to-up volatility of firm-specific weekly returns (*DUVOL*). Both measures are related to future crash occurrences in a one-year-ahead forecast window. Using an OLS regression and a sample of 12,841 U.S. public firms for the period 1996 to 2014, we find robust evidence that co-option is positively associated

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[1] Prior literature measures board friendliness based on social connections via common educational background, memberships in the same non-business organization, and common prior employment (Hwang & Kim, 2009; Kang, Liu, Low, & Zhang, 2018; Schmidt, 2015).

with stock price crash risk, consistent with our conjecture that co-option attenuates the monitoring roles of the board, thereby facilitating the withholding of negative information by management. Our results are robust after controlling for a conventional measure of monitoring effectiveness, *independence*, suggesting that co-option measures capture novel aspects of board-monitoring effectiveness beyond those of the conventional measure. The positive relation is also robust to three tests for endogeneity, namely, the propensity score matching (PSM) procedure, a dynamic panel generalized method of moments (GMM) test, and a diagnostic test of coefficient stability.

Given the strong relation between board co-option and firm's future stock price crash risk, we further investigate whether a CEO who prefers to withhold negative information is more likely to take advantage of co-opted directors. Andreou, Louca, and Petrou (2017) and Li and Zhan (2017) argue that younger CEOs and those who work in a more competitive environment are more concerned about their careers, leading to a greater risk of a stock price crash. Kothari et al. (2009) find that managers have stronger incentives to conceal negative information when they are more concerned about their careers. Accordingly, we employ CEO age and product market competition as proxies for managers' preferences for withholding negative information. Consistent with the career-concern view, our subsample analyses reveal that the positive relation between co-option and crash risk is significant only for young CEOs and for CEOs in a highly competitive product market. These results indicate that the positive relation depends on managers' preferences for disclosing negative information.

Finally, consistent with Coles et al. (2014), we find that the monitoring effectiveness of board members can be hampered by the presence of co-option, regardless of their essential independence. This suggests that independent directors, who should be there to oversee and discipline management on behalf of shareholders, may be loyal to the CEO who appointed them after assuming office. We also find that the increase in the risk of a crash risk as a result of co-option is greater for non-independent directors than for independent directors, implying that board independence mitigates part of the effect of co-option. This result may have important implications for the traditional way of measuring board-monitoring effectiveness. Overall, the evidence in our analysis supports the prediction that managers in firms with greater co-option show a higher tendency to conceal negative information from shareholders, resulting in higher stock price crash risk.

Our study contributes to the extant literature in three ways. First, we contribute to the literature on the firm's future stock price crash risk. A growing body of recent empirical literature has identified firm, governance, and behavioral characteristics that are determinants of future stock price crashes (An & Zhang, 2013; Bao, Fung, & Su, 2018; Bhargava, Faircloth, & Zeng, 2017; Callen & Fang, 2013, 2015; He, 2015; Kim & Zhang, 2016; Kim et al., 2011a; Kim, Wang, & Zhang, 2016; Xu, Li, Yuan, & Chan, 2014; Yuan, Sun, & Cao, 2016). Our research is closely related to that of Kao, Huang, and Fung (2018), who investigate the impact of co-option and gender diversity on the risk of a crash using a sample of Chinese firms, and that of Jiraporn, Kim, and Lee (2018), who show the relation between co-opted boards and firm risk. However, to the best of our knowledge, this research is the first to examine the relation between co-option and a crash risk using a large sample of U.S. public firms. Our study provides evidence that a CEO with a co-opted board can exacerbate the risk of a stock price crash because co-opted directors do not monitor the firm as effectively, thus making it possible for the CEO to withhold negative information from shareholders.

Second, our study extends the growing literature on board friendliness in U.S. public firms and its economic consequences (Coles et al., 2014; Jiraporn et al., 2018; Kang et al., 2018). The implications of board co-option for crash risks produce valuable insights into board friendliness. Consistent with Coles et al. (2014), our findings show that although the conventional board *independence* attenuates a crash risk, friendly boards are positively associated with future stock crashes, regardless of whether they are classified as independent directors. These findings support the notion that not all independent directors are beneficial (Hwang & Kim, 2009). Furthermore, our findings provide evidence on the heterogeneous effects of friendly boards. Consistent with our results, Coles et al. (2014) suggest that co-option has harmful effects on economic outcomes by weakening the board's monitoring roles. However, Kang et al. (2018) indicate that friendly boards enhance corporate innovation outcomes by strengthening board advisory roles. Our evidence also suggests that the impact of co-option on a firm's crash risk depends on the degree of managerial preferences for withholding negative information. In summary, board friendliness is neither universally harmful nor universally beneficial to firms and shareholders.

The rest of the paper proceeds as follows. Section 2 reviews the prior literature and develops our hypotheses. Section 3 describes the research design. Section 4 presents our empirical results. Finally, section 5 concludes the paper.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Recent studies have examined the determinants of corporate managers' incentives to withhold negative information, finding that these include equity incentives (Kim et al., 2011a), corporate tax avoidance (Kim et al., 2011b), institutional investors (An & Zhang, 2013; Callen & Fang, 2013), excess corporate perks (Xu et al., 2014), CEO inside debt holdings (He, 2015), county-level religiosity (Callen & Fang, 2015), accounting conservatism (Kim & Zhang, 2016), CEO overconfidence (Kim et al., 2016), directors' and officers' liability insurance (Yuan et al., 2016), state anti-takeover laws (Bhargava et al., 2017), and clawback provisions (Bao et al., 2018). These studies suggest that managers' preferences for information disclosure, induced by their private benefits, contribute to a firm's stock price crash risk.[2]

Agency theory suggests that board monitoring plays a critical function on behalf of shareholders (Fama & Jensen, 1983). Effective board monitoring mitigates opportunistic managerial behaviors, agency

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[2] The theoretical explanation of a crash risk includes the agency theory-based argument/bad news concealment theory (Hutton, Marcus, & Tehranian, 2009; Kothari et al., 2009), heterogeneity in investors' belief (Hong & Stein, 2003), information blockages (Cao, Coval, & Hirshleifer, 2002), volatility feedback effects (Campbell & Hentschel, 1992; French, Schwert, & Stambaugh, 1987), and the default risk-based explanation (Campbell, Hilscher, & Szilagyi, 2008). Our findings are based mainly on bad news concealment theory.

costs, and information asymmetry between managers and outside stakeholders, thus reducing the risk of a stock price crash (Ajinkya, Bhojraj, & Sengupta, 2005; Attig, Fong, Gadhoum, & Lang, 2006; Chung, Elder, & Kim, 2010; Karamanou & Vafeas, 2005; Shleifer & Vishny, 1997). In contrast, ineffective board monitoring may allow managers to withhold negative information for their own benefit. In other words, the risk of a stock price crash might be more pronounced when managers' preferences for disclosing negative information are not aligned with those of shareholders, owing to attenuated board-monitoring functions. Consistent with this notion, the corporate governance literature provides empirical evidence that governance mechanisms are important determinants of stock price crash risks. Andreou et al. (2016) find that strong board-monitoring mechanisms, measured by ownership structure, accounting opacity, board structure, and managerial incentives, mitigate the risk of a stock price crash. In addition, Callen and Fang (2013) find that institutional investor stability, measured by the average standard deviation of institutional shareholding proportions across all investors in a firm over a five-year period, alleviates the risk of a stock price crash.

Our study investigates the relation between board monitoring and the firm-specific risk of a stock price crash by considering recently developed measures of board-monitoring effectiveness, namely, board *co-option* measures (Coles et al., 2014). *Board independence*, defined as the proportion of outside directors to the total number of directors on the board, has been widely used in the corporate governance literature to estimate firm-specific board-monitoring intensity. However, Coles et al. (2014) argue that the traditional measure might not clearly explain board-monitoring effectiveness, because a large proportion of independent directors are captured by the CEO by being appointed after the CEO takes office. Their results show that board co-option hampers board-monitoring effectiveness. In addition, they find that the harmful effects of board co-option are driven mainly by co-opted independent directors, indicating that the relation between board-monitoring effectiveness and a crash risk can be better explained by co-option measures. Therefore, we conjecture that co-opted boards may induce managers to withhold negative information from shareholders, increasing the risk of a stock price crash. Specifically, we test the following hypothesis.

H1: All else being equal, board co-option is positively associated with the risk of a stock price crash.

Next, we consider the conditions under which the positive relation between co-option and a crash risk might be more pronounced. We conjecture that if board co-option provides a CEO with opportunities to withhold negative information by attenuating board-monitoring effectiveness, the aforementioned positive relation might be exacerbated because this will strengthen the CEO's personal incentives to conceal information from shareholders. In other words, a CEO with a stronger preference for withholding negative information is more likely to take advantage of a co-opted board.

We test this prediction using two measures that might be related to a CEO's incentives to conceal negative information from shareholders: CEO age and product market competition. Andreou et al. (2017) argue that younger CEOs, who are in the early stages of their careers, enjoy permanent increases in compensation for a longer period in comparison with older CEOs. The greater pay-performance sensitivity of younger CEOs may incentivize them to conceal adverse operating performance from investors. Consistent with this argument, Andreou et al. (2017) show that younger CEOs are more likely to hide and accumulate negative information, thus increasing the risk of a stock price crash. In a similar vein, Li and Zhan (2017) argue that competitive pressure from the product market might aggravate a CEO's career concerns by decreasing the firm's profitability and increasing the CEO turnover rate. Consistent with this view, they find that firms under greater competitive pressure are more prone to stock price crashes. If a younger age and greater product market competition increase a CEOs' concerns over his/her career, we hypothesize that younger CEOs and those who are under greater competitive pressure from the product market are more likely to exploit the weakened monitoring induced by board co-option. Therefore, we test the following hypothesis.

