Co-opted Boards and Stock Price Crash Risk*

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Abstract

We investigate whether co-opted boards increase future stock price crash risk. Co-opted directors appointed after the CEO assumes office tend to have allegiance to the CEO, attenuating board monitoring roles. Using a sample of firms for the period 1996-2014, we find robust evidence that board co-option is positively associated with stock crash risk, suggesting that weak monitoring induced by co-opted directors facilitates managerial bad news hoarding activities. Further analyses show that the impact of co-option on crash risk is more pronounced when the CEO has higher career concerns, as measured by product market competition and age, indicating that the CEO who has greater preferences for bad news hoarding is more likely to exploit opportunities relating to attenuated board monitoring to promote their personal benefits. Overall, our findings suggest that board co-option appears to decrease the effectiveness of board monitoring and the role of board monitoring is particularly important when the CEO has stronger incentives to hoard bad news.

Keywords: Co-option, Board Friendliness, Board Monitoring, Independence, Crash Risk

1. Introduction

A board of directors refers to a group of people appointed to jointly oversee and advise top management on behalf of shareholders, thereby reducing potential agency problems (Jensen, 1993). This arises a natural question: who are the most effective monitors on the board? Although prior empirical studies have employed the traditional measure of board effectiveness, *Independence*, defined as the proportion of independent directors on the board, to investigate the disciplinary roles of independent directors, they provide mixed and weak evidence (Coles, Daniel, and Naveen, 2014), suggesting the importance of identifying substantive monitors on the board. Coles et al. (2014) provide a possible solution to address this issue, *co-option*, measured as the proportion of board members appointed after the CEO assumes office. The rationale behind this measure is that co-opted directors who might be initially appointed by the CEO are more likely to have allegiance to the CEO, increasing *board friendliness*. Consistent with this view, they find that co-opted directors exert attenuated monitoring, regardless of whether they are classified as independent directors.

In recent year, 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 future stock price crash risk. 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 future stock price crash risk. However, this literature has not examined the relation between crash risk and *board friendliness*, which has drawn considerable interest in recent corporate governance literature and might affect managerial bad news hoarding activities. This paper attempts to fill the gap by investigating the impact of co-opted boards on stock price crash risk.

Managers have incentives to conceal information on their bad performance from shareholders to prevent their personal wealth (Ball, 2009). Prior studies document factors that contribute to corporate managers' incentives to hoard bad news, such as formal compensation contracts and career concerns (Kothari, Shu, and Wysocki, 2009; and LaFond and Watts, 2008), managerial opportunism (Kim, Li, and Zhang, 2011a), and option portfolio value (Kim, Li, and Zhang, 2011b). If managers withhold bad news for an extended period, negative information is accumulated within a firm. Once the amount of accumulated bad information reaches a certain threshold, however, the accumulated negative information is released to the stock market at once, resulting in stock price crashes (Jin and Myers, 2006). We conjecture that board friendliness, measured by co-option, facilitates managerial bad news withholding activities, leading to stock price crashes.

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 number of total board members. Second, *TW CO-OPTION*, a tenure-weighted measure of co-option, is defined as the ratio of the sum of the tenure of each co-opted director to the sum of the tenure of all board members, reflecting that co-option might grow while co-opted directors work with the CEO for extended period. The higher values for both measures indicate greater board capture. We expect that both measures are positively associated with one-year ahead stock price crash risk.

Following prior studies (Chen, Hong, and Stein, 2001; Kim et al, 2011a; and Kim et al., 2011b), we measure firm-specific stock price crash risk by the negative skewness of firm-specific weekly returns (*NCSKEW*) and the down-to-up volatility of firm-specific weekly returns (*DUVOL*). Using the OLS regression and a sample of 12,841 U.S. public firms from 1996 to 2014, we find robust evidence that co-option is positively associated with future stock price crash risk, consistent with our conjecture that co-option attenuates monitoring roles of the board, thereby facilitating managerial bad news hoarding activities. Our results are robust to controlling for the conventional measure of monitoring effectiveness, *Independence*, suggesting that co-option measures explain the novel aspects of board monitoring effectiveness beyond the conventional measure. The positive relation is also robust to two tests to address our endogeneity concerns, including propensity score matching (PSM) procedure and the diagnostic test of coefficient stability developed by Oster (2017).

