The impact of top executive gender on asset prices: Evidence from stock price crash risk*

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Abstract

We examine the implication of executive gender on asset prices. Using a large sample of US public firms during 2006–2015, we find a negative association between female CFOs and future stock price crash risk. However, the impact of female CEOs on crash risk is not statistically significant. The results support the notion that CFOs play a stronger role than CEOs in curbing bad news hoarding activities because CFOs' primary duties are financial reporting and planning. Our findings are robust to several econometric specifications controlling for potential endogeneity and to alternative measures of crash risk. At last, we show that the negative relation between female CFOs and future stock price crash risk is more pronounced among firms with weaker corporate governance, less market competition, lower analyst coverage, and higher financial leverage. Collectively, our evidence highlights the importance of CFO gender for firm financial decision making and stock return tail risk.

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1. Introduction

Of 323.1 million people counted in the US 2016 Census, around 50.8% were women. But when it comes to the C-level jobs at Fortune 500 companies, only one woman climbed to the top of the corporate ladder as Chief Executive Officer (CEO) in 1998 and 30 women held Chief Financial Officer (CFO) positions in 2000. There has been a steady but slow improvement of executive gender diversity over the past 20 years. In 2015, 24 female CEOs and 58 CFOs served at Fortune 500 companies.[1] With the rise of female top executives in corporate America, recent studies have documented a material impact of executive gender on corporate decision making. For example, Huang and Kisgen (2013) find that firms with male top executives engage in more acquisitions and have more debt issuances than those with female executives. Faccio et al. (2016) show that firms managed by female CEOs have lower leverage, less volatile earnings, and a higher survival rate than those managed by male CEOs. Furthermore, Barua et al. (2010) and Francis et al. (2015) report that the appointments of female CFOs improve accruals quality and increase the degree of accounting conservatism. The purpose of this paper is to extend this line of inquiry from corporate activities to stock prices. In particular, we examine whether top executive gender and underlying innate behavioral traits have an impact on future stock price crash risk.

Earlier sociology, cognitive psychology, and behavioral economics studies indicate that there exist several behavioral differences between men and women. First, women have a higher risk aversion than men in terms of their gambling habits and investment portfolio risk profiles (e.g., Levin et al., 1988; Jianakoplos and Bernasek, 1998; Sundén and Surette, 1998; Agnew et al., 2003; Brooks et al., 2017). Second, women are less overconfident and optimistic than men when it comes to driving ability, exam answer confidence, stock trading, and the choice of compensation scheme (e.g., Svenson, 1981; Feingold, 1994; Lundeberg et al., 1994; Barber and Odean, 2001; Niederle and Vesterlund, 2007). Third,

[1] Data source: S&P Capital IQ.

women have a better compliance with taxation rules, business ethics, financial reporting guidelines, financial market regulations, and professional financial advice than men (e.g., Baldry, 1987; Barnett et al., 1994; Bernardi and Arnold, 1997; Fallan, 1999; Ittonen et al., 2013; Brooks et al., 2017). Graham et al. (2013) find that corporate financial policies are influenced by top executives' behavioral traits. Therefore, when the gender differences documented in the previous studies exist among well-educated top executives, firms run by female executives may adopt different firm policies from those run by male executives. In turn, it is naturally to ask whether firm stock prices are influenced by executive gender. We focus on the firm-specific stock price crash risk that captures the left tail risk of stock returns. Tail risk, the third moment of stock returns, has come under the spotlight after the 2008 financial crisis. Both institutional and individual investors care about crash risk, because a sudden dramatic decline of stock prices can impose significant losses on their portfolios.[2]

The literature on crash risk suggests that managerial bad news hoarding activities increase firms' future stock price crash risk. Due to a variety of managerial incentives, such as career and compensation concerns, firm managers have an incentive to withhold bad news from outside investors for an extended period (e.g., Jin and Myers, 2006; Hutton et al., 2009; Kothari et al., 2009). However, when bad news stockpiled within the firm reaches a tipping point, the costs of hoarding bad news will exceed the benefits of doing so (Baik et al., 2011). Once bad news gets revealed all together in the market, investors will immediately revise their expectations about firm growth prospects, leading to a stock price crash. Consistent with the bad news hoarding conjecture, empirical evidence suggests that financial opacity (Hutton et al., 2009), tax avoidance (Kim et al., 2011b), and CFOs' compensation incentives and overconfidence (Kim et al., 2011a, 2016) are positively associated with future stock price crash risk, while institutional investor stability (Callen and Fang, 2013), mandatory International Financial Reporting Standards (IFRS) adoption

[2]The loss on paper may lead to the real wealth loss when investors have to cut their losses during extreme negative events.

(DeFond et al., 2015), religiosity at the county level (Callen and Fang, 2015), and CEO age (Andreou et al., 2016) are negatively associated with future stock price crash risk.

We expect female executives to affect crash risk through two channels. First, most gender studies support the view that women are more risk averse and less optimistic than men. Firms with female executives are less likely to invest in risky projects in the beginning, which may lead to bad operating performance. Also, since female executives are less overconfident compared with their male counterparts, they are more likely to terminate money-losing projects at an early stage. By avoiding risky investment and terminating early failures, firms run by female executives are less likely to have bad news in the first place. Second, since female executives are more likely to comply with financial market regulations and report high-quality financial information than male executives, firms run by female executives are less likely to withhold bad news intentionally when bad news actually arrives. Collectively, we conjecture a negative empirical relation between female top executives and firm stock price crash risk.

In our empirical analysis, we separately examine CEO and CFO gender because these two top executives may affect crash risk through different mechanisms. CEOs are firms' highest-ranking executives and their primary responsibilities include making major corporate decisions, managing the overall operations and resources of a company, and acting as the communication bridge between the board of directors and corporate operations. CEOs may affect crash risk primarily through managerial risk taking that leads to bad firm performance. CFOs are the senior executives responsible for managing the financial actions of a company. The CFO's primary duties include financial reporting, tracking cash flow and financial planning, as well as analyzing the company's financial strengths and weaknesses. Jiang et al. (2010) find that accrual management and earnings surprise are more sensitive to CFO equity incentives than to those of the CEO. Kim et al. (2011a) further show that CFO equity incentives are strongly associated with higher firm crash risk, while the relation between CEO equity incentives and crash risk is much weaker. Anecdotal evidence, such as Enron (2001), Worldcom (2002), Lehman Brothers (2010), and Autonomy Corporation (2012), also indicates that CFOs are likely to be involved in a series of accounting scandals. Given that CFOs retain the ultimate responsibility for reporting firm financial performance (Mian, 2001), female CFOs may influence crash risk primarily through mitigating the bad news hoarding activities. It remains an empirical question whether CFO gender may have a stronger impact on crash risk than CEO gender.