H2 (The career concern view): All else being equal, the positive association between board co-option and the risk of a stock price crash is more pronounced for firms a) with younger CEOs and b) under greater competitive pressure from the product market.

Finally, we examine whether the positive relation between co-option and the risk of a stock price crash depends on the independence of captured directors. Dependent (inside) directors are essentially non-effective monitors because they are already co-opted, whereas the key function of independent (outside) directors is to monitor and discipline the CEO (Weisbach, 1988). Two additional questions arise from this argument. If board co-option is a powerful mechanism that undermines the effectiveness of board monitoring, its presence should affect all directors, regardless of their nominal independence. Consistent with this view, Coles et al. (2014) find that captured independent directors are also weak monitors, suggesting that the traditional board independence measure does not differentiate between nominal (co-opted) and real independent board members. Therefore, we predict that co-option weakens independent directors' monitoring effectiveness, thus increasing the risk of a stock price crash. However, the effect of board capture may vary with the independence of directors. Given that independent directors are appointed from outside the company, co-opted independent directors may still be more independent than co-opted non-independent directors, in which case, the monitoring-attenuation effect of co-option might be moderated by captured directors' nominal independence level. These considerations lead to our third hypothesis.

H3: All else being equal, a) co-opted independent directors increase the risk of a stock price crash, and b) the positive relation between co-option and the risk of a stock price crash is more pronounced for co-opted non-independent directors than it is for co-opted independent directors.

3. RESEARCH DESIGN

3.1 Construction of the sample

Our initial sample includes all firms in the ISS database (formerly known as RiskMetrics) for the period 1996–2014, which covers CEO and board-related information of S&P 1,500 firms. The co-option data computed using the ISS database is taken from Coles et al. (2014). We then match the ISS data with one-year-ahead stock price crash risk measures, estimated using weekly returns from the Center for Research in Security Prices (CRSP). In constructing our crash risk measures and control variables, we delete observations with missing firm-specific accounting information in the Compustat annual files and missing stock returns and trading volume information in the CRSP data. Following the existing literature, we exclude firms in regulated industries (financial services (SIC 6000-6999) and utilities (SIC 4800-4999)) and firm-years with fewer than 26 weeks of return data in a fiscal year (Hutton et al., 2009; Andreou et al., 2017). These criteria yield 1,614 firms and 12,841 firm-year observations.

3.2. Variables

3.2.1. Dependent variables

Following the existing literature (Chen et al., 2001; Jin & Myers, 2006; Kim et al., 2011a, 2011b), we construct two measures of a firm-specific stock price crash risk: i) the negative coefficient of the skewness of firm-specific weekly returns (NCSKEW), and ii) the down-to-up volatility of firm-specific weekly returns (DUVOL). We first estimate the residual weekly returns for each firm and year, $\varepsilon_{j,w}$, using the following expanded market model regression:

$$r_{j,w} = \alpha_j + \beta_{1,j} r_{m,w-2} + \beta_{2,j} r_{m,w-1} + \beta_{3,j} r_{m,w} + \beta_{4,j} r_{m,w+1} + \beta_{5,j} r_{m,w+2} + \varepsilon_{j,w},$$

where $r_{j,w}$ is the return on stock j in week w, and $r_{m,w}$ is the return on the CRSP value-weighted market index in week w. We include the lead and lag terms for the market returns to correct for non-synchronous trading (Dimson, 1979). The firm-specific weekly return for firm j in week w is estimated as the natural logarithm of one plus the residual return (i.e., $R_{j,w} = \ln(1 + \varepsilon_{j,w})$).

We use the negative conditional skewness of firm-specific weekly returns over the fiscal year (*NCSKEW$_t$*) as our first measure of a firm-specific crash risk. Here, *NCSKEW$_t$* is defined as the negative coefficient of the third moment of the firm-specific weekly returns for each firm in a fiscal year, divided by the standard deviation of the firm-specific weekly returns raised to the third power. Specifically, for each firm j in fiscal year t, this is calculated as follows:

$$NCSKEW_{j,t} = \frac{-[n(n-1)^{\frac{3}{2}} \sum R_{j,w}^{3}]}{(n-1)(n-2)(\sum R_{j,w}^{2})^{\frac{3}{2}}},$$

where n is the number of observations (firm-specific weekly returns) during fiscal year t.

Our second measure of a crash risk is the down-to-up volatility measure of the crash likelihood, *DUVOL$_t$*. For each firm j in fiscal year t, we assign all firm-specific weeks to two subsamples: i) "down" weeks, with firm-specific weekly returns below the annual mean; and ii) "up" weeks, with returns above the annual mean. We then calculate the standard deviation of firm-specific weekly returns for each group. Finally, we compute the firm-specific *DUVOL$_t$* by taking a log transformation of the ratio of the standard deviation of "down" weeks to the standard deviation of "up" weeks. Specifically, for each firm j in fiscal year t, the measure is calculated as follows:

$$DUVOL_{j,t} = \log\left[\frac{(n_u - 1)\sum_{DOWN} R_{j,w}^{2}}{(n_d - 1)\sum_{UP} R_{j,w}^{2}}\right],$$

where n_u and n_d are the number of up and down weeks, respectively, during fiscal year t. For both *NCSKEW$_t$* and *DUVOL$_t$*, higher values suggest a greater crash risk.

3.2.2. Main variables of interest: Co-option measures

Following Coles et al. (2014), we employ two variables to measure the proportion of co-opted directors on the board. The standard measure of board co-option, *CO-OPTION*$_{t-1}$, is defined as the proportion of directors elected after a CEO takes office at $t-1$.

$$\text{Co-option}_{t-1} = \frac{\text{Number of Co-opted Directors}_{t-1}}{\text{Board Size}_{t-1}}$$

An alternative measure of co-option is tenure-weighted co-option (*TW CO-OPTION*$_{t-1}$), which accounts for the fact that co-option might be enhanced when co-opted directors work with a CEO for an extended period. Here, *TW CO-OPTION*$_{t-1}$ is defined as the sum of the tenures of co-opted directors divided by the sum of the tenures of all directors on the board:

$$\text{TW Co-option}_{t-1} = \frac{\sum_{i=1}^{\text{board size}} \text{Tenure}_{i,t-1} \times \text{Co-opted Director Dummy}_{i,t-1}}{\sum_{i=1}^{\text{board size}} \text{Tenure}_{i,t-1}}$$

where $\text{Co-opted Director Dummy}_{i,t-1}$ indicates the co-opted director i at time $t-1$ and $\text{Tenure}_{i,t-1}$ denotes the corresponding tenure of director i as of $t-1$. Both measures have a range of 0 to 1, and higher values indicate greater co-option of the board.

4. EMPIRICAL ANALYSIS

4.1 Descriptive statistics

[Insert Table 1 Here]

Panel A of Table 1 reports the descriptive statistics for the variables used in our analysis. The sample includes 12,841 firm-year observations. The mean values for our dependent variables, *NCSKEW*$_t$ and *DUVOL*$_t$, are 0.205 and 0.142, respectively, which are much higher than those reported in prior studies (Chen et al., 2001; Kim et al., 2011a, 2011b). This is not surprising, considering that we use a different sample period and data set.[3] The sample firms have an average *CO-OPTION*$_{t-1}$ of 0.477, suggesting that

[3] Kim et al. (2011a) suggest there is considerable variation in crash risk measures across years.

non-trivial fractions of the boards (about half) have been captured by CEOs. The mean *TW CO-OPTION*$_{t-1}$ is 0.315. The mean values of co-option measures are comparable to the estimates of Coles et al. (2014). On average, the sample firms have boards of which 71% of the directors are independent. The average change in trading volume is 0.001. On average, the firms in our sample have a weekly stock return of -0.3 percent and a market-to-book ratio of 2.105.

Panel B of Table 1 shows the Pearson correlation matrix for the crash risk measures, standard co-option measure, and other controls used in our study. The two stock price crash risk measures (i.e., *NCSKEW*$_t$ and *DUVOL*$_{t)}$) are highly correlated with each other (ρ = 0.92), suggesting that they measure similar dimensions of information related to stock price crashes. More importantly, our key variables of interest, *CO-OPTION*$_{t-1}$ and *TW CO-OPTION*$_{t-1}$, are significantly and positively correlated with *NCSKEW*$_t$ and *DUVOL*$_t$, which is consistent with our prediction that firms with greater co-option of the board are more at risk of a stock price crash. Finally, we observe negative correlations between accrual earnings management (ACC) and the co-option measures. Although this result could be caused by the different empirical proxies we employ, another possibility is that co-opted directors and accrual management are substitutes for CEOs inflating earnings news and hiding negative information owing to weak monitoring. Note too that this negative correlation is contrary to our predictions, because Hutton et al. (2009) find that ACC is positively related to the risk of a crash. This is actually good news for our study, in the sense that a positive relation between co-opted directors and the risk of a crash, once observed, is unlikely to simply be picking up the positive effects of ACC on the crash risk shown by Hutton et al. (2009).