Given the strong relation between board co-option and future stock price crash risk, we further investigate whether the CEO with stronger preferences for negative is more likely to take advantage of the existence of co-opted directors. Kothari et al. (2009) find that managers have stronger incentives to conceal negative information when they have greater career concerns. Accordingly, we employ career concerns as a proxy for managerial preferences for negative information withholding. Following Andreou, Louca, and Petrou (2017) and Li and Zhan (2017), we measure managerial career concerns using CEO age and product market competition. Consistent with our prediction, our subsample analyses reveal that the positive relation between co-option and stock price is significant only for the subsample with greater managerial career concerns. Specifically, we find that the positive coefficients are significant only for the subsample with young CEOs and with high product market competition. The results indicate that the positive relation depends on managerial preferences for bad news disclosure.

Overall, the evidence in our analysis supports the prediction that managers in firm 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 third ways. First, this study contributes to the literature on 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 (Kim et al, 2011a; An and Zhang, 2013; Callen and Fang, 2013; Xu, Li, Yuan, and Chan, 2014; He, 2015; Callen and Fang, 2015; Kim and Zhang, 2016; Kim, Wang, and Zhang, 2016; Yuan, Sun, and Cao, 2016; Bhargava, Faircloth, and Zeng, 2017; Bao, Fung, and Su, 2018). Our research is closely related to that of Kao, Huang, and Fung (2018), who investigate the impact of co-option and gender diversity on crash risk using a sample of Chinese firms, and Jiraporn, Kim, and Lee (2018), who show the relation between co-opted boards and firm risk. To the best of our knowledge, however, this research is the first study to examine the relation between co-option and crash risk using a sample of U.S. public firms. Our study provides evidence that the CEO with co-opted boards can exacerbate future stock price crash risk because directors who have allegiance to the CEO do not play a role as effective monitor, thereby facilitating bad news withholding by the CEO.

Second, our study extends the growing literature on board friendliness in U.S. public firms and its economic consequences (Coles et al., 2014; Kang, Liu, Low, and Zhang, 2018; Jiraporn et al, 2018). The implication of board co-option for crash risk produces valuable insights into board friendliness. Consistent with Coles et al. (2014), our findings show that although the conventional board *Independence* attenuates 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 and Kim, 2009). Furthermore, findings also 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 monitoring roles. Kang et al. (2018), however, indicate that friendly boards enhance corporate innovation outcomes by strengthening board advisory roles. Our evidence also suggests that the impact of co-option on crash risk depends on managerial preferences. In sum, board friendliness is neither universally harmful nor universally beneficial to firm and shareholders.

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

2. Literature Review and Hypotheses Development

Recent studies demonstrate determinants to corporate managers' incentives to hoard bad news, including equity incentives (Kim et al., 2011a), corporate tax avoidance (Kim et al., 2011b), institutional investors (An and Zhang, 2013; Callen and Fang, 2013), corporate excess perks (Xu et al., 2014), CEO inside debt holdings (He, 2015), county level religiosity (Callen and Fang, 2015), accounting conservatism (Kim and Zhang, 2016), CEO overconfidence (Kim et al., 2016), directors' and officers' liability insurance (Yuan et al., 2016), state antitakeover 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 stock price crash risk.

Agency theory suggests that board monitoring plays a critical function on behalf of the shareholders (Fama and Jensen, 1983). Effective board monitoring mitigates opportunistic managerial behaviors, agency costs, and information asymmetry between managers and outside stakeholders, leading to lower stock price crash risk (Ajinkya, Bhojraj, and Sengupta, 2005; Karamanou and Vafeas, 2005; Attig, Fong, Gadhoum, and Lang, 2006; Chung, Elder, and Kim, 2010). On the contrary, ineffective board monitoring may allow managers to withhold bad news for their self-benefits. In other words, stock price crash risk problem might be more pronounced when managers' preferences to disclose negative information are misaligned to those of shareholders due to attenuated board monitoring functions. Consistent with this notion, corporate governance literature provides empirical evidence that governance mechanisms are important determinants of stock price crash risk. Andreou et al. (2016) find that strong board monitoring mechanisms, measured by ownership structure, accounting opacity, board structure, and managerial incentives, mitigate future stock price crash risk. In addition, Callen and Fang (2013) find that institutional investor stability alleviates future stock price crash risk.