We investigate the empirical link between executive gender and crash risk using a sample of S&P 1500 companies from 2006–2015. Following previous studies, we adopt three measures of crash risk: a stock price crash week indicator, the negative skewness of firm-specific weekly returns, and the asymmetric volatility of negative and positive stock returns (e.g., Kim et al., 2011b; Callen and Fang, 2015). In our baseline regressions, we find no empirical evidence that CEO gender is related to future stock price crash risk. However, our results show that firms with female CFOs have a significantly lower one-year-ahead stock price crash risk than those with male CFOs, after controlling for other predictors of future stock price crash risk. The coefficient estimate of our main variable of interest in the baseline model suggests that a firm with a female CFO has a 2.9% lower likelihood of experiencing a stock price crash than a comparable firm with a male CFO. The impact of CFO gender on crash risk is economically meaningful given that the sample mean value of unconditional probability of stock price crash is 25.4%. The empirical link between female CFOs and crash risk remains statistically significant when we include both CEO and CFO gender in our regressions.

An identification challenge for us is to address the potential endogeneity in our empirical analysis. Firms with female executives or male executives may differ in unobservable firm characteristics. Therefore, directly comparing future crash risk between firms with female or male executives may simply capture the effect of the unobservable firm differences instead of the effect of executive gender. Furthermore, executive candidates and corporate boards may mutually select each other in the labor market, which raises a possibility that female executive candidates choose to work for firms with ex ante low crash risk. We use three econometric identification strategies to mitigate the potential endogeneity due to the omitted variables and the reverse causality. First, we employ a propensity score matching (PSM) approach to identify control firms with male executives, which are otherwise indistinguishable by the observed firm characteristics from our treatment firms with female executives. Second, we adopt a high-dimensional fixed effects model to control for unobservable firm characteristics. Finally, we apply a difference-in-differences research design and investigate the impact of male-to-female executive transition on the changes in future stock price crash risk, compared with the impact of male-to-male executive transition. Overall, our three identification tests suggest that the negative relation between CFO gender and crash risk remains statistically significant after addressing the endogeneity concern.

We further conduct a battery of supplementary analyses. First, we implement subsample analyses and find that the empirical relation between CFO gender and crash risk is more pronounced for firms with weaker corporate governance, lower product market competition, higher information asymmetry, and larger ex ante firm risk (leverage). Second, our results are robust after controlling for the compensation incentive, age, and tenure of CFOs, CEO pay slice, and board gender diversity. Third, we show that moderating firm earning manipulation is one possible channel through which female CFOs reduce firm future stock price crash risk. Fourth, we provide the evidence that overconfidence is more important than risk aversion in terms of explaining the empirical relation between CFO gender and crash risk. Fifth, we find that the impact of CFO gender on crash risk is weak when CEOs are the chairman of firm boards. Sixth, we adopt alternative measures of crash risk in the previous studies and still find a negative relation between female CFOs and these measures. In summary, our findings consistently demonstrate the importance of the influence a specific manager has on corporate decision making and reveal how managerial characteristics such as gender may interact with corporate monitoring mechanisms.

Our paper contributes to several strands of the literature. To the best of our knowledge, this study is the first to examine the implication of executive gender on stock return distributions at the firm level.[3] Previous gender studies examining the relation between gender diversity and firm performance usually focus on firms' financial performance measured by either Tobin's Q or return on assets. Adams and Ferreira (2009) study the role of female directors and find that the average effect of gender diversity on firm performance is negative. However, Hoogendoorn et al. (2013) show evidence in their field experiment that teams with an equal composition of male and female members achieve a better performance than those dominated by male members in terms of sales and profits. Our crash risk measures directly capture the tail risk in actual stock return distributions, which has become a key component of corporate and portfolio risk management. It is important to notice that we focus on the third moment of stock returns, not the first moment average returns or the second moment return volatilities. Given the behavioral differences between female and male executives, we believe that the presence of female executives has an ambiguous effect on firm stock performance.[4] In addition, Gul et al. (2011) have already provided evidence that board gender diversity improves the informativeness of stock prices, measured by idiosyncratic volatilities.

Our study also adds to the emerging literature on the different roles of CEOs and CFOs in corporate operations. Both Jiang (2010) and Kim et al. (2011a) examine the compensation incentives of CEOs and CFOs and find that CFO compensation incentives are more strongly related to earning management and bad news hoarding activities than CEO compensation incentives. Our evidence corroborates the findings in these two studies. Furthermore, recent literature has documented the important role of CFOs in the corporate decision making process. For example, Barua et al. (2010) show that firms with female CFOs have a better accrual quality than those with male CFOs. Ge et al. (2011) document a systematic association between CFO styles and corporate accounting choices. Francis et al. (2015) find that the switch from male to female CFOs is associated with a significant

[3]Previous studies have examined the relation between fund manager gender and portfolio returns. However, these studies mainly focus on the impact of fund manager gender on portfolio construction and management.

[4]Stock price crash risk may only be one of the factors which a firm considers when hiring a female executive.

increase in firms' accounting conservatism. We contribute to these studies by establishing an empirical link between CFO gender and firm stock price crash risk. Consistent with the contention that CFOs have an important role in financial reporting, we show that it is CFO gender, rather than CEO gender, which influences future stock price crash risk.

Finally, we contribute to the literature on stock price crash risk by showing that female CFOs mitigate the likelihood of firms experiencing stock price crashes due to bad news hoarding activities. Recent studies find that managerial bad news hoarding decisions are related to corporate financial opacity (Hutton et al., 2009), CFO option sensitivity (Kim et al., 2011a), tax avoidance (Kim et al., 2011b), institutional investor stability (Callen and Fang, 2013), corporate social responsibility (Kim et al., 2014), religious beliefs at the US county level (Callen and Fang, 2015), mandatory IFRS adoption (DeFond et al., 2015), CEO age and overconfidence (Andreou et al., 2016; Kim et al., 2016), and accounting conservatism (Kim and Zhang, 2016). Unlike these factors documented in the previous studies, gender is an individual's innate nature which does not change over time. The behavioral traits based on gender are different from those based on social norms such as religion (Callen and Fang, 2015). Our paper provides novel evidence that female CFOs are less likely to engage in bad news hoarding activities which lead to stock price crashes.

The remainder of the paper is structured as follows. Section 3, presents our empirical predictions. Section 3 discusses the data collection, key variable definitions, and descriptive statistics. Section 4 presents main results of the empirical relation between executive gender and firm future stock price crash risk. Section 5 provides supplementary test results and Section 6 concludes.