4.2. Main regression analysis: Effect of co-opted boards on the stock price crash risk

In this section, we investigate the effects of co-opted boards on the risk of a stock price crash. We employ the following ordinary least squares (OLS) regression to test our first hypothesis that the stock price crash risk increases with the co-option measures:

$$Crash\_Risk_{i,t} = \beta_0 + \beta_1 Co\_Option\ Measures_{i,t-1} + \beta_2 Independence_{i,t-1} + \gamma' Controls_{i,t-1} + Year\ Dummies + Industy\ Dummies + \varepsilon_{i,t-1}.$$

The dependent variable $Crash\_Risk_t$ is one of our two crash-risk proxies, $NCSKEW_t$ and $DUVOL_t$, and is measured in year t. The independent variables, including our key variables, are measured in year t – 1. Our two main explanatory variables of interest are $CO\text{-}OPTION_{t-1}$, which is the proportion of co-opted directors on the board, and tenure-weighted co-option, $TW\ CO\text{-}OPTION_{t-1}$. To test whether our key variables have explanatory power after controlling for the conventional measure of board-monitoring effectiveness, we include IND_{t-1}, calculated as the number of independent directors divided by the board size, in all specifications.

Motivated by the existing literature, we control for several variables that have been shown to be potential predictors of a crash risk. We include the detrended stock turnover, $DTURN_{t-1}$, as a proxy for the potential divergence of opinions among investors, because Chen et al. (2001) show that differences in investors' beliefs predict the likelihood of a future crash. To address concerns related to dynamic endogeneity induced by the potential persistence of a firm's crash risk, we include the negative skewness of firm-specific past stock returns, $NCSKEW_{t-1}$. Because firms that are more volatile tend to be more crash-prone, we include the standard deviation of firm-specific past stock returns, $SIGMA_{t-1}$. Jin and Myers (2006) argue that long tails in stock return distributions predict future crashes. Thus, we control for the kurtosis of firm-specific weekly returns, KUR_{t-1}. In addition, we control for performance-matched discretionary accruals, ACC_{t-1}, as a proxy for earnings-management activities. Finally, we also include firm characteristics such as firm size ($SIZE_{t-1}$), market-to-book ratio (MB_{t-1}), leverage (LEV_{t-1}), return on assets (ROA_{t-1}), past returns (RET_{t-1}), R&D intensity (R&D$_{t-1}$), and a dummy variable indicating missing R&D

($R\&D\_MISSING_{t-1}$).[4] In all of the regression specifications, we include industry fixed effects by including the 48 industry categories suggested by Fama and French (1997) and year fixed effects. Including these effects allows us to control for unobservable time-invariant factors across industries, as well as any unobservable changes over time in terms of firm heterogeneity within each industry. In addition, the *p*-values reported are based on standard errors, corrected for year clustering (Petersen, 2009). Appendix A provides detailed definitions of the variables used in our analysis.

[Insert Table 2 Here]

Table 2 reports the regression results. Models (1) and (2) (Models (3) and (4)) report the coefficients estimated when regressed on $NCSKEW_t$ ($DUVOL_t$). Models (1) and (3) report the coefficients of our standard measure, $CO\text{-}OPTION_{t-1}$, and Models (2) and (4) provide the coefficients of the tenure-weighted co-option measure, $TW\ CO\text{-}OPTION_{t-1}$. Model (1) shows that the coefficient of $CO\text{-}OPTION_{t-1}$ is 0.036 and is non-significant (*p*-value = 0.200). However, consistent with our hypothesis H1, Model (2) shows that the coefficient on $TW\ CO\text{-}OPTION_{t-1}$ is 0.042, which is significant at the 10% level (*p*-value = 0.095). Thus, all else being equal, firms with higher tenure-weighted co-option are more at risk of a stock price crash. Models (3) and (4), in which the dependent variable is $DUVOL_t$, show that the estimated coefficients of $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$ are 0.037 (*p*-value = 0.028) and 0.044 (*p*-value = 0.004), respectively, and are both significant. For the baseline Model (4) in Table 2, the coefficient of $DUVOL_t$ is 0.044. If tenure-weighted co-option increases by one standard deviation (0.330 in Table 1), this coefficient implies that the crash risk increases by 0.044 × 0.330 = 0.015, which amounts to roughly 10% of the mean crash risk, $DUVOL_t$ (0.142 in Table 1). This suggests that the magnitude of the impact of co-opted directors on the risk of a crash is economically meaningful.

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[4] We treat all observations with missing values for R&D as zero, and a dummy variable indicating these missing values, $R\&D\_MISSING_{t-1}$, is included in the regressions.

Another way to express the impact on firms with co-opted directors is to compare the relative effects of the firm's market-to-book ratio (MB) and co-option. Specifically, in Model (4), a one-standard-deviation (0.330) increase in co-option is associated with a $0.044 \times 0.330 = 0.015$ increase in the risk of a crash. A-one-standard-deviation increase in the MB (1.613) is associated with an increase in the risk of a crash of $0.031 \times 1.613 = 0.05$. Based on this comparison, the variation in co-option has an effect of about one-third of that of the variation in MB on the risk of a stock price crash.

With regard to the control variables, the coefficients are generally consistent with those in the literature. We find that IND_{t-1} is significantly and negatively related to the risk of a stock price crash in all specifications, suggesting that even though the conventional measure of board independence has strong power in terms of capturing monitoring effectiveness, our key variables are still successful in explaining the risk of a stock price crash. Firms with higher firm-specific returns (RET_{t-1}) and future growth opportunities (MB_{t-1}) are more at risk of a stock price crash. Future crashes are also positively related to a firm's return on assets (ROA_{t-1}).

In summary, we find strong evidence consistent with the detrimental effects of co-opted boards, as highlighted by Coles et al. (2014). The results are consistent with the notion that a CEO is more likely to withhold negative information when more directors on the board are captured, thus increasing the risk of a stock price crash.

4.3. Endogeneity

Our baseline analysis thus far shows that the one-year-ahead crash risk is a function of the co-option measures. Although we include lagged co-option measures, various firm characteristics, and year and industry characteristics in all specifications to mitigate the problem of endogeneity, the potential endogenous relation between the co-option measures and the risk of a crash remains a concern, because board co-option is unlikely to occur randomly. In addition, an omitted-variable bias can arise when the co-option measures and the crash-risk measures are determined jointly by unobservable firm-specific factors. To address this concern, we conduct three econometric tests to re-estimate our baseline specifications. We discuss these analyses in detail below.

The first test employs the PSM approach,[5] which is widely used in the corporate finance literature. If firms with a higher proportion of co-opted directors have characteristics that differ from firms with a lower proportion of co-opted directors, the effect of board co-option on stock price crashes might be biased when the linear control variables employed are insufficient, because board co-option might detect nonlinear effects of the control variables on stock price crashes. The PSM approach constructs two samples that are comparable across all observable factors but differ only in the magnitude of board co-option. This allows us to more clearly identify the effects of board co-option, rather than those induced by the observable factors associated with board co-option.

Following Heckman, Ichimura, and Todd (1997), we use a one-to-one nearest-neighbor matching, with replacement.[6] Specifically, we first transform our two continuous variables, $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$, into two binary variables, $FRIENDLY_{t-1}$ and $TW\ FRIENDLY_{t-1}$, based on their sample median values, 0.444 and 0.180, respectively, to operationalize the estimation. Then, the method uses a logit regression, in which the dependent variables are the two binary variables and the explanatory variables are the same as those employed in our baseline specifications. The outputs of the estimation are the propensity scores for each co-option measure, reflecting the probability of being a treated firm ($FRIENDLY_{t-1} = 1$ and $TW\ FRIENDLY_{t-1} = 1$) conditional on all of the explanatory variables. For each treated firm, we select the control firm with the closest propensity scores (predictions from the logit model) to the propensity

[5] See Rosenbaum and Rubin (1983) and Roberts and Whited (2012) for a discussion of matching methods.
[6] According to Roberts and Whited (2012), "Matching with replacement allows for better matches and less bias, but at the expense of precision… We prefer to match with replacement since the primary objective of most empirical corporate finance studies is proper identification. Additionally, many studies have large amounts of data at their disposal, suggesting that statistical power is less of a concern." (pages 74–75)

score of the treated firm and a co-option value below the sample medians (*FRIENDLY*$_{t-1}$ = 0 and *TW FRIENDLY*$_{t-1}$ = 0). To ensure the quality of the match, we require that the difference in propensity scores between a treated and a control firm not exceed the caliper width of 0.0005.[7] This approach leads to 6,343 and 6,184 unique pairs of firm-years, respectively, matched on each co-option measure.

[Insert Table 3 Here]

Panels A and B of Table 3 report the mean values of the control variables for both the unmatched and matched samples, and test the differences in the characteristics. In Panels A and B, firms are matched according to the propensity scores estimated using *FRIENDLY*$_{t-1}$ and *TW FRIENDLY*$_{t-1}$, respectively. Both panels clearly show that most of the control variables differ significantly across the two groups. However, for the matched sample, we find that, other than for the return on assets in Panel A and the MB in Panel B, there are no statistically significant differences in the means across the two groups. This suggests that the firms matched by the propensity scores are comparable with the treated firms across virtually all dimensions and, thus, our matching is effective.