In this study, we investigate the relation between board monitoring and firm-specific future stock price crash risk by considering recently developed measures of board monitoring effectiveness, 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 the firm-specific board monitoring intensity. Coles et al. (2014), however, argue that the traditional measure might not clearly explain board monitoring effectiveness because a large proportion of independent directors is captured by the CEO by being appointed after the CEO takes office. Their results show that board co-option blunts board monitoring effectiveness. In addition, they find that the harmful effects of board co-option are mainly driven by co-opted independent directors, indicating that the relation between board monitoring effectiveness and crash risk can be better explained by co-option measures. Therefore, we conjecture that co-opted boards may induce managers to engage in more bad news withholding. Specifically, we test the following hypothesis:

H1: All else equal, board co-option is positively associated with future stock price crash risk.

Next, we consider situations in which the positive relation between co-option and crash risk might be more pronounced. We conjecture that if the existence of board co-option provides the CEO with opportunities to engage in bad-news withholding activities by attenuating board monition effectiveness, such relation might be exacerbated as the CEO's personal incentives to conceal information from shareholders become strengthened. In other words, the CEO with stronger preferences for bad-news withholding is more likely to take advantage of co-opted boards. Recent literature indicates that managers have stronger incentives to hide negative information when they have greater career concerns (Kothari et al., 2009; Andreou et al., 2017; and Li and Zhan, 2017). Therefore, we test the following hypothesis:

H2: All else equal, the relation between board co-option and crash risk is stronger in the existence of CEO career concerns.

3. Research Design

3.1 Construction of Sample

Our initial sample includes all firms in the ISS database (formerly known as RiskMetrics) during the period 1996-2014, which covers CEO and board-related information of S&P 1,500 firms. The co-option data computed based on the ISS database is 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 Center for Research in Security Prices (CRSP). In constructing our crash risk measures and control variables used in the regressions, we delete observations with missing firm-specific accounting information in Compustat annual files and missing stock returns and trading volume information in CRSP. Following earlier literature, we exclude firms in the regulated industries (financial service (SIC 6000-6999) and utilities (SIC 4800-4999)) and firm-years with fewer than 26 weeks of return data in a fiscal year (Hutton, Marcus, and Tehranian, 2009; Andreou et al., 2017). These criteria yield a final sample of 12,841 firm-year observations, which correspond to 1,614 firms.

3.2. Variables

3.2.1. Dependent Variables

Following the prior literature (Chen et al., 2001; Kim et al., 2011a, 2011b), we construct two firm-specific measures of stock price crash risk: the negative coefficient of skewness of firm-specific weekly returns (NCSKEW) and the down-top volatility of firm-specific weekly returns (DUVOL). The firm-specific weekly returns are defined as $W_{j,w} = \ln(1 + \varepsilon_{j,w})$. We first estimate firm-specific residual weekly returns, $\varepsilon_{j,w}$, from the following expanded market model regression:

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

where $r_{j,w}$ is the return of stock j in week w, and $r_{m,w}$ is the return on the CRSP value-weighted market return in week w. The lead and lag terms for the market return is included to correct for non-synchronous trading (Dimson, 1979).

We use the negative conditional skewness of firm-specific weekly returns over the fiscal year (*NSCKEW$_t$*) as our first measure of firm-specific crash risk. *NSCKEW$_t$* is defined as the negative of the third moment of firm-specific weekly returns for each firm in a fiscal year divided by the standard deviation of firm-specific weekly returns raised to the third power (Chen et al., 2001; Kim et al., 2011a, 2011b). Specifically, for each firm j in a fiscal year t, it is calculated as:

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

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

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

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

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

3.2.2. Main Variables of Interest: Co-option Measures

Following Coles et al. (2014), we adopt 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 CEO takes office at *t-1*.