2. Empirical predictions

In neoclassical economics, managers are homogeneous and make the same rational decisions on the basis of the same information set. However, recent upper echelons theory suggests that managers act on the basis of their personalized interpretations of information and these personalized construals are a function of individual-specific attributes such as experiences, disposition, compensation incentive, and gender (e.g., Hambrick and Mason, 1984; Hambrick, 2007). Consistent with upper echelons theory, recent studies of corporate activities provide evidence that executive gender has an impact on corporate outcomes such as financial reporting (Barua et al., 2010; Francis et al., 2015), bank loan contracts (Francis et al., 2013), risk taking activities (Huang and Kisgen, 2013), and efficiency of capital allocation (Faccio et al., 2016). Based on these studies, it is worthwhile to empirically examine whether executive gender may inherently influence firm stock returns because stock prices should reflect any impact of executive gender on corporate outcomes in an efficient market.

In the crash risk literature, managerial bad news hoarding activities are the primary cause of stock price crashes. When corporate governance mechanisms fail to alleviate managerial compensation related agency problems (e.g. Jin and Myers, 2006; Kim et al., 2011a; Andreou et al., 2016), executives may choose to hide bad news until it is necessary to disclose it to the public. Additional determinants of stock price crashes, which can be ascribed to executives, include accrual manipulation (Hutton et al., 2009), overconfidence (Kim et al., 2016), and accounting conservatism (Kim and Zhang, 2016). Previous gender studies have acknowledged that in general, women are more risk averse, less overconfident, and better compliant than men. If these gender differences in the general population still exist among top executives, then female executives are more conservative when making investment decisions, more likely to terminate early failure projects timely, and more likely to follow accounting rules and supply transparent financial information. Nevertheless, Adams and Funk (2012) use a large survey of directors and show that the gender differences among directors are different from those in the general population. For example, female directors are more risk loving than male directors. Although the relationship between executive gender and stock price crash risk remains an open empirical question, we predict that, ceteris paribus, the incremental effect of female executives should be to reduce future stock price crash risk.

We further note that CFOs could be more influential than CEOs in the corporate financial decision making process. CFOs are mainly responsible for disclosing financial information, choosing appropriate accounting measures, and assuring financial statement quality. Instead, CEOs are mainly responsible for firm investment, expansion, and development. Consistent with this view, recent studies find that CFO compensation incentives have a stronger impact on floating-to-fixed rate debt structure (Chava and Purnanandam, 2007), earnings management (Jiang et al., 2010), debt maturity structure and earnings smoothing decisions (Chava and Purnanandam, 2010), and crash risk (Kim et al., 2011a) than CEO compensation incentives. Given that stock price crashes are mainly due to managerial bad news hoarding, we expect CFO gender to play a stronger role than CEO gender in mitigating future stock price risk.

An alternative possibility is that CFOs may become involved in bad news hoarding activities because of pressure from CEOs. Friedman (2014) develops a theoretical model and shows that powerful CEOs may compromise the independence of CFOs. A survey study by Matejka (2007) indicates that CEOs may exert pressure on CFOs regarding their financial reporting decisions because CEOs can influence the decisions of corporate boards related to CFOs' compensation package and promotion opportunities. Feng et al. (2011) also provide archival evidence that CFOs are involved in material accounting manipulations because they succumb to pressure from powerful CEOs. Powerful CEOs may influence corporate organizational structure so that CFOs may not have an opportunity to report directly to the board. Previous studies support the view that powerful CEOs can exert their will and influence corporate decisions, including those related to CFOs (e.g., Finkelstein, 1992; Adams et al., 2005). Therefore, we acknowledge the possibility that powerful CEOs may have an impact on the empirical relation between CFO gender and future crash risk, and provide empirical evidence for this prediction.

3. Sample, variables, and summary statistics

3.1. Sample selection and data sources

Our sample starts with firm–year observations for which executive gender information is available on the ExecuComp database.[5] The ExecuComp database provides detailed biographical and compensation information on executives, such as their gender, age, and tenure. We identify firm CEOs and CFOs by using data items "CEOANN" and "CFOANN" in the ExecuComp database. Our period of study on executive gender is 2006–2015, because the data item "CFOANN" is only available from 2006 and our stock price crash risk measures are calculated up to the end of 2016. We then delete observations with missing Compustat accounting data and missing Centre for Research in Security Prices (CRSP) stock price data. Consistent with earlier studies (e.g., Hutton et al., 2009; Kim et al., 2011a), we further exclude firm–years with non-positive book values and total assets, low fiscal-year-end stock prices (less than $1), and fewer than 26 weekly stock return observations. To control for potential outliers, we follow Kim et al. (2016) and exclude firm–year observations that fall in the top and bottom percentiles of leverage, return on asset, market value of equity, and market-to-book ratio. After applying these data selection filters, our CFO sample consists of 12,745 firm–year observations for 3,408 unique CFO–firm combinations, and our CEO sample consists of 13,018 firm–year observations for 3,006 unique CEO–firm combinations.

In our empirical tests, we collect financial analyst data from the Institutional Brokers' Estimate System (I/B/E/S), institutional ownership data from the Thompson Reuters institutional holdings' database, institutional investor type classification from Brian Bushee's website, managerial entrenchment and director-level data from the Institutional Shareholder Services (ISS, formerly RiskMetrics) database, Fama–French industry returns from Kenneth R. French's website, and earnings restatement data from AuditAnalytics.

[5] The ExecuComp database covers most public companies in the Standard & Poor's (S&P) 1500 index, including the S&P 500, S&P MidCap 400, and S&P SmallCap 600 indexes.

3.2. Dependent variables: Firm-specific crash risk

To investigate the effect of executive gender on future stock price crash risk, we first construct three firm-specific measures of (ex post) stock price crash risk for each firm–year observation following the prior crash risk literature (e.g., Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011a,b): (1) $Crash$, an indicator variable for firms experiencing at least one stock price crash week during a fiscal year; (2) $Ncskew$, the negative conditional skewness of firm-specific weekly returns during one fiscal year; (3) $Duvol$, the down-to-up volatility of firm-specific weekly returns during one fiscal year.

We estimate firm-specific residual weekly returns from the following extended market index model regression over fiscal year T:

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-2} + \beta_{2,j} r_{m,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{m,t+1} + \beta_{5,j} r_{m,t+1} + \epsilon_{j,t} \tag{1}$$

where $r_{j,t}$ is the return of stock j in week t and $r_{m,t}$ is the return of the CRSP value-weighted market index in week t. We supplement the standard market index model with the two lead and lag terms to correct for non-synchronous trading (Dimson, 1979). This regression separates a firm's return into the one correlated with the stock market movement and the one due to the firm-specific shock ($\epsilon_{j,t}$). For firm j in week t, its firm-specific weekly return is defined as $W_{j,t} = \ln(1 + \epsilon_{j,t})$. The natural logarithm transformation reduces the positive skewness in the stock return distribution and improves the symmetry of $W_{j,t}$.