Panel C shows that the results of the PSM regressions are qualitatively similar to those of our baseline regressions in Table 2. Interestingly, the effects of *CO-OPTION*$_{t-1}$ and *TW CO-OPTION*$_{t-1}$ on the crash riskbecome greater after addressing the selection bias using the PSM approach. Using the comparison samples, the coefficients of *CO-OPTION*$_{t-1}$ in Models (1) and (3) of Table 3 become statistically and economically more significant than those in Table 2. For example, Model (3) shows that the coefficient of *CO-OPTION*$_{t-1}$ is 0.070, which is significant at the 1% level (p-value = 0.006). This indicates that a one standardized unit increase in *CO-OPTION*$_{t-1}$ leads to an increase in the risk of a crash of 0.070 × 0.320 =

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[7] The choice of caliper width varies across studies. For example, Andreou et al. (2017) and Hoitash, Hoitash, and Kurt (2016) set the value to 0.01, whereas Heese, Khan, and Ramanna (2017) perform matching with a 0.0005 caliper. Although a narrower caliper width reduces the size of the matched sample, it improves the performance of the PSM approach by leading to closer matches. An untabulated analysis reveals that our results are qualitatively similar if we match using a caliper width of 0.01.

0.0224, which amounts to roughly 16% of the mean crash risk $DUVOL_t$ (0.142 in Table 1). Although the coefficients of *CO-OPTION*$_{t-1}$ in Models (2) and (4) of Table 3 become less statistically significant than those in Table 2, they remain economically significant. Overall, the regression results in Panel B of Table 3 indicate that the effect of board co-option on stock price crashes is unlikely to be driven by observable control variables other than board co-option itself.

Second, we incorporate the dynamic relation between co-option and stock price crash risk measures, while accounting for other sources of endogeneity. Reverse causality can arise from the dependence of the current value of co-option on current and/or past values of stock price crash risk in the presence of unobservable firm effects. For example, CEOs of firms that have been more at risk of a crash in the past may choose to increase the degree of board co-option, possibly owing to their preference for withholding negative information. In such a scenario, the past and/or current crash risk influences the current co-option value, which, in turn, affects the firm's future crash risk. Wintoki, Linck, and Netter (2012) suggest that the reverse causality of the corporate governance variable is dynamic. To investigate whether the financial constraints on firms affect their risk of a stock price crash, He and Ren (2017) use a dynamic panel GMM estimator to mitigate the concern of the past or current crash risk affecting a firm's financial constraints and, in turn, influencing the firm's future crash risk. Similarly, to address this concern of this dynamic endogeneity, we follow Wintoki et al. (2012) and apply the dynamic panel GMM to our baseline analysis. Our dynamic GMM model is specified as follows:

$$\begin{aligned} Crash\_Risk_{i,t} = {} & \beta_0 + Crash\_Risk_{i,t-1} + Crash\_Risk_{i,t-2} + \beta_1 Co\_Option\ Measures_{i,t-1} \\ & + \beta_2 Independence_{i,t-1} + \gamma' Controls_{i,t-1} + +Year\ Dummies + Industy\ Dummies \\ & + \theta_i + u_{i,t-1}, \end{aligned}$$

where $Controls_{i,t-1}$ is the same set of control variables used in our baseline regressions, except that

$NCSKEW_{t-1}$ and θ_i represent unobserved firm fixed effects.[8]

Our baseline analysis includes $NCSKEW_{t-1}$ in all specifications, regardless of the dependent variables. However, in our dynamic GMM specifications, we include two lags of crash risk measures, each corresponding to a dependent variable, to control for the effect of the current and one-year lagged crash risks on the future stock price crash risk. In the estimation procedure, the unobserved firm fixed effect is removed using first-differencing, because it does not vary over time. Our dynamic GMM model assumes that including two lags of crash risk measures is sufficient for dynamic completeness, suggesting that three or more lags could be suitable candidates as instruments. Therefore, we include the values of the crash risk and all explanatory variables lagged from three to six periods as instruments for the GMM estimation.

[Insert Table 4 Here]

Table 4 reports the results of our dynamic GMM estimations. The coefficients of the dynamic GMM regressions are still qualitatively comparable to our baseline results in Table 2 after addressing the dynamic endogeneity problem. In all specifications, the co-option measures are positively associated with future crash risk measures. More importantly, the coefficients on all regressions become economically more meaningful than those in our baseline regressions. For instance, Model (3) demonstrates that one standardized unit increase in $CO\text{-}OPTION_{t-1}$ is associated with an increase in $DUVOL_t$ of 0.279 × 0.320 = 0.0893, thus explaining about two-thirds (63%) of the mean value of $DUVOL_t$ (0.142 in Table 1). Consistent with the assumption of the GMM specification, the Arellano–Bond (1991) AR(1) tests reject the null hypothesis of no first-order serial correlations between the residuals in the first differences in all specifications. However, the AR(2) tests do not reject the null hypothesis of no second-order serial

8 The dynamic GMM estimation is administered using the Stata command *xtabonds*. The procedure suggests that the power of the Hansen test for over-identification can be weakened by including too many instruments. Therefore, we use industry dummies based on the 17 Fama–French industry categories rather than using the 48 industry categories in our GMM specifications.

correlations. The Hansen test for over-identification suggests that the null hypothesis that all instruments are valid cannot be rejected. Overall, the results suggest that the positive association between co-option and the future stock price crash risk is unlikely to be driven by dynamic endogeneity.

The third approach employs the diagnostic test developed recently by Oster (2017), based on the method of Altonji, Elder, and Taber (2005). This approach tests the sensitivity of the coefficient of interest to possible selection on unobservable factors, and identifies an omitted-variable bias by observing movements in both the coefficient and the R-squared between uncontrolled (omitting controls) and controlled (including controls) regressions. Intuitively, if the coefficient of interest decreases, but the R-squared increases significantly as additional controls are added to a regression, then the regression result might suffer from an omitted-variable bias, because the result might be overturned if unobservable factors are included in the regression.

Oster's (2017) formula provides a coefficient of proportionality, δ, to compare the relative strengths of selection on unobservable and observable factors. For example, $\delta > 1$ suggests that for the selection on unobservable factors to drive the coefficient of interest to zero, it would have to be stronger than the selection on observable factors. However, if we include most of the first-order determinants of the dependent variables identified in the literature, the selection on unobservable factors is unlikely to be more important than the selection on observable factors. Therefore, Oster (2017) proposes $\delta = 1$ as a cutoff value for robustness. To implement the diagnostic test, we need to specify R_{max}, the R-squared value from a hypothetical regression of a dependent variable on both observed and unobserved controls, which is clearly unknown. Specifying a higher value of R_{max} assumes that the unobserved controls have stronger explanatory power in the hypothetical regression, leading to a more conservative (lower) δ-value in the diagnostic test. Based on experimental evidence obtained by replicating recent studies published in top economics journals, she suggests using $R_{max} = 1.3 \times \tilde{R}$, where $\tilde{R}$ is the R-squared from the OLS regression that includes all observed controls.

[Insert Table 5 Here]

Table 5 reports the estimates of δ for each of variables of interest in our baseline regressions in Table 2, $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$, obtained using Oster's approach.[9] Panel A of Table 5 reports the movements of the coefficients and the R-squared values between the uncontrolled and controlled regressions. The coefficients and R-squared values for the controlled regressions are the same as those in our baseline regressions in Table 2. We find that the coefficients of our main variables decrease slightly, but that the R-squared values increase significantly as controls are added to our regressions. This suggests that our baseline results remain robust to the inclusion of additional unobserved control variables.

Panel B of Table 5 shows Oster's δ for each regression, computed based on the movements in Panel A. We report the values of δ for $R_{max} = 1.3 \times \tilde{R}$ as the main results of the diagnostic test, but we also provide those for more conservative values of δ, namely, $R_{max} = 2.0 \times \tilde{R}$ and $R_{max} = 3.0 \times \tilde{R}$. The results shown in Panel B indicate that the selection on unobservable controls needs to be 12.708 (Model (1)) and 10.124 (Model (2)) times more important than the selection on observable controls in the $NCSKEW_t$ regressions, and 17.695 (Model (3)) and 16.075 (Model (4)) times more important in the $DUVOL_t$ regressions to drive the coefficients of interest to zero. These situations seem unlikely, given that our baseline regressions control for many first-order determinants of stock price crash risks, as well as industry and year fixed effects. When repeating the analysis using the more conservative R_{max}, we find that the values of δ are still consistently greater than one. Overall, the diagnostic tests strongly suggest that the coefficients of our key variables are stable, and that the selection on unobservable factors is unlikely to render our baseline results non-significant.

[9] The diagnostic test is administered using the Stata command *psacalc*, provided by Oster (2017).

In summary, the results of the PSM, dynamic panel GMM estimation, and coefficient stability tests show that the positive relations between board co-option and stock price crashes in Table 2 are not driven by endogeneity concern.

4.4. Additional evidence: Co-opted boards, information-withholding incentives, and stock price crash risk

In this section, we examine the channels through which co-opted boards increase the risk of a stock price crash. To do so, we explore our second hypothesis (the career-concern view) that CEOs with greater incentives to conceal negative information from investors are more likely to take advantage of board friendliness. As discussed in Section 2, we use two measures that might trigger CEOs' incentives to withhold negative information, following the existing literature (Andreou et al., 2017; Li & Zhan, 2017): CEO age and product market competition (industry concentration). Thus, we examine the relation between co-opted boards and crash risks, conditional on the CEO incentive measures, by re-running our baseline regressions. We partition our sample into firms above and below the median of each incentive measure, and report the results in Table 6.

[Insert Table 6 Here]

4.4.1 CEO age

The first measure is an indicator variable that takes the value one if the age of the CEO is below the sample median, and zero otherwise ($YOUNG_{t-1}$). We obtain the information on CEO ages from the ISS database. Andreou et al. (2017) argue that younger CEOs, who are in the early stages of their business careers, are more concerned about their careers than are their older counterparts, suggesting that they might have stronger incentives to conceal negative information from shareholders than older CEOs do. Consistent with this notion, they show a positive relation between firms with younger CEOs and the risk of a stock price crash.