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

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

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

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

4. Empirical Analysis

4.1 Descriptive Statistics

Table 1 reports the descriptive statistics for the variables used in our analysis. 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 literature (Kim et al., 2011a, 2011b; Chen et al. 2001), which is not surprising considering that we use different sample period and datasets.[1] The sample firms have an average *CO-OPTION*$_{t-1}$ of 0.477, suggesting that about half of the board has been captured by the CEO. Mean *TW CO-OPTION*$_{t-1}$ is 0.315. The mean values of co-option measures are comparable to the estimates in Coles et al. (2014). On average the sample firms have a 71% of independent directors on the board. The average change in trading volume is 0.001. On average the firms in our sample have weekly stock return of -0.3 percent, a market to book ratio of 2.105, a return volatility of 0.049, a leverage of 0.178, a return on assets of 0.060, and a R&D intensity of 0.034.

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

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

$$Crash\_Risk_t = \beta_0 + \beta_1 Co\_Option\ Measures_{t-1} + \beta_2 Independence_{t-1} + \gamma' Controls_{t-1} + \varepsilon.$$

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*, while independent variables including our key variables are measured in year *t-1*. Our two main explanatory variables of interest are *CO-OPTION*$_{t-1}$, which is the proportion of co-opted directors on the board, tenure-weighted co-option, *TW CO-OPTION*$_{t-1}$. To test whether our key variables have an explanatory power after controlling for the conventional measure of board monitoring effectiveness, we include *IND*$_{t-1}$, defined as the number of independent directors divided by board size, in all specifications.

Motivated by prior literature, we control for various variables that have been shown to be potential predictors of crash risk. We include the detrended stock turnover, *DTURN*$_{t-1}$, as proxy for the potential

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[1] Kim et al. (2011a) suggest a considerable variation of crash risk measures across years.

divergence of opinions among investors since Chen et al. (2001) show that differences in investor belief predict the likelihood of future crash. To address concerns on dynamic endogeneity induced by the potential persistence of a firm's crash risk, we include the negative skewness of firm-specific past stock returns, $NCSKEW_{t-1}$. Since more volatile firms tend to be more crash prone, we include the standard deviation of firm-specific past stock returns, $SIGMA_{t-1}$. Since Jin and Myers (2006) argue that long tails in stock return distributions predict future crash, we control for the kurtosis of firm-specific weekly returns, KUR_{t-1}. In addition, we control 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}), research and development intensity ($R\&D_{t-1}$), and R&D missing dummy ($R\&D\_MISSING_{t-1}$).[2] In the regressions, we include industry fixed effects by including the 48 industry categories suggested by Fama and French (1997) and year fixed effects to control for the unobserved industry and year characteristics. In addition, *p*-values reported are based on standard errors corrected for year clustering (Petersen, 2009). Appendix A provides detailed definitions of variables used in our analysis.

[Insert Table 2 Here]

Table 2 reports the regression results, Column (1) and (2) (Column (3) and (4)) report coefficients estimated when regressed on $NCSKEW_t$ ($DUVOL_t$). Colum (1) and (3) report coefficients on our standard measure, $CO\text{-}OPTION_{t-1}$, while Colum (2) and (4) provide coefficients on tenure-weighted co-option measure, $TW\ CO\text{-}OPTION_{t-1}$. Column (1) shows that the coefficient on $CO\text{-}OPTION_{t-1}$ is 0.036 and insignificant (*p*-value=0.200). Consistent with our hypothesis H1, however, Column (2) shows that the coefficient on $TW\ CO\text{-}OPTION_{t-1}$ is 0.042, significant at 10% level (*p*-value=0.095), indicating that, all else

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

being equal, firms with the higher tenure-weighted co-options have higher stock price crash risk. Column (3) and (4), in which the dependent variable is $DUVOL_t$, show that the coefficient estimates on *CO-OPTION*$_{t-1}$ and *TW CO-OPTION*$_{t-1}$ are significant at 0.037 (*p*-value=0.028) and 0.044 (*p*-value=0.004), respectively.

Across all columns, the coefficient estimates on co-option measures are positive and magnitudes are quantitatively similar, ranging from 0.036 to 0.044. More importantly, the impact of our co-option measures is economically significant in all specifications, albeit variations in statistical significance. For example, in Column (3) and (4), one standardized unit increase in *CO-OPTION*$_{t-1}$ (*TW CO-OPTION*$_{t-1}$) leads to an increase in $DUVOL_t$ by 0.0118 (0.0145), which accounts for 8.34 % (10.23%) of mean value of $DUVOL_t$ for our sample and is economically significant.