Our first measure of firm-specific crash risk is $Crash_{j,T}$, an indicator variable that equals one for a firm–year experiencing one or more firm-specific crash weeks during fiscal year T, and zero otherwise. Following Hutton et al. (2009), we identify crash weeks in fiscal year T for firm j as those weeks during which the firm-specific weekly return $W_{j,t}$ is 3.09 standard deviations (0.1% frequency in the normal distribution[6]) below the average firm-specific weekly returns over fiscal year T. $Crash_{j,T}$ captures the likelihood of a firm's

[6] If firm-specific weekly returns are normally distributed, the likelihood of a crash during a fiscal year would be $1 - (1 - 0.1\%)^{52} = 5.07\%$.

stock price crash in a given fiscal year.

The second measure of firm-specific crash risk is $Ncskew_{j,T}$, the negative coefficient of skewness of firm-specific weekly returns. Following Chen et al. (2001), Kim et al. (2011a), and Kim et al. (2011b), we calculate $Ncskew_{j,T}$ as the negative third central moment of $W_{j,t}$ divided by the cubed standard deviation of $W_{j,t}$. Specifically, $Ncskew_{j,T}$ is defined as:

$$Ncskew_{j,T} = -\frac{n_{j,T}(n_{j,T}-1)^{\frac{3}{2}}\sum_{t=1}^{n_{j,T}} W_{j,t}^3}{(n_{j,T}-1)(n_{j,T}-2)(\sum_{t=1}^{n_{j,T}} W_{j,t}^2)^{\frac{3}{2}}} \tag{2}$$

where $n_{j,T}$ is the number of available firm-specific weekly returns for firm j during fiscal year T. Scaling the raw third central moment by the normalization factor, the cubed standard deviation in the denominator – allows for comparison across firm-specific returns with different variance. The first minus sign in Equation (2) ensures that an increase in $Ncskew_{j,T}$ corresponds to firm j having a higher stock price crash risk in fiscal year T, i.e., a more negative-skewed return distribution.

The third measure of firm-specific crash risk is $Duvol_{j,T}$, the ratio of down-side volatility to up-side volatility. Following Chen et al. (2001), Kim et al. (2011a), and Kim et al. (2011b), we calculate $Duvol_{j,T}$ as follows:

$$Duvol_{j,T} = \ln\left\{\frac{(n_{u,j,T}-1)\sum_{t=1}^{n_{d,j,T}} W_{j,t}^2}{(n_{d,j,T}-1)\sum_{t=1}^{n_{u,j,T}} W_{j,t}^2}\right\} \tag{3}$$

where $n_{u,j,T}$ ($n_{d,j,T}$) is the number of up (down) weeks for firm j's stock during fiscal year T. For each stock j over fiscal year T, we define the up (down) weeks as those when the firm-specific weekly returns are above (below) its annual mean. Intuitively, $Duvol_{j,T}$ is the natural logarithm ratio of the standard deviations of $W_{j,t}$ on down weeks to the standard deviations of $W_{j,t}$ on up weeks. Similar to the convention of $Ncskew_{j,T}$, an increase in $Duvol_{j,T}$ corresponds to firm j having a higher stock price crash risk in fiscal year T

We forward these three measures by one year in our main analyses, so that our dependent variables refer to the one-year-ahead future stock price crash risk: $Crash_{T+1}$,

$Ncskew_{T+1}$, and $Duvol_{T+1}$.

3.3. Independent variables of interest and control variables

Our primary independent variables of interest are executive gender indicator variables: $FemaleCEO_{j,T}$ and $FemaleCFO_{j,T}$, which equal one if firm j's corresponding executive is female in fiscal year T, and zero otherwise. Following Jiang et al. (2010), we identify an executive to be a CEO (CFO) if ExecuComp's data item "CEOANN" ("CFOANN") is equal to "CEO" ("CFO").

Following the earlier crash risk literature (e.g., Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011a, 2016), we control for the following variables in our main analyses. $Dturn_T$ is the detrended stock trading volume, which is a proxy for the heterogeneity of investor opinions. Chen et al. (2001) find that firms with high intensity of the differences of opinions among investors are more likely to experience stock price crashes. $Ncskew_T$ is the prior stock price crash risk. $Sigma_T$ is the volatility of firm-specific weekly stock returns. $Return_T$ is the mean of firm-specific weekly stock returns. We include these three variables to control for the potential persistence of the third moment, second moment, and first moment of stock returns, respectively. Chen et al. (2001) also find that firms with a higher past stock return mean and volatility are more likely to crash in the future. $Size_T$ is the natural logarithm of market capitalization. Mtb_T is the market-to-book ratio. $Leverage_T$ is the ratio of long-term debts to total assets. Roa_T is the return on assets. We follow Kim et al. (2011a) and control for these four observable firm characteristics. $Accm_T$ is the three-year moving sum of the absolute value of discretionary accruals, which is a proxy for financial reporting opacity. Hutton et al. (2009) document a positive relation between financial reporting opacity and future stock price crash risk. Finally, we follow Fang et al. (2009) and Callen and Fang (2015), and control for $Litigationrisk_T$, which indicates industries with a high litigation risk. To account for the variations of executive gender across different industries and over time, we control for Fama–French 48 industry (Fama and French, 1997) and year fixed effects in all our regressions. Detailed definitions of all variables are described in Appendix A.

3.4. Summary statistics

Table 1 presents the summary statistics for the variables used in our empirical analysis. The sample period for our three crash risk measures is 2007–2016, while the sample period for the rest of the variables is 2006–2015. The mean values (standard deviations) of $Crash$, $Ncskew$, and $Duvol$ are 0.254 (0.435), 0.098 (0.866), and 0.004 (0.380), respectively. The means and standard deviations of our crash risk measures are comparable to those reported in the studies focusing on the ExecuComp samples (e.g., Kim et al., 2011a, 2016; Andreou et al., 2016). Of $12,745$ firm–year observations in our CFO sample, $3,237$ (25.4%) firm–years experience at least one crash. The mean values of $FemaleCEO$ and $FemaleCFO$ are 0.034 and 0.089, suggesting that firms on average appoint more female CFOs than CEOs. In a given year, our sample has on average 44 firms with female CEOs and 113 firms with female CFOs. The ratios of female executives in our sample are similar to those reported in Bugeja et al. (2012) and Francis et al. (2013). The distribution of the other variables is broadly consistent with those reported in earlier studies.[7]

4. Main empirical analysis results

In this section, we examine the impact of executive gender on firm future stock price crash risk.