Panel A of Table 6 reports the regression results based on the CEO Age variable ($YOUNG_{t-1}$). We find that for both future crash risk measures, the coefficients on $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$ are positive in both subsamples, but are statistically significant only for firms with young CEOs (Models (1) to (4)). When firms have older CEOs (Models (5) to (8)), the relation between co-opted boards and the risk of a crash is non-significant. In addition, the magnitudes of the coefficients on $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$ are much larger for the subsample with young CEOs than they are for the sample with older CEOs.

4.4.2 Product market competition

Our second measure is an indicator variable that takes the value one if a firm is part of an industry with a concentration ratio below the median in a given fiscal year, and zero otherwise ($HIGH\text{-}COMPETITION_{t-1}$). Li and Zhan (2017) suggest that CEOs' incentives to withhold negative information are reinforced as product market competition increases, because the competitive pressure exacerbates their career concerns. Following Moatti, Ren, Anand, and Dussauge (2015), we measure industry concentration using the four-firm industry concentration ratio.[10] Specifically, the concentration ratio is measured as the total market share held by the four largest firms in each of the Fama–French 48 industry classifications, where market share is measured by sales. A high concentration ratio indicates a low level of product market competition.

In panel B of Table 6, we split the sample into two subsamples: those below the median of the four-firm industry concentration ratio ($HIGH\text{-}COMPETITION_{t-1} = 1$), and those above the median ($HIGH\text{-}COMPETITION_{t-1} = 0$). Consistent with the results in Panel A, the coefficients of $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$ are positive for the subsample with a high level of competition, but are non-significant for the subsample with a low level of competition. Furthermore, the coefficients are more economically

[10] We obtain similar results when we perform the same analyses using alternative measures of product market competition, such as five-firm and 10-firm industry concentration ratios and the Herfindahl index.

significant for the high product market competition group.

Product market competition might have two conflicting effects on stock price crashes. On the one hand, as suggested by Li and Zhan (2017), competitive pressure from the product market aggravates managerial career concerns, increasing the risk of a crash. On the other hand, if product market competition mitigates managerial slack by acting as an external monitoring mechanism (Giroud & Mueller, 2010), it should be negatively associated with the risk of a crash. Consistent with the latter view, but inconsistent with our findings, Kim et al. (2011a) show that the positive effect of CFO option sensitivity on the risk of a crash is more pronounced for a subsample with low product market competition. However, our findings suggest that the former effect dominates when product market competition interacts with board friendliness. Overall, the findings in Table 6 support our second hypothesis that board co-option facilitates CEOs incentives to withhold negative information when they are concerned about their careers. However, for those with low career concerns, this effect is attenuated, indicating that the crash risk-increasing effect of board friendliness depends on the level of managerial career concerns.

4.5. Co-opted independent directors versus co-opted non-independent directors

Our results thus far have shown that co-opted boards increase the risk of a stock price crash and that the positive relation depends on managerial incentives to withhold negative information. However, as suggested by Coles et al. (2014), the standard measure $CO\text{-}OPTION_{t-1}$ and tenure-weighted measure $TW\ CO\text{-}OPTION_{t-1}$ do not differentiate between the effects of capturing non-independent directors and independent directors. Given that non-independent directors are virtually insiders who do not monitor management activities, it is natural that co-option further attenuates their monitoring roles. Similarly, if co-option prevents independent directors from overseeing management activities, this will increase the risk of a stock price crash. Thus, we conjecture that the risk of a crash is present for both independent and non-independent co-opted directors, but will be more pronounced in the latter group. Thus, it is important that we examine whether co-option affects non-independent and independent directors differently.

To test this prediction, we isolate co-opted independent directors from co-opted boards. Following Coles et al. (2014), we define two additional variables: $CO\text{-}OPTED\ IND_{t-1}$ is the proportion of captured independent directors and $CO\text{-}OPTED\ NON\text{-}IND_{t-1}$ is the proportion of captured non-independent directors. The latter is computed by simply subtracting $CO\text{-}OPTED\ IND_{t-1}$ from $CO\text{-}OPTION_{t-1}$. We also construct respective tenure-weighted variables, $TW\ CO\text{-}OPTED\ IND_{t-1}$ and $TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$, in the same manner.

[Insert Table 7 Here]

In Table 7, we reproduce the baseline regression results shown in Table 2 after replacing the co-option measures with the co-opted independent and co-opted non-independent variables. Panel A reports the results for the co-opted independent variables, $CO\text{-}OPTED\ IND_{t-1}$ and $TW\ CO\text{-}OPTED\ IND_{t-1}$, and Panel B presents those for the co-opted non-independent variables, $CO\text{-}OPTED\ NON\text{-}IND_{t-1}$ and $TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$.

As shown in Panels A and B, both co-opted independent directors and co-opted non-independent directors, respectively, increase the risk of a stock price crash, which is consistent with our prediction. The coefficients of $CO\text{-}OPTED\ IND_{t-1}$ and $TW\ CO\text{-}OPTED\ IND_{t-1}$ are highly significant and have the expected positive signs (0.046, with p = 0.045, and 0.049, with p = 0.030, respectively) in Models (3) and (4) in Panel A. Similarly, the coefficients of $CO\text{-}OPTED\ NON\text{-}IND_{t-1}$ and $TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$ are also significant and have the expected positive signs (0.112, with p = 0.061, and 0.097, with p = 0.016, respectively). These significantly positive relations between co-opted independent and non-independent directors and the risk of a stock price crash supports H3, suggesting that captured directors, whether independent or not, do not function as guardians of shareholders. Furthermore, the magnitudes of the coefficients of the co-opted non-independent variables in Panel B are much larger than those of the co-opted independent variables in Panel A. This suggests that the effect of board capture is more detrimental in the case of non-independent directors, especially when they are tenured. However, consistent with the findings of Coles et al. (2014), the results in Panel A suggest that board capture attenuates the monitoring effectiveness of independent directors. Overall, the findings in this section indicate that decomposing the conventional measure of board independence into independent directors and non-independent directors better captures the effect of the proportion of effective monitors on the risk of a stock price crash.

5. CONCLUSION

Using the novel measure of board-monitoring effectiveness developed by Coles et al. (2014), *co-option*, this study shows that firms that have a CEO with a co-opted board are more likely to be associated with future stock price crashes. The results support the notion that directors appointed after a CEO assumes office do not provide effective monitoring roles, thereby allowing the CEO to withhold negative information more easily. Further analyses show that such crashes are more pronounced when the CEO is more concerned about his/her career, that is, when he or she is younger or when the firm operates within a competitive industry. This finding indicates that a CEO with stronger incentives to withhold negative information is more likely to exploit opportunities related to attenuated board monitoring for his/her own benefit. Overall, this study suggests that a CEO's concern over his/her career is an important determinant of the relationship between co-option and the risk of a stock price crash.

Our findings have important implications for the role of board monitoring. We have focused on the harmful effects of board friendliness and provide new evidence on the economic consequences of co-opted boards. The independence of a board member might not be determined purely by the classification. Directors appointed from outside the firm might be loyal to the CEO if they are appointed after the CEO takes office, thus weakening their managerial oversight related to the CEO withholding negative information. Our findings also offer important policy implications. Although certain regulations (e.g., the

Sarbanes–Oxley Act of 2002) limit the direct influence of the CEO in the nominating process, board friendliness issues, including co-option and social ties, still exist. Coles et al. (2014) suggest that a large proportion of independent directors in U.S. public firms might be captured by the CEO. Because our study highlights a significant impact of co-option on the risk of a stock price crash, regulators and policymakers should consider the possibility that directors appointed after a CEO assumes office may be connected to the CEO, regardless of their independence, thus creating serious agency problems.

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APPENDIX. Variable Definitions

Variable	Definition
Crash Risk Variables	
$NCSKEW_t$	Negative of the third moment of firm-specific weekly returns for each firm and fiscal year divided by the standard deviation of firm-specific weekly returns raised to the third power.
$DUVOL_t$	Natural log of the ratio of the standard deviation of firm-specific weekly returns below the annual mean for the fiscal year to the standard deviation of firm-specific weekly returns above the annual mean for the fiscal year.
Co-option Variables	
$CO\text{-}OPTION_{t-1}$	Number of co-opted director / Board size
$TW\ CO\text{-}OPTION_{t-1}$	Sum of tenure of co-opted directors divided by the sum of tenure of all directors.
$CO\text{-}OPTED\ IND_{t-1}$	Number of co-opted independent directors / Board size
$TW\ CO\text{-}OPTED\ IND_{t-1}$	Sum of tenure of co-opted independent directors divided by the sum of tenure of all directors.
$CO\text{-}OPTED\ NON\text{-}IND_{t-1}$	Number of co-opted non-independent directors / Board size = $CO\text{-}OPTION_{t-1}$ - $CO\text{-}OPTED\ IND_{t-1}$
$TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$	Sum of tenure of co-opted non-independent directors divided by the sum of tenure of all directors. = $TW\ CO\text{-}OPTION_{t-1}$ - $TW\ CO\text{-}OPTED\ IND_{t-1}$
Other Control and Conditional Variables	
IND_{t-1}	Number of independent directors / Board size
$DTURN_{t-1}$	Detrended turnover, defined as the difference between the average monthly share turnover over the current fiscal-year period and the average monthly share turnover over the previous fiscal-year period, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.
$NCSKEW_{t-1}$	One-year lagged value of $NCSKEW_{t.}$
$SIGMA_{t-1}$	Standard deviation of firm-specific weekly stock returns over the fiscal year.
RET_{t-1}	Average firm-specific weekly return during the entire fiscal year
$SIZE_{t-1}$	Natural log of total assets.
MB_{t-1}	Ratio of the market value of equity to the book value of equity.
LEV_{t-1}	Long-term debt divided by total assets.
ROA_{t-1}	Income before extraordinary items divided by lagged total assets