Turning to the control variables, the coefficients are generally consistent with prior literature. We find that *IND*$_{t-1}$ is significantly and negatively related to stock price crash risk in all specifications, suggesting that even though the conventional measure of board independence has strong power to capture monitoring effectiveness, our key variables are still successful in explaining stock price crash risk. Firms with higher firm-specific returns (*RET*$_{t-1}$) and future growth opportunities (*MB*$_{t-1}$) have greater future stock price crash risk. Future crashes are also positively related to return on assets (*ROA*$_{t-1}$).

In sum, 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 hoard bad news when more directors on the board are captured, leading to higher future stock price crash risk.

4.3. Endogeneity

Our baseline analysis so far shows that one-year ahead crash risk is a function of 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 co-option measures and crash risk is still a concern in our analysis because our board co-option is unlikely to occur randomly. An omitted variable bias can arise when co-option measures and crash risk measures are jointly determined by unobservable firm-specific factors. To address this concern, we conduct two econometric approaches developed in economics literature to re-estimate our baseline specifications. We discuss these analyses in detail below.

The first approach is the propensity score matching (PSM), an econometric approach widely used in corporate finance literature. If firms with higher proportion of co-opted directors have characteristics different from those with lower proportion of co-opted directors, the effect of board co-option on stock price crashes might be biased when linear control variables employed are insufficient because board co-option might pick up nonlinear effects of the control variables on stock price crashes. The rationale of conducting PSM approach is to construct two samples that are comparable across all observable factors but differ only in the magnitude of board co-option, allowing us to more clearly identify the effects of board co-option itself rather 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. More 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 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 the explanatory variables. For each treated firm, we select one matched firm with the closest propensity scores and 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 difference in propensity scores between treated and matched firms does not exceed the caliper width of 0.0005.[3] This approach leads to 6,343 and 6,184 unique pairs of firm-years matched based on each co-option measure, respectively.

[Insert Table 3 Here]

Panel 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 Panel A and Panel 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. For the matched sample, however, we find that other than return on assets in Panel A and market to book in Panel B, there are no statistically significant difference in means across the two groups, suggesting that the firms matched by the propensity scores are comparable the treated firms across virtually all dimensions and our matching is effectively done.

Panel B shows that the results of propensity score matching regressions are qualitatively comparable those in our baseline regressions in Table 2. Using comparison samples, the coefficients on $CO\text{-}OPTION_{t-1}$ in Model (1) and Model (3) of Table 3 become statistically and economically more significant than those in Table 2. Although the coefficients on $CO\text{-}OPTION_{t-1}$ in Model (1) and Model (3) of Table 3 become less statistically significant than those in Table 2, they are still 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.

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

The second approach is the diagnostic test recently developed in Oster (2017) based on the method in Altonji, Elder, and Taber (2005). This approach tests the sensitivity of the coefficient of interest to possible selection on unobservable factors. This approach identifies omitted variable bias by observing movement in both the coefficient and the R-squared between uncontrolled (omitting controls) and controlled (including controls) regressions. The intuition behind this approach is that if the coefficient of interest falls, but R-squared increases significantly as additional controls are added to a regression, then the regression result might suffer from 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 strength of selection on unobservable and observable factors. For example, δ>1 suggests that for selection on unobservable factors to drive the coefficient of interest to zero, it would have to be stronger than selection on observable factors. Given that one includes most of the first order determinants of the dependent variables that have been well identified by prior literature, selection on unobservable factors is unlikely to be more important than selection on observable factors. Therefore, Oster (2017) proposes δ=1 as a cutoff value for robustness. To implement the diagnostic test, one needs 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 higher value of R_{max} means that one assumes that unobserved controls have stronger explanatory power in the hypothetical regression, leading to more conservative (lower) δ value in the diagnostic test. Based on experimental evidence obtained by replicating studies recently 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 4 Here]

Table 4 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 from Oster's approach.[4] Panel A of Table 4 reports the movements of coefficients and R-squared values between uncontrolled and controlled regressions. The coefficients and R-squared values for controlled regressions are the same as those in our baseline regressions in Table 2. We find that the coefficients of our main variables slightly fall, but R-squared values dramatically increase as controls are added in our regressions, suggesting that our baseline results might not be easily overturned by additional unobserved controls.