4.1. Baseline panel regression model

First, we test how the presence of female executives affects firm future stock price crash risk after controlling for other potential determinants of crash risk. Our baseline

[7]For brevity, we only report the summary statistics of these variables in our CFO sample.

panel model is as follows:

$$\text{Crash risk}_{j,T+1} = \beta_0 + \beta_1 \text{Executive gender}_{j,T} + \gamma' \text{Control variables}_{j,T} + \theta_i + \mu_T + \epsilon_{j,T} \quad (4)$$

where Crash risk_{T+1} is measured by one of $Crash_{T+1}$, $Ncskew_{T+1}$, or $Duvol_{T+1}$. We follow previous crash risk studies and use logit regressions when the dependent variable is $Crash_{T+1}$[8] and OLS regressions when the dependent variables are $Ncskew_{T+1}$ and $Duvol_{T+1}$. All regressions control for Fama–French 48 industry (θ_i) (Fama and French, 1997) and year (μ_T) fixed effects. Robust z-values and t-values are corrected for clustering the regression residuals at the firm and year levels (Petersen, 2009).

Columns (1)–(3) of Table 2 show that in the sample of firm–years with CFO gender information, the estimated coefficients of $FemaleCFO_T$ are negative and statistically significant. The results indicate that firms with female CFOs experience a lower one-year-ahead firm-specific crash risk than those with male CFOs. Columns (4)–(5) of Table 2 present the regression results in the sample of firm–years with CEO gender information. The estimated coefficients of $FemaleCEO_T$ are not statistically significant at the 10% level, suggesting that CEOs' gender is not related to future firm-specific crash risk. Finally, we include both $FemaleCFO_T$ and $FemaleCEO_T$ in Equation (4) and report the results in columns (7)–(9) of Table 2. In line with the results reported in columns (1)–(6), we find that only female CFOs are associated with lower future crash risk, and the coefficient of CEO gender remains statistically insignificant across all three measures of crash risk. In untabulated tests, we add an interaction variable $FemaleCEO_T \times FemaleCFO_T$ in columns (7)–(9). We find that the coefficients of the interaction variable are not statistically significant, suggesting that the impact of female CFOs on crash risk is not conditional on CEO gender.[9] The estimated coefficients of our control variables are generally comparable with previous studies. Future stock price crash risk is higher for firms with greater

[8] The inclusion of year fixed effects in logit regressions may lead to the incidental parameter problem. Our results are robust to using linear probability models.

[9] In our sample, there are 63 firm–year observations with both female CFOs and CEOs.

prior stock price crash risk ($Ncskew_T$), stock return volatility ($Sigma_T$), firm size ($Size_T$), operating performance (Roa_T), and accrual manipulation ($Accm_T$).

To further examine the economic significance of our results in columns (1)–(3), we follow the intuition in Hutton et al. (2009) and Callen and Fang (2015).[10] We first re-estimate the marginal effect of $FemaleCFO_T$ on $Crash_{T+1}$ in the logit regression. The marginal effect of $FemaleCFO_T$ is -2.9%: that is, a firm with a female CFO has a 2.9% lower probability of crash than a comparable firm with a male CFO. Given the sample mean value of unconditional probability of crash to be 25.4%, the drop in stock price crash risk in any year corresponding to a female CFO is 11.4% of the sample mean. Regarding the economic significance of $Ncskew_{T+1}$ and $Duvol_{T+1}$, a female CFO will lead to a 58% (= 0.057/0.098) decrease in $Ncskew$ at the mean and 575% (= 0.023/0.004) decrease in $Duvol$ at the mean.[11] Thus, the effect of CFO gender on future stock price crash risk is both statistically and economically significant.

4.2. Endogeneity

Our analysis so far indicates that female CFOs are associated with lower future stock price crash risk, while the relation between CEO gender and crash risk is statistically insignificant. Nevertheless, we recognize that female executives may not be randomly assigned to firms, therefore the potential endogeneity of executive gender makes it questionable to establish an empirical causal relation between executive gender and crash risk.

The endogeneity concern may arise due to unobservable heterogeneity when unobservable firm characteristics can affect both executive gender and crash risk. Corporate boards and female executive candidates may mutually select each other in the labor market. On the one hand corporate boards may favor candidates with a certain type of gender

[10] Hutton et al. (2009) and Callen and Fang (2015) set their continuous independent variables of interest to the 25th to the 75th percentiles and hold all other control variables at the mean. Next, they estimate the drop in a crash risk measure relative to its sample mean, corresponding to a shift of the independent variables of interest from the 25th to the 75th percentiles.

[11] The magnitude and the economic significance of $FemaleCFO_T$'s coefficients are comparable to those reported in Kim et al. (2016) that also uses indicator variables as the explanatory variable of interest.

in the executive nomination process, but on the other hand female executive candidates may be attracted to firms with certain female-friendly characteristics. The factors which affect the mutual selection between corporate boards and female candidates could be associated with the results documented in Table 2. In addition, reverse causality could be an alternative explanation of our results. Female executive representation is not uniformly distributed across all firms covered by the ExecuComp database. Female executive candidates may simply apply for jobs in firms with less crash risk. Huang and Kisgen (2013) argue that because of the "overcrowding" effect of male candidates in the executive job market (Bergmann, 1974), we may observe more female executives in consumer products related firms. It is possible that the industries favoring female executive candidates are naturally less crash prone than the other industries. Although we mitigate the reverse causality issue by using current executive gender to predict future stock price crash risk and by controlling for industry fixed effects, the concern of simultaneity may still remain if executive gender is persistent over time.

In the remainder of this section, we adopt three econometric approaches to mitigate the potential endogeneity concern: (1) a propensity score matching (PSM) approach, (2) a higher-order fixed effects model, and (3) a difference-in-differences framework.[12]

4.2.1. Propensity score matching

If the difference in crash risk between firms with female executives and those with male executives depends on the firm characteristics affecting whether or not female executives are hired, then the negative relation between female CFOs and crash risk is not due to CFO gender per se. When we directly compare crash risk between firms with female and male executives in Table 2, the estimated regression coefficients may be biased due to potential confounding variables. To mitigate this estimation bias, we employ a PSM procedure (Rosenbaum and Rubin, 1983) and estimate the treatment effect of executive gender on firm crash risk. For firms with female executives (treatment group), we identify

[12] As we have discussed in the following, these three methodologies are not free of possible limitations.

a group of control firms with male executives (control group) that exhibit no observable differences in firm characteristics. When we compare the treatment sample to the control sample, executive gender is the only distinguishable firm characteristic. PSM helps us to address the non-random mutual selection concern and improves the causal inference in our empirical analysis.