ACC_{t-1}	Performance-matched discretionary accruals following Kothari, Leone, and Wasley (2005).
$R\&D_{t-1}$	Ratio of research and development expenses to total assets. Missing values of research and development expenses are replaced with zero.
$R\&D\_MISSING_{t-1}$	Dummy variable that equals one if the value of research and development expenses is missing.
KUR_{t-1}	Kurtosis of firm-specific weekly returns over the fiscal year.
$FRIENDLY_{t-1}$	Dummy variable that takes one if the value of $CO\text{-}OPTION_{t-1}$ is above median, and zero otherwise
TW $FRIENDLY_{t-1}$	Dummy variable that takes one if the value of $CO\text{-}OPTION_{t-1}$ is above median, and zero otherwise
$HIGH\text{-}COMPETITION_{t-1}$	Dummy variable that equals one if the value of four-firm industry concentration ratio is below median, and zero otherwise
$YOUNG_{t-1}$	Dummy variable that equals one if the age of CEO is below median, and zero otherwise

TABLE 1. Descriptive statistics and correlation matrix

This table reports the descriptive statistics for stock price crash risk measures, co-option measures, and other control variables used in our analysis. The sample covers 12,841 U.S. public firm-year observations in ISS database from 1996 to 2014. Panel A presents the descriptive statistics of the full sample and Panel B reports a Pearson correlation matrix. In Panel B, statistical significance at 10% level or better is represented in bold. All variables are defined in the Appendix A.

Panel A. Descriptive Statistics

Variable	N	Mean	SD	10th Pctl	50th Pctl	90th Pctl
Crash Risk Measures						
$NCSKEW_t$	12841	0.205	1.054	-1.017	0.146	1.478
$DUVOL_t$	12841	0.142	0.784	-0.820	0.116	1.150
Co-option Measures						
$CO\text{-}OPTION_{t-1}$	12841	0.477	0.320	0.000	0.444	1.000
TW $CO\text{-}OPTION_{t-1}$	12841	0.315	0.330	0.000	0.180	1.000
Other Firm Controls and Conditional Variables						
IND_{t-1}	12841	0.710	0.161	0.500	0.750	0.889
$DTURN_{t-1}$	12841	0.001	0.097	-0.080	0.001	0.080
$NCSKEW_{t-1}$	12841	0.185	1.036	-1.007	0.123	1.422
$SIGMA_{t-1}$	12841	0.049	0.024	0.024	0.044	0.081
RET_{t-1}	12841	-0.002	0.007	-0.010	-0.001	0.006
$SIZE_{t-1}$ ($ mil)	12841	3143.56	9333.09	151.19	780.83	7076.46
MB_{t-1}	12841	2.105	1.613	1.049	1.659	3.540
LEV_{t-1}	12841	0.178	0.161	0.000	0.160	0.381
ROA_{t-1}	12841	0.060	0.164	-0.022	0.064	0.158
ACC_{t-1}	12841	-0.007	0.236	-0.189	-0.005	0.171
$R\&D_{t-1}$	12841	0.034	0.059	0.000	0.007	0.107
$R\&D\_MISSING_{t-1}$	12841	0.318	0.466	0.000	0.000	1.000
KUR_{t-1}	12841	2.186	3.289	-0.208	1.179	5.556
$Friendly_{t-1}$	12841	0.489	0.500	0.000	0.000	1.000
TW $Friendly_{t-1}$	12841	0.500	0.500	0.000	0.000	0.000
HIGH $COMPETITION_{t-1}$	12827	0.547	0.498	0.000	1.000	1.000
$YOUNG_{t-1}$	12574	0.539	0.499	0.000	1.000	1.000

TABLE 1. Descriptive statistics and correlation matrix (continued)

Panel V

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) NCSKEW$_t$	1.00																
(2) DUVOL$_t$	**0.92**	1.00															
	(0.00)																
(3) CO-OPTION$_{t-1}$	0.01	**0.02**	1.00														
	(0.14)	**(0.05)**															
(4) TW CO-OPTION$_{t-1}$	**0.02**	**0.02**	**0.93**	1.00													
	(0.07)	**(0.02)**	**(0.00)**														
(5) IND$_{t-1}$	-0.01	-0.00	**-0.04**	**-0.06**	1.00												
	(0.12)	(0.70)	**(0.00)**	**(0.00)**													
(6) DTURN$_{t-1}$	0.01	-0.00	-0.01	-0.01	**-0.03**	1.00											
	(0.46)	(0.71)	(0.41)	(0.26)	**(0.00)**												
(7) NCSKEW$_{t-1}$	**-0.02**	**-0.03**	**0.02**	**0.02**	**-0.02**	**0.05**	1.00										
	(0.04)	**(0.00)**	**(0.07)**	**(0.07)**	**(0.08)**	**(0.00)**											
(8) SIGMA$_{t-1}$	**-0.05**	**-0.07**	**0.10**	**0.12**	**-0.20**	**0.16**	**0.12**	1.00									
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**										
(9) RET$_{t-1}$	**0.06**	**0.07**	**-0.04**	**-0.04**	**0.04**	0.01	**-0.58**	**-0.15**	1.00								
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.18)	**(0.00)**	**(0.00)**									
(10) SIZE$_{t-1}$	-0.00	0.01	**-0.10**	**-0.14**	**0.18**	**0.03**	-0.00	**-0.36**	**0.05**	1.00							
	(0.88)	(0.38)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.87)	**(0.00)**	**(0.00)**								
(11) MB$_{t-1}$	**0.07**	**0.08**	**0.05**	**0.07**	**-0.07**	**0.04**	**-0.12**	**0.02**	**0.22**	**-0.07**	1.00						
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.01)**	**(0.00)**	**(0.00)**							
(12) LEV$_{t-1}$	**-0.03**	**-0.03**	**-0.04**	**-0.05**	**0.02**	**0.04**	0.01	0.00	**-0.03**	**0.23**	**-0.17**	1.00					
	(0.00)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.01)**	**(0.00)**	(0.17)	(0.76)	**(0.00)**	**(0.00)**	**(0.00)**						
(13) ROA$_{t-1}$	**0.05**	**0.05**	-0.01	-0.01	0.00	0.01	**-0.05**	**-0.24**	**0.14**	**0.04**	**0.22**	**-0.12**	1.00				
	(0.00)	**(0.00)**	(0.32)	(0.32)	(0.83)	(0.20)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**					
(14) ACC$_{t-1}$	0.01	0.01	**-0.02**	**-0.02**	0.01	0.01	**-0.02**	-0.01	**0.05**	0.00	**-0.03**	**0.03**	**0.20**	1.00			
	(0.45)	(0.49)	**(0.01)**	**(0.03)**	(0.21)	(0.12)	**(0.07)**	(0.25)	**(0.00)**	(0.84)	**(0.00)**	**(0.00)**	**(0.00)**				
(15) R&D$_{t-1}$	0.01	0.00	**0.08**	**0.09**	**0.02**	**-0.04**	**0.02**	**0.26**	**-0.07**	**-0.17**	**0.28**	**-0.19**	**-0.17**	**-0.04**	1.00		
	(0.53)	(0.72)	**(0.00)**	**(0.00)**	**(0.05)**	**(0.00)**	**(0.01)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**			
(16) R&D_Missing$_{t-1}$	0.00	0.00	0.00	**-0.02**	**-0.11**	**0.03**	-0.00	**-0.05**	**0.02**	-0.00	**-0.12**	**0.15**	**0.02**	**0.02**	**-0.40**	1.00	
	(0.85)	(0.81)	(0.60)	**(0.05)**	**(0.00)**	**(0.00)**	(0.59)	**(0.00)**	**(0.04)**	(0.66)	**(0.00)**	**(0.00)**	**(0.02)**	**(0.05)**	**(0.00)**		
(17) KUR$_{t-1}$	0.01	0.01	0.01	**0.02**	**0.03**	**0.05**	**0.39**	**0.23**	**-0.18**	**-0.09**	**-0.03**	-0.01	**-0.03**	-0.00	**0.06**	**-0.03**	1.00
	(0.22)	(0.48)	(0.32)	**(0.04)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.13)	**(0.00)**	(0.94)	**(0.00)**	**(0.00)**	