Panel B of Table 4 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 stringent $R_{max} = 2.0 \times \tilde{R}$ and $R_{max} = 3.0 \times \tilde{R}$ for robustness. The values of Panel B indicate that selection of unobservable controls needs to be 12.708 (Model (1)) and 10.124 (Model (2)) times more important than selection on observable controls in $NCSKEW_t$ regressions, and 17.695 (Model (3)) and 16.075 (Model (4)) times more important in $DUVOL_t$ regressions, respectively, 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 risk as well as industry and year fixed effects. When repeating the analysis using 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 selection on unobservable factors is unlikely to render our baseline results insignificant.

In sum, the results in PSM and coefficient stability tests show that the positive relations between board co-option and stock price crashes observed in our baseline regressions in Table 2 are not driven by the endogeneity of co-option measures.

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

4.4. Additional Evidence: Co-opted Boards, Managerial Career Concerns, and Stock Price Crash Risk

In this section, to shed light on channels through which co-opted boards increase stock price crash risk, we explore our second hypothesis that CEOs with career concern are more likely to take advantage of board friendliness to conceal bad information from shareholders. We use three measures of career concerns, CEO age, product market competition (industry concentration), and state level anti-takeover legislations, to proxy for CEO career concerns. We examine the relation between co-opted boards and crash risk conditional on CEO career concerns by re-running our baseline regressions with subsamples partitioned by the median of each career concern measure and report the results in Table 5. We discuss these analyses in detail below

[Insert Table 5 Here]

4.4.1 CEO Age

The first measure is an indicator variable that takes one if the age of CEO is below sample median, and zero otherwise ($YOUNG_{t-1}$). We obtain the CEO age information from the ISS database. Younger CEOs, who are in the early stages of business career, have greater career concerns relative to their older counterparts, suggesting that they might have stronger incentives to conceal negative information from shareholders than old CEOs. Consistent with this notion, Andreou et al. (2017) show that firms with younger CEOs are negatively associated with future stock price crash risk.

Panel A of Table 5 reports the regression results based on the CEO Age variable ($YOUNG_{t-1}$). We find that, for both crash risk measures, the coefficients on $CO\text{-}OPTION_{t-1}$ and $TW\ CO\text{-}OPTION_{t-1}$ are positive on both subsamples, but statistically significant only for firms with young CEOs (From Model (1) to (4)). When firms have old CEOs (from Model (5) to (8)), the relation between co-opted boards and crash risk is insignificant. In addition, 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 for the sample with old CEOs.

4.4.2 Product Market Competition

Our second measure of CEO career concerns is an indicator variable equal to one if a firm is affiliated in a competitive industry with below-median concentration ratio in a given fiscal year, and zero otherwise (*HIGH-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 exacerbate their career concerns. Following Moatti, Ren, Anand, and Dussauge (2015), we measure industry concentration by the four-firm industry concentration ratio.[5] Specifically, concentration ratio is measured as the total market share held by four largest firms in each of the Fama-French 48 industry classification, where the market shares are measured by sales. High concentration ratio indicates low product market competition.

In panel B of Table 5, we split sample into the subsample with below median four-firm industry concentration ratio (*HIGH-COMPETITION*$_{t-1}$ = 1) and above median (*HIGH-COMPETITION*$_{t-1}$ = 0). Consistent with the results in Panel A, the coefficients on *CO-OPTION*$_{t-1}$ and *TW CO-OPTION*$_{t-1}$ are positive for the subsample with high product market competition, but those are insignificant for the subsample with low competition. Furthermore, the coefficients are more economically 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, leading to higher crash risk. On the other hand, if product market competition mitigates managerial slack by acting as an external monitoring mechanism (Giroud and Mueller, 2010), one can expect that product market competition is negatively associated with crash risk. Consistent with the

[5] We obtain the similar results when we perform the same analyses using the alternative measures of product market competitions, such as five-firm and ten-firm industry concentration ratios as well as herfindahl index.

latter view and inconsistent with our findings, Kim et al. (2011a) show that the positive effect of CFO option sensitivity on crash risk is more pronounced in for the subsample with low product market competition. Our findings, however, suggest that the former effect dominates when product market competition interacts with board friendliness.