We first estimate a probit model to calculate the probability (i.e., the propensity score) that a firm with a set of firm-level characteristics is run by a female CFO. Columns (1) and (3) of Panel A of Table 3 report the coefficients estimated by the probit model. The covariates which we use to predict the propensity scores are the control variables in Table 2. Column (1) indicates that comparing to firms with male CFOs, those with female CFOs are associated with larger firm size, a lower market-to-book ratio, lower leverage, higher return-on-asset, lower accrual management, and higher litigation risk. Column (3) shows that comparing to firms with male CEOs, those with female CEOs are associated with a higher market-to-book ratio, lower return-on-asset, lower accrual management, and lower litigation risk.

To ensure that firms in the treatment sample and control sample are comparable, we adopt the nearest neighbor matching approach and require that the maximum difference between the propensity score of a firm with a female executive and that of the matched firm does not exceed 0.5% in absolute value. Each firm with a female CFO (CEO) is matched to a firm with a male CFO (CEO) and with the closest propensity score. We conduct two diagnostic tests to verify that firms in the treatment and control groups have the similar observable characteristics. First, we re-estimate the probit model for the post-match sample and report the results in columns (2) and (4) of Panel A of Table 3. All the estimated coefficients are statistically insignificant, indicating that firms between the treatment and control groups do not have distinguishable firm characteristics. In addition, the estimated coefficients in columns (2) and (4) have much smaller absolute value than the corresponding estimated coefficients in columns (1) and (3), suggesting that the decrease in the statistical significance is not just due to the drop in the sample size. The pseudo

R-square in the CFO (CEO) sample falls from 0.037 (0.095) for the pre-match sample to 0.010 (0.017) for the post-match sample. Second, we directly compare observable firm characteristics between the treatment and control groups. Panel B of Table 3 show that all the univariate difference test statistics are statistically insignificant. These two diagnostic tests suggest that the difference in crash risk between the treatment and control groups is only due to executive gender, not other observable firm characteristics.

Finally, we compare our three measures of stock price crash risk between firms in the treatment and control groups, and report the average treatment effects estimated by PSM in Panel C of Table 3. Consistent with our main findings, we find that firms with female CFOs are associated with significantly lower crash risk than those with male CFOs. However, there are no significant differences in crash risk between firms with female CEOs and those with male CEOs.

4.2.2. High-dimensional fixed effects

One weakness of our PSM analyses is that we only control for observed firm characteristics. If the correlation between executive gender and crash risk is affected by unobservable firm characteristics that can not be accounted for in our PSM procedure, then any hidden bias due to latent variables may still remain after matching. Gormley and Matsa (2014) recommend implementing a fixed effects model to mitigate the potential endogeneity concern due to unobserved heterogeneity across firms and time-varying heterogeneity across industries. We follow their advice and control for the firm and interacted industry-year fixed effects in Equation 4, our baseline panel model.

In column (1) of Table 4, we re-estimate the empirical association between $Crash_{T+1}$ and $FemaleCFO_T$ by controlling for firm and year fixed effects.[13] In columns (2) and (3) of Table 4, we re-estimate the OLS regressions for $Ncskew_{T+1}$ and $Duvol_{T+1}$ and control for unobserved time invariable firm characteristics and time varying industry effects (firm and year $\times$ Fama–French 48 industry dummies). Consistent with the results reported in Table

[13] Gormley and Matsa (2014) develop a computer memory-saving procedure to estimate high-dimensional fixed effects model. However their method is not compatible with the probit model.

2, the estimated coefficients of $FemaleCFO_T$ are negative and statistically significant at the 5% level across three measures of crash risk. For comparison, we also employ the high-dimensional fixed effects analyses in our CEO sample and report the results in columns (4)–(6) of Table 4. The relation between female CEOs and crash risk still remains statistically insignificant. Our main results are robust after controlling for unobserved firm characteristics.

4.2.3. Difference-in-differences

Our third identification method is to employ a difference-in-differences framework around the appointments of female executives to identify the effect of such executives on future stock price crash risk. We follow Huang and Kisgen (2013) and compare firm stock price crash risk before and after transitions from a male to female executive with a control sample of firms undergoing male-to-male executive transitions. The difference-in-differences approach compares firms' future crash risk for two similar groups with and without the appointment of female executives but would otherwise be subject to similar influence from executive turnovers. Therefore, any difference in the changes in future crash risk before and after the appointment of female executives is more likely due to the impact of female executives rather than the difference between the two groups prior to the appointment of female executives.

Over our sample period of 2006–2015, we first identify firm–year observations in which a firm experiences either a male-to-male or male-to-female executive transition. We require that a new executive keep his/her position for at least three consecutive years. The transition year T is defined as the first year when the new executive comes into power. Then we construct our difference-in-differences test sample as firm–year observations three years before and three years after an executive transition, excluding the transition year T. To be included in the sample, firms must have available accounting data in Compustat for at least two years before the transition year T. Our final CFO (CEO) difference-in-differences sample contains 637 (581) cases of male-to-male transitions and 99 (44) cases of male-to-female transitions.[14] Our difference-in-differences regression model is:

$$\begin{aligned}\text{Crash risk}_{j,T+1} =& \beta_0 + \beta_1 CFOPost_{j,T+1} + \beta_2 CFOTransition_j \times CFOPost_{j,T+1} + \\ & \gamma' \text{Control variables}_{j,T} + \mu_T + \theta_i + \epsilon_{j,T}\end{aligned} \tag{5}$$

where $CFOTransition_j$ is an indicator variable that equals one if firm j's transition year T is a male-to-female transition and zero if firm j's transition year T is a male-to-male transition, $CFOPost_{j,T+1}$ is an indicator variable that equals one if firm–year $T+1$ is after the CFO transition and zero otherwise. Consistent with Huang and Kisgen (2013), we control for firm (θ_i) and year (μ_T) fixed effects in Equation (5).[15]

Our difference-in-differences test has several advantages. First, we require a new executive to be in power for at least three years so that he/she has enough time to influence firm activities. Second, our sample covers multiple firm–years before and after the executive transitions, which offers us a balanced comparison and removes the potential noise in the year of executive transition. Last, our test design reduces time invariant unobservable firm effects by taking male-to-female transition firms as the treatment sample and male-to-male transition firms as the control sample. In other words, if the reduction of crash risk around the executive transition can be alternatively explained by a latent firm characteristic variable, it not only must have coincidentally changed over the transition but also be unrelated to the transition itself. Columns (1)–(3) of Table 5 present the results of our difference-in-differences tests for the CFO gender transition sample. The estimated coefficients of the product term $CFOTransition_j \times CFOPost_{j,T+1}$ are negative and statistically significant across three measures of crash risk, indicating that female CFOs reduce firms' future stock price crash risk at a significantly higher rate than male CFOs. We repeat our difference-in-differences tests in the CEO gender transition sample by replacing $CFOPost_{j,T+1}$ with $CEOPost_{j,T+1}$ in Equation (5). The test results are reported in columns (4)–(6) of Table 5.