TABLE 2. Effects of co-option on stock price crash risk

This table reports OLS regression results where dependent variables are firm-specific future stock price crash risk measures. The sample covers 12,841 U.S. public firm-year observations in ISS database from 1996 to 2014 with non-missing values for the crash risk measures and all independent variables. The dependent variable in Model (1) and (2) is the negative coefficient of skewness, $NCSKEW_t$, and the dependent variable in Model (3) and (4) is the down-to-up volatility measure of the crash likelihood, $DUVOL_t$. Model (1) and (3) (Model (2) and (4)) test the effect of $CO\text{-}OPTION_{t-1}$ ($TW\ CO\text{-}OPTION_{t-1}$) on stock price crash risk. All models include controls, year, and industry fixed effects. Reported in parentheses are p-values based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Variables	*NCSKEW$_t$*		*DUVOL$_t$*	
	(1)	(2)	(3)	(4)
$CO\text{-}OPTION_{t-1}$	0.036		0.037**	
	(0.200)		(0.028)	
$TW\ CO\text{-}OPTION_{t-1}$		0.042*		0.044***
		(0.095)		(0.004)
IND_{t-1}	-0.149**	-0.147**	-0.106***	-0.104***
	(0.013)	(0.014)	(0.004)	(0.004)
$DTURN_{t-1}$	0.184	0.184	0.083	0.083
	(0.107)	(0.106)	(0.315)	(0.312)
$NCSKEW_{t-1}$	0.021**	0.021**	0.016	0.016
	(0.040)	(0.039)	(0.108)	(0.105)
$SIGMA_{t-1}$	-0.500	-0.514	-0.239	-0.254
	(0.585)	(0.575)	(0.788)	(0.774)
RET_{t-1}	10.822**	10.842**	9.437**	9.459**
	(0.011)	(0.011)	(0.016)	(0.015)
$SIZE_{t-1}$	0.006	0.006	0.009	0.009
	(0.530)	(0.503)	(0.352)	(0.329)
MB_{-1}	0.032***	0.032***	0.031***	0.031***
	(0.003)	(0.003)	(0.001)	(0.001)
LEV_{t-1}	-0.004	-0.004	-0.050	-0.051
	(0.961)	(0.956)	(0.458)	(0.454)
ROA_{t-1}	0.108*	0.108*	0.067	0.066
	(0.081)	(0.082)	(0.228)	(0.230)
ACC_{t-1}	0.023	0.023	0.019	0.019
	(0.557)	(0.557)	(0.528)	(0.529)
$R\&D_{t-1}$	-0.199	-0.199	-0.146	-0.146
	(0.492)	(0.494)	(0.581)	(0.582)
$R\&D\_MISSING_{t-1}$	0.023	0.024	0.023	0.023
	(0.529)	(0.518)	(0.443)	(0.429)
KUR_{t-1}	0.003	0.003	0.002	0.002
	(0.598)	(0.598)	(0.634)	(0.634)
Constant	0.225**	0.226**	0.118	0.118
	(0.019)	(0.019)	(0.195)	(0.198)
Year/Industry FE	Y	Y	Y	Y
Observations	12,841	12,841	12,841	12,841
R-squared	0.028	0.028	0.041	0.041
Adjusted R-squared	0.023	0.023	0.036	0.036

TABLE 3. Endogeneity control using propensity score matching

This table reports results from one-to-one propensity score matching where firms with co-options measures above sample median are matched with those with co-option measures below sample median. The sample covers the years of 1996-2014. We estimate propensity scores for each firm with a logit regression where the dependent variables are two binary variables, $FRIENDLY_{t-1}$ and $TW\ FRIENDLY_{t-1}$, created based on the sample median values of our key variables, $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$, respectively, and explanatory variables are the same as those used in our baseline regressions in Table 2. Panel A and Panel B report summary statistics for unmatched and matched sample. In Panel A and Panel B, firms are matched by propensity scores reflecting the probability of being a *Friendly* ($FRIENDLY_{t-1}$=1 in Panel A and $TW\ FRIENDLY_{t-1}$=1 in Panel B) firm, respectively. *Unfriendly* denotes a firm with $FRIENDLY_{t-1}$=0 in Panel A and $TW\ FRIENDLY_{t-1}$=0, respectively. Panel C presents the results of propensity score matching regression. All models include controls, year, and industry fixed effects as in Table 2. Reported in parentheses are p-values based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.. All variables are defined in Appendix A.

Panel A. Summary Statistics for Firm Characteristics between Treated firm and Matched Firm – $CO\text{-}OPTION_{t-1}$

Variables	Unmatched				Matched			
	Friendly	Unfriendly	Difference	*t*-statistics	Friendly	Unfriendly	Difference	*t*-statistics
$DTURN_{t-1}$	0.000	0.002	-0.002	-1.300	0.001	0.001	0.000	0.020
$NCSKEW_{t-1}$	0.195	0.176	0.019	1.030	0.188	0.194	-0.006	-0.350
$SIGMA_{t-1}$	0.051	0.048	0.003***	7.230	0.050	0.049	0.001	1.460
RET_{t-1}	-0.002	-0.002	0.000***	2.580	-0.002	-0.002	0.000	-0.140
$SIZE_{t-1}$	6.719	6.884	-0.165***	-6.360	6.741	6.718	0.023	0.890
MB_{t-1}	2.170	2.039	0.130***	4.570	2.112	2.093	0.019	0.760
LEV_{t-1}	0.172	0.184	-0.012***	-4.120	0.173	0.174	-0.001	-0.400
ROA_{t-1}	0.060	0.060	0.000	0.010	0.062	0.066	-0.004*	-1.740
ACC_{t-1}	-0.012	-0.002	-0.010**	-2.480	-0.010	-0.012	0.001	0.320
IND_{t-1}	0.707	0.712	-0.005	-1.630	0.708	0.712	-0.004	-1.440
$R\&D_{t-1}$	0.037	0.031	0.006***	6.260	0.034	0.033	0.001	1.400
$R\&D\_MISSING_{t-1}$	0.325	0.311	0.014*	1.670	0.330	0.341	-0.011	-1.260
KUR_{t-1}	2.186	2.187	-0.002	-0.030	2.132	2.139	-0.006	-0.110
N	6,514	6,327			6,343	6,343		

Panel B. Summary Statistics for Firm Characteristics between Treated firm and Matched Firm – $TW\ Co\text{-}option_{t-1}$

Variables	Unmatched	Matched

	Friendly	Unfriendly	Difference	*t*-statistics	Friendly	Unfriendly	Difference	*t*-statistics
$DTURN_{t-1}$	0.000	0.002	-0.002	-1.080	0.000	0.002	-0.002	-0.960
$NCSKEW_{t-1}$	0.199	0.172	0.027	1.460	0.190	0.189	0.001	0.030
$SIGMA_{t-1}$	0.051	0.047	0.003***	8.100	0.050	0.049	0.000	0.700
RET_{t-1}	-0.002	-0.002	0.000***	2.930	-0.002	-0.002	0.000	0.240
$SIZE_{t-1}$	6.683	6.919	-0.236***	-9.120	6.716	6.717	-0.001	-0.050
MB_{t-1}	2.191	2.020	0.171***	6.000	2.095	2.055	0.041*	1.690
LEV_{t-1}	0.171	0.184	-0.013***	-4.540	0.173	0.174	-0.001	-0.350
ROA_{t-1}	0.059	0.061	-0.001	-0.410	0.063	0.064	-0.001	-0.530
ACC_{t-1}	-0.012	-0.002	-0.011***	-2.600	-0.009	-0.013	0.004	1.220
IND_{t-1}	0.710	0.709	0.001	0.330	0.711	0.715	-0.004	-1.490
$R\&D_{t-1}$	0.038	0.030	0.008***	7.440	0.034	0.034	0.000	0.440
$R\&D\_MISSING_{t-1}$	0.320	0.316	0.004	0.440	0.327	0.326	0.001	0.130
KUR_{t-1}	2.216	2.157	0.059	1.020	2.176	2.196	-0.019	-0.330
N	6,421	6,420			6,184	6,184		

Panel C. Influence of Co-opted Directors on Future Stock Price Crash Risk based on Propensity Score Matching

Variables	*NCSKEW*$_t$		*DUVOL*$_t$	
	(1)	(2)	(3)	(4)
$Co\text{-}option_{t-1}$	0.079**		0.070***	
	(0.048)		(0.006)	
$TW\ Co\text{-}option_{t-1}$		0.046		0.042*
		(0.184)		(0.078)
Controls in Table 2	Y	Y	Y	Y
Year/Industry FE	Y	Y	Y	Y
Observations	12,686	12,368	12,686	12,368
Adjusted R-squared	0.024	0.025	0.037	0.038

TABLE 4. Endogeneity control using dynamic panel GMM

This table reports the results of re-estimating our baseline specification in Table 2 using the dynamic panel generalized method of moments (GMM). The sample covers the years of 1996-2014. The dependent variable in Model (1) and (2) is the negative coefficient of skewness, $NCSKEW_t$, and the dependent variable in Model (3) and (4) is the down-to-up volatility measure of the crash likelihood, $DUVOL_t$. Model (1) and (3) (Model (2) and (4)) test the effect of $CO\text{-}OPTION_{t-1}$ ($TW\ CO\text{-}OPTION_{t-1}$) on stock price crash risk. We report the *p*-value for Arellano-Bond (1991) test of first-order and second-order serial correlation (AR (1) and AR (2)) for each specification. The Hansen test of overidentification tests the null hypothesis that all the instruments in our GMM specification are valid. Reported in parentheses are p-values based on robust standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