Overall, the findings in Table 5 are consistent with our second hypothesis that board co-option facilitate the bad-news-hoarding incentives of CEOs with high career concerns. For those with low career concerns, however, this effect is attenuated, indicating that the crash risk-increasing effect of board friendliness depends on managerial career concerns.

4.5. Co-opted Independent Directors versus Co-opted Non-Independent Directors

Our results so far demonstrate that co-opted boards increase stock price crash risk and that the positive relation depends on managerial incentives to withhold bad news. However, as suggested by Coles et al. (2014), the standard measure *CO-OPTION*$_{t-1}$ and tenure-weighted measure *TW CO-OPTION*$_{t-1}$ do not differentiate the effect of board capture on non-independent directors and independent directors. In this section, we examine whether co-opted independent directors also exert weak monitoring functions. To investigate this question, we further isolate co-opted independent directors from co-opted boards. Following Coles et al. (2014), we define two additional variables. *CO-OPTED IND*$_{t-1}$ is defined as the proportion of captured independent directors, whereas *CO-OPTED NON-IND*$_{t-1}$ is defined as the proportion of captured non-independent directors, which can be computed by simply subtracting *CO-OPTED IND*$_{t-1}$ from *CO-OPTION*$_{t-1}$. We also construct tenure-weighted variables *TW CO-OPTED IND*$_{t-1}$ and *TW CO-OPTED NON-IND*$_{t-1}$ in the same manner.

[Insert Table 6 Here]

In Table 6, we reproduce the baseline regression results in Table 2 by replacing the co-option measures with the isolated variables. Panel A reports the results with co-opted independence variables *CO-*

OPTED IND_{t-1} and *TW CO-OPTED* IND_{t-1}, whereas Panel B presents those with co-opted non-independence variables *CO-OPTED NON-*IND_{t-1} and *TW CO-OPTED NON-*IND_{t-1}.

In Model (1) and (2) in Panel A where $NCSKEW_t$ is used as a dependent variable, we find that the coefficients on both *CO-OPTED* IND_{t-1} and *TW CO-OPTED* IND_{t-1} are insignificant. In Model (3) and (4) where $DUVOL_t$ is used as the proxy for crash risk, however, the coefficients on both variables are significant, indicating that co-opted independence is associated with greater stock price crash risk. In Panel B, we find that co-opted non-independence has no effect on crash risk (Model (1) and (3)), but tenure-weighted co-opted non-independence is associated with higher crash risk. Furthermore, the coefficients on co-opted non-independence in Panel B aremuch larger than those on co-opted independence in Panel A, suggesting that the effect of board capture is more detrimental for non-independent directors. Consistent with Coles et al. (2014), however, the results in Panel A suggest that board capture attenuates the monitoring effectiveness of independent directors. Overall, the findings in this section indicate that the conventional measure of board independence does not fully capture the proportion of effective monitors on the board.

5. Conclusions

Using a novel measure of board monitoring effectiveness developed by Coles et al. (2014), *co-option*, this study shows that the CEO with co-opted boards is more likely to associate with future stock price crashes. The evidence supports the idea that directors appointed after the CEO assumes office do not provide effective monitoring roles, resulting in greater crash risk. Further analysis shows that such crashes are more likely to occur when the CEO with co-opted boards has greater career concerns, namely, when he or she is younger or affiliated in competitive industries. This finding indicates that the CEO with stronger incentives to hoard bad news is more likely to exploit opportunities relating to attenuated board monitoring to promote their personal benefits. Overall, this study suggests that CEO age is important determinant of stock price crash risk.

Our findings have important implications for the role of board monitoring. We focus on harmful effects of board friendliness and provide new evidence on the economic consequences of co-opted boards. Independence of a board member might not be determined by the classification itself. A director appointed from outside might have allegiance to the CEO if they are appointed after the CEO takes office. Our evidence also has important policy implications. Although regulations, such as Sarbanes Oxley Act of 2002 (SOX), limit the direct influence of the CEO in the nominating process, board friendliness issues, such as co-option and social ties, still exist. Coles et al. (2014) suggest that a large fraction of independent directors might be captured by the CEO.