[14]Due to the small number of female-to-male and female-to-female transitions in our sample, we can not examine the impact of a female-to-male transition on crash risk.

[15]After controlling for the firm fixed effects, it is not necessary to include $CFOTransition_j$ separately in Equation (5) (Huang and Kisgen, 2013).

The estimated coefficients of the product term $CEOTransition_j \times CEOPost_{j,T+1}$ are not statistically significant, suggesting that male-to-female CEO transition is not associated with the decrease in future crash risk.

One concern on this difference-in-difference approach is that some executive turnovers in our sample are not exogenous. For example, if a firm plans to change its corporate policies correlating to a lower level of crash risk, it may strategically hire a certain type of new executives. Therefore, the results of our difference-in-differences analysis may not establish the causal relationship between female CFOs and reduced crash risk. To mitigate this concern, we drop executive turnovers that are likely to be endogenous and restrict our difference-in-differences analysis to a subset of executive turnovers that are less likely to be related to firms' intention of reducing crash risk.[16]

For all executive turnovers in our original difference-in-differences sample, we search each of these cases on Factiva for articles mentioning the names of departing executives or their successions. We read these articles to determine the reasons for each executive turnover. Then we manually classify an executive turnover as an endogenous one if we can identify the following conditions: i) an executive is fired; ii) an executive resigns due to corporate policy differences; and iii) an executive resigns due to board pressure (Parrino, 1997). For the turnovers which we could not identify any of the above three conditions, we follow Parrino (1997) and take the turnovers as exogenous ones if the departing executives are above 60 years old at the time of the turnover. Turnovers in which the outgoing executive is under age 60 are reviewed further to identify as exogenous if the press reports the reason for departure as death, poor health, and the acceptance of another position, the press reports that the executive is retiring but does not announce the retirement within 6 months before the retirement, or the relevant articles convincingly explain the departures as due to reasons unrelated to the firms' activities (Parrino, 1997). The remaining turnovers are taken as endogenous turnovers.

Columns (7)–(12) of Table 5 reports the results of our difference-in-differences tests af-

[16]We thank the anonymous referee for suggesting this analysis.

ter dropping the endogenous executive turnovers from our turnover sample. The estimated coefficients of $CFOTransition_j \times CFOPost_{j,T+1}$ are all negative and statistically significant except in column (9). The estimated coefficients of $CEOTransition_j \times CEOPost_{j,T+1}$ remain statistically insignificant. Overall, our main findings are robust to the difference-in-differences specification.

5. Additional analyses and further discussions

So far, we have documented that firms with female CFOs have less future stock price crash risk than those with male CFOs, while CEO gender is not related to crash risk. In this section, we provide analyses and discussions that, in general, are aimed at establishing channels through which female CFOs curb firm bad news hoarding behavior and answering the question of whether our results are robust.

5.1. Sub-sample analyses

In this section, we divide our CFO sample into two sub-samples based on the median of corporate governance quality, product market competition, information asymmetry, and ex ante firm risk, respectively. Then we conduct sub-sample analyses to investigate whether the relation between CFO gender and crash risk can be explained by the variations in these important firm characteristics.[17]

5.1.1. Corporate governance

First, we examine whether the effect of CFO gender on crash risk is related to firms' corporate governance quality. Comparing to male CFOs, female CFOs tend to be more risk averse, less overconfident, and more likely to comply with financial reporting rules. These behavioral traits may naturally mitigate the agency problems such as managerial risk taking and bad news hoarding activities. According to agency theory, we expect to

[17] Untabulated F-test results suggest that the difference of the impact of CFO gender on crash risk between the two subsamples are statistically significant.

observe more managerial risk taking and bad news hoarding activities when firms lack effective governance monitoring mechanisms. For behavioral CFOs to have a material impact on firm crash risk, corporate governance must be limited in its ability to constrain them into making rational decisions (Baker and Wurgler, 2012). Therefore, we posit that the relation between CFO gender and future stock price crash risk is stronger for firms with worse governance monitoring mechanisms.

We use two proxies for corporate governance quality. The first proxy, $Eindex_T$, is the managerial entrenchment index composed of the six most important anti-takeover provisions in the G-index (Gompers et al., 2003; Bebchuk et al., 2009). When a firm has more firm-level anti-takeover provisions, it has a higher $Eindex$ but poorer corporate governance. The second proxy, Dio_T, measures a firm's monitoring institutional ownership, which is the percentage of shares outstanding held by dedicated and quasi-index institutional investors at the end of the fiscal year. Bushee (1998) classifies institutional investors into three categories: dedicated, quasi-index, and transient. Following Chen et al. (2007), we combine dedicated and quasi-index institutions together and take them as monitoring institutional investors.

Panel A of Table 6 presents the relation between CFO gender and crash risk in high and low $Eindex$ sub-samples. The estimated coefficients of $FemaleCFO_T$ are negative for both sub-samples. However, the coefficients are only statistically significant in the high $Eindex$ sub-sample for all three measures of crash risk. Panel B of Table 6 reports the results of sub-sample analyses for firms with high and low monitoring institutions' ownership. A higher proportion of monitoring institutional holdings indicates better corporate governance quality. The estimated coefficients of $FemaleCFO_T$ are negative for both sub-samples, but only statistically significant for sub-samples with low monitoring institutional ownership. In both Panel A and B, the absolute value of the estimated coefficients of $FemaleCFO_T$ is much greater in the low corporate governance quality sub-samples than in the corresponding high corporate governance quality sub-samples. Taken as a whole, our findings indicate that the impact of female CFOs on crash risk is associated with corporate governance quality. Managerial bad news hoarding activities are more likely to be observed in firms with less internal and external monitoring mechanisms.