VARIABLES	$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)	(3)	(4)
$CO\text{-}OPTION_{t-1}$	0.357*		0.279*	
	(0.067)		(0.061)	
$TW\ CO\text{-}OPTION_{t-1}$		0.418**		0.273*
		(0.042)		(0.076)
$NCSKEW_{t-1}$	-0.173	-0.202		
	(0.445)	(0.361)		
$NCSKEW_{t-2}$	0.007	0.006		
	(0.744)	(0.779)		
$DUVOL_{t-1}$			-0.417	-0.447*
			(0.100)	(0.075)
$DUVOL_{t-2}$			0.008	0.008
			(0.721)	(0.737)
IND_{t-1}	-0.559	-0.486	-0.564	-0.511
	(0.351)	(0.408)	(0.215)	(0.257)
$DTURN_{t-1}$	0.524	0.506	0.561	0.530
	(0.523)	(0.529)	(0.373)	(0.393)
$SIGMA_{t-1}$	-15.522***	-16.320***	-12.633***	-13.225***
	(0.006)	(0.004)	(0.004)	(0.003)
RET_{t-1}	-10.518	-12.301	-28.819	-31.810
	(0.625)	(0.573)	(0.155)	(0.118)
$SIZE_{t-1}$	0.243**	0.259**	0.274***	0.284***
	(0.020)	(0.015)	(0.001)	(0.001)
MB_{t-1}	0.229***	0.232***	0.216***	0.218***
	(0.002)	(0.001)	(0.000)	(0.000)
LEV_{t-1}	0.243	0.297	-0.043	-0.016
	(0.658)	(0.597)	(0.923)	(0.972)
ROA_{t-1}	-3.487**	-3.500**	-3.167***	-3.145***
	(0.011)	(0.011)	(0.003)	(0.003)
ACC_{t-1}	0.729	0.913	0.994**	1.117**
	(0.223)	(0.139)	(0.039)	(0.023)
$R\&D_{t-1}$	1.570	1.395	0.231	0.067
	(0.557)	(0.618)	(0.914)	(0.975)
$R\&D\_MISSING_{t-1}$	0.008	-0.057	-0.072	-0.099
	(0.978)	(0.851)	(0.751)	(0.664)
KUR_{t-1}	0.045	0.047	0.036	0.032
	(0.488)	(0.455)	(0.438)	(0.488)

Year/Industry FE	Y	Y	Y	Y
Observations	9,302	9,302	9,302	9,302
AR (1) test (*p*-value)	0.009***	0.011**	0.025**	0.025**
AR (2) test (*p*-value)	0.609	0.517	0.221	0.182
Hansen test of over-identification (*p*-value)	0.694	0.777	0.853	0.460

TABLE 5. Unobservable selection and coefficient stability

This table presents the results of coefficient stability test proposed by Oster (2017) for our baseline regressions in Table 2. Panel A shows movements between uncontrolled and controlled specification for each model. In Panel B, we present the values of δ to evaluate the sensitivity of the baseline results to selection of unobservable factors. The values of δ using R_{max} equal to 1.3 × $\tilde{R}$ as well as 2.0 × $\tilde{R}$ and 3.0 × $\tilde{R}$ are reported for robustness, where R_{max} is the R-squared value from a hypothetical regression including both observable and unobservable controls and controlled and $\tilde{R}$ is the R-squared value from our baseline regression. Following Oster (2017) we use δ=1 as a cutoff value for coefficient stability.

Panel A. Movements of βs and R^2s between Uncontrolled and Controlled Regressions

Models	Dependent Variables	Test Variables	β uncontrolled	β controlled	R^2 uncontrolled	R^2 controlled ($\tilde{R}$)
(1)	$NCSKEW_t$	$Co\text{-}option_{t-1}$	0.043	0.036	0.000	0.028
(2)	$NCSKEW_t$	$TW\ Co\text{-}option_{t-1}$	0.051	0.042	0.000	0.028
(3)	$DUVOL_t$	$Co\text{-}option_{t-1}$	0.042	0.037	0.000	0.041
(4)	$DUVOL_t$	$TW\ Co\text{-}option_{t-1}$	0.050	0.044	0.000	0.041

Panel B. Oster's δ

R_{max} = 1.3 × $\tilde{R}$

Models	Dependent Variables	Test Variables	R_{max}	δ
(1)	$NCSKEW_t$	$Co\text{-}option_{t-1}$	0.037	12.708
(2)	$NCSKEW_t$	$TW\ Co\text{-}option_{t-1}$	0.037	10.124
(3)	$DUVOL_t$	$Co\text{-}option_{t-1}$	0.053	17.695
(4)	$DUVOL_t$	$TW\ Co\text{-}option_{t-1}$	0.053	16.075

R_{max} = 2.0 × $\tilde{R}$

Models	Dependent Variables	Test Variables	R_{max}	δ
(1)	$NCSKEW_t$	$Co\text{-}option_{t-1}$	0.056	3.861
(2)	$NCSKEW_t$	$TW\ Co\text{-}option_{t-1}$	0.056	3.076
(3)	$DUVOL_t$	$Co\text{-}option_{t-1}$	0.082	5.385
(4)	$DUVOL_t$	$TW\ Co\text{-}option_{t-1}$	0.082	4.919

R_{max} = 3.0 × $\tilde{R}$

Models	Dependent Variables	Test Variables	R_{max}	δ
(1)	$NCSKEW_t$	$Co\text{-}option_{t-1}$	0.084	1.936
(2)	$NCSKEW_t$	$TW\ Co\text{-}option_{t-1}$	0.084	1.542
(3)	$DUVOL_t$	$Co\text{-}option_{t-1}$	0.123	2.701
(4)	$DUVOL_t$	$TW\ Co\text{-}option_{t-1}$	0.123	2.470

TABLE 6. Subsample analysis on the effect of co-opted boards on crash risk

This table presents regression results of subsample analysis where dependent variables are firm-specific future stock price crash risk measures. Panel A splits the sample based on the median value of CEO age. Panel B partitions the sample based on the median value of four-firm industry concentration ratios, where industry is defined by the Fama-French 48 industry classifications. The dependent variable in Model (1) and (2) is the negative coefficient of skewness, $NCSKEW_t$, and the dependent variable in Model (3) and (4) is the down-to-up volatility measure of the crash likelihood, $DUVOL_t$. Model (1) and (3) (Model (2) and (4)) test the effect of $CO\text{-}OPTION_{t-1}$ ($TW\ CO\text{-}OPTION_{t-1}$) on stock price crash risk. All models include controls, year, and industry fixed effects. Reported in parentheses are p-values based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A. CEO Age

	$YOUNG_{t-1}$ = 1				$YOUNG_{t-1}$ = 0			
VARIABLES	$NCSKEW_t$		$DUVOL_t$		$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CO\text{-}OPTION_{t-1}$	0.073**		0.054**		0.009		0.030	
	(0.021)		(0.015)		(0.845)		(0.400)	
$TW\ CO\text{-}OPTION_{t-1}$		0.076**		0.061**		0.017		0.037
		(0.017)		(0.013)		(0.729)		(0.307)
Controls in Table 2	Y	Y	Y	Y	Y	Y	Y	Y
Year/Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6,772	6,772	6,772	6,772	5,802	5,802	5,802	5,802
Adjusted R-squared	0.023	0.023	0.035	0.035	0.023	0.023	0.037	0.037

Panel B. Product Market Competition

	$HIGH\text{-}COMPETITION_{t-1}$ = 1				$HIGH\text{-}COMPETITION_{t-1}$ = 0			
VARIABLES	$NCSKEW_t$		$DUVOL_t$		$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CO\text{-}OPTION_{t-1}$	0.096***		0.068***		-0.020		0.010	
	(0.003)		(0.005)		(0.646)		(0.725)	
$TW\ CO\text{-}OPTION_{t-1}$		0.075**		0.055***		0.011		0.038
		(0.012)		(0.009)		(0.778)		(0.146)
Controls in Table 2	Y	Y	Y	Y	Y	Y	Y	Y
Year/Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,815	5,815	5,815	5,815	7,012	7,012	7,012	7,012
Adjusted R-squared	0.029	0.029	0.044	0.044	0.024	0.023	0.038	0.038

TABLE 7. Co-opted independence versus co-opted non-independence

This table reproduces regression results of subsample analysis where dependent variables are firm-specific future stock price crash risk measures. Panel A tests the impact of co-opted independent directors ($CO\text{-}OPTED\ IND_{t-1}$ and $TW\ CO\text{-}OPTED\ IND_{t-1}$), whereas Panel B examine the influence of co-opted non-independent directors ($CO\text{-}OPTED\ NON\text{-}IND_{t-1}$ and $TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$).The dependent variable in Model (1) and (2) is the negative coefficient of skewness, $NCSKEW_t$, and the dependent variable in Model (3) and (4) is the down-to-up volatility measure of the crash likelihood, $DUVOL_t$. Model (1) and (3) (Model (2) and (4)) test the effect of co-option (tenure-weighted co-option) on stock price crash risk. All models include controls, year, and industry fixed effects. Reported in parentheses are p-values based on standard errors clustered by year. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A. Co-opted Independence

VARIABLES	$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)	(3)	(4)
$CO\text{-}OPTED\ IND_{t-1}$	0.037			
	(0.321)			
$TW\ CO\text{-}OPTED\ IND_{t-1}$		0.036		0.049**
		(0.317)		(0.030)
Other Controls as in Table 2	Y	Y	Y	Y
Industry/Year Fixed Effects	Y	Y		Y
Observations	12,841	12,841		12,841
Adjusted R-squared	0.023	0.023		0.036

Panel B. Co-opted Non-Independence

VARIABLES	$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)		(4)
$CO\text{-}OPTED\ NON\text{-}IND_{t-1}$	0.086		0.059	
	(0.194)			
$TW\ CO\text{-}OPTED\ NON\text{-}IND_{t-1}$		0.112*		0.097**
		(0.061)		(0.016)
Other Controls as in Table 2	Y	Y		Y
Industry/Year Fixed Effects	Y	Y	Y	Y
Observations	12,841	12,841		12,841
Adjusted R-squared	0.023	0.023		0.036