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Appendix A. Variable Definitions

Variable	Source	Definition
Crash risk variables		
$NCSKEW_t$	CRSP	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.
$DUVOL_t$	CRSP	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-OPTED-DIRECTOR	RiskMetrics	Director who joined the board after the CEO assumed office.
CO-OPTION$_{t-1}$	RiskMetrics	Number of co-opted director / Board size =Co-opted Independence + Co-opted Non-Independence
TW CO-OPTION$_{t-1}$	RiskMetrics	Sum of tenure of co-opted directors divided by the sum of tenure of all directors.
CO-OPTED_IND$_{t-1}$	RiskMetrics	Number of co-opted independent directors / Board size
TW-CO-OPTED-IND$_{t-1}$	RiskMetrics	Sum of tenure of co-opted independent directors divided by the sum of tenure of all directors.
CO-OPTED NON-IND$_{t-1}$	RiskMetrics	Number of co-opted non-independent directors / Board size
Other Control variables		
IND_{t-1}	RiskMetrics	Number of independent directors / Board size
$DTURN_{t-1}$	CRSP	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.
$NCSKEW_{t-1}$	CRSP	Lagged $NCSKEW_t$.
$SIGMA_{t-1}$	CRSP	Standard deviation of firm-specific weekly stock returns over the fiscal year.
RET_{t-1}	CRSP	Average firm-specific weekly return during the entire fiscal year
$SIZE_{t-1}$	Compustat	Natural log of total assets.

MB_{t-1}	Compustat	Ratio of the market value of equity to the book value of equity.
LEV_{t-1}	Compustat	Long-term debt divided by total assets.
ROA_{t-1}	Compustat	Income before extraordinary items divided by lagged total assets
ACC_{t-1}	CRSP	Performance-matched discretionary accruals following Kothari, Leone, and Wasley (2005).
$R\&D_{t-1}$	Compustat	Ratio of research and development expenses to total assets. Missing values of research and development expenses are replaced with zero.
$R\&D\_MISSING_{t-1}$	Compustat	Dummy variable that equals one when the value of research and development expenses is missing.
KUR_{t-1}	CRSP	Kurtosis of firm-specific weekly returns over the fiscal year.

Table 1. Descriptive Statistics

This table presents descriptive statistics on variable used in our analyses. The sample contains 12,841 U.S. public firms in ISS (formerly known as RiskMetrics) from 1996 to 2014 with non-missing values for the crash risk measures and all independent variables. All variables are defined in Appendix A.

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						
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
$SIZE_{t-1}$	12841	6.801	1.471	5.019	6.660	8.865
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
$HIGH\ COMPETITION_{t-1}$	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 2. Effects of Co-option on Stock Price Crash Risk

This table reports regression results where dependent variables are firm-specific future stock price crash risk measures. 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. Propensity Score Matching

This table reports results from one-to-on propensity score matching where firms with co-options measures above sample median are matched with those with co-option measures below sample median. 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 $TW\ CO\text{-}OPTIO_{t-1}$, 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. Propensity Score Matching Regression

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. 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 $1.3 \times \tilde{R}$ as well as $2.0 \times \tilde{R}$ and $3.0 \times \tilde{R}$ 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

$R_{max} = 1.3 \times \tilde{R}$				
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
$R_{max} = 2.0 \times \tilde{R}$				
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
$R_{max} = 3.0 \times \tilde{R}$				
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 5. 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 6. 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-OPTED* IND_{t-1} and *TW CO-OPTED* IND_{t-1}), whereas Panel B examine the influence of co-opted non-independent directors (*CO-OPTED NON-*IND_{t-1} and *TW CO-OPTED NON-*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-OPTED IND_{t-1}	0.037		0.046**	
	(0.321)		(0.045)	
TW CO-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	Y
Observations	12,841	12,841	12,841	12,841
Adjusted R-squared	0.023	0.023	0.036	0.036

Panel B. Co-opted Non-Independence

VARIABLES	$NCSKEW_t$		$DUVOL_t$	
	(1)	(2)	(3)	(4)
CO-OPTED NON-IND_{t-1}	0.086		0.059	
	(0.194)		(0.152)	
TW CO-OPTED NON-IND_{t-1}		0.112*		0.097**
		(0.061)		(0.016)
Other Controls as in Table 2	Y	Y	Y	Y
Industry/Year Fixed Effects	Y	Y	Y	Y
Observations	12,841	12,841	12,841	12,841
Adjusted R-squared	0.023	0.023	0.035	0.036