5.1.2. Product market competition

Second, we study whether the empirical association between CFO gender and crash risk is different for firms in non-competitive and competitive industries. Because firms operating in a competitive product market have a higher probability of being driven out of the business, product market competition may mitigate managerial slack and conflict of interest (Giroud and Mueller, 2010). Giroud and Mueller (2011) show that the benefits of corporate governance are significantly larger for firms facing lower product market competition. Consistent with this notion, Li (2010) finds that market competition improves corporate disclosure quality, and in turn reduces information asymmetry between insiders and outsiders. Kim et al. (2014) also find that the negative relation between CFO option incentives and crash risk is only statistically significant for firms in low competitive industries.

We define $Competition_T$ as the Herfindahl-Hirschman index estimated by firms' total sales over the fiscal year within the same industry. A greater $Competition_T$ is associated with a lower degree of product market competition. Panel C of Table 6 shows that the estimated coefficients of $FemaleCFO_T$ are all negative but only statistically significant in the low product market competition sub-samples. The absolute value of the estimated coefficients is also greater for the sub-sample of firms in non-competitive industries than for those in competitive industries. This finding suggests that executive gender interacts with the corporate governance mechanism and that firms in non-competitive industries benefit more from female executives than do firms in competitive industries.

5.1.3. Information asymmetry

Third, we examine the impact of a firm's asymmetric information on the relation between CFO gender and crash risk. When outside investors are less informed, they have to exert more effort and incur a higher cost to monitor firm managers. Therefore, we expect to observe more bad news hoarding activities for firms facing greater asymmetric information. According to Lang et al. (2003), financial analyst coverage reduces information asymmetry between managers and outside investors. Yu (2008) further finds that firms followed by more financial analysts manage their earnings less.

We use a firm's financial analyst coverage as the proxy for firm-level information asymmetry. $Analyst_T$ is calculated as the natural logarithm of one plus the number of following analysts who issue earnings forecasts for the firm during the fiscal year. A lower $Analyst_T$ indicates a higher level of information asymmetry. Panel D of Table 6 presents the relation between CFO gender and crash risk in above- and below-median analyst coverage sub-samples. The estimated coefficients of $FemaleCFO_T$ are all negative but only statistically significant in the below-median analyst coverage sub-samples. Across three measures of crash risk, the absolute value of the estimated coefficients is significantly greater in the below-median analyst coverage sub-sample than in the above-median analyst coverage sub-sample. These findings lend further support to our main hypothesis that female CFOs tend to engage in less bad news hoarding activities.

5.1.4. Firm risk

Last, we investigate whether firm riskiness has an impact on the relation between CFO gender and crash risk. Gender difference in risk attitudes has been extensively studied in the earlier psychology and economics literatures. Most studies support the view that women are relatively more risk averse and less overconfident than men (e.g., Croson and Gneezy, 2009; Huang and Kisgen, 2013). On the one hand, firms run by female CFOs may undertake less risky projects than those run by male CFOs in the first place, hence we naturally observe less activities of hiding risk taking behavior in firms run by female CFOs. One the other hand, given the same ex ante incentives to hide risk taking, female CFOs are more likely to choose not to do so. Both possibilities lead to the same prediction that the negative relation between CFO gender and crash risk is more pronounced for firms with higher ex ante incentives to hide risk taking activities.

Empirically, we use firm existing financial leverage, $Leverage_T$, as a proxy for firm riskiness. Panel E of Table 6 reports the sub-sample analysis of the relation between CFO gender and crash risk for above- and below-median leverage firms. The estimated coefficients of $FemaleCFO_T$ are negative in both sub-samples, but they are only statistically significant for above-median leverage firms. The absolute value of the estimated coefficients is also greater for the sub-sample of firms with high leverage than for those with low leverage. Our results suggest that the impact of CFO gender on future crash risk is more concentrated in firms with high risk profiles.

5.2. Managerial characteristics and board gender diversity

One of the key findings in our paper is that CFO gender is more strongly related to future crash risk than CEO gender. Our study supports the work by Kim et al. (2011a), who also examine the different roles of CEO and CFO in moderating crash risk. Kim et al. (2011a) find that CFOs' pay for performance sensitivity, measured by the sensitivity of option portfolio value to stock price, is significantly and positively associated with future crash risk, while the relation between CEOs' pay for performance sensitivity and future crash risk is weak. To rule out the possibility that our results are driven by CFOs' compensation incentives, we directly control for CFOs' option incentive ($CFO\_Opt\_Inc_T$) in Equation (4). Previous crash risk studies usually do not control for CFO managerial characteristics. A recent work by Andreou et al. (2016) shows that firms with older CEOs are less likely to experience future stock price crashes. Armstrong and Vashishtha (2012) also find that manager tenure is negatively related to firm systematic and idiosyncratic risk. We further add CFO_Age_T and CFO_Tenure_T as control variables in Equation (4). CFO age and tenure may also proxy for CFO work experience and expertise, which may partly explain the impact of CFO gender on future crash risk. Columns (1)–(3) of Table 7 present the regression results of Equation (4) after controlling for $CFO\_Opt\_Inc_T$, CFO_Age_T, and CFO_Tenure_T. The estimated coefficients of $FemaleCFO_T$ remain negative and statistically significant across all three measures of crash risk. However, the coefficients of $CFO\_Opt\_Inc_T$ are all statistically insignificant. It seems that the relation between CFO pay for performance sensitivity and crash risk is weak if we include CFO gender into consideration.[18] Furthermore, there is no evidence that CFO age and tenure have a significant effect on future stock price crash risk.

Bebchuk et al. (2011) find that the CEO pay slice may reflect the extent to which the CEO is able to extracts rents. Therefore, the variation in the CEO pay slice may help to explain the empirical relationship between CFO characteristics and firm financial reporting quality. In columns (4)–(6), we control for $CEO\_Payslice_T$, the annual compensation of a CEO divided by the sum of top five executives' annual compensation. The estimated coefficients of $FemaleCFO_T$ remain negative and statistically significant across all three measures of crash risk. The coefficients of $CEO\_Payslice_T$ are all positive but only statistically significant in columns (4) and (6).

Previous studies show that board gender diversity affects corporate decisions. Gul et al. (2011) find that stock prices of firms with gender-diverse boards reflect more firm-specific information. Levi et al. (2014) use mergers and acquisitions as their empirical setting and show that boards with female directors can mitigate managerial empire building activities. Chen et al. (2017) show that female independent directors are more likely to impose high dividend payouts. Therefore, it is important for us to differentiate the effect of CFO gender from the effect of board gender diversity on stock price crash risk. We collect director-level data from ISS (formerly RiskMetrics), which provides director profiles for S&P 1500 firms including director name, title, gender, and committee membership, etc. We construct variable $Female\_Director_T$, the ratio of female independent director number to the board size (Chen et al., 2017), for 10,172 firm-year observations and 1,601 unique firms in our main sample. The number of firm-year observations with female CFOs on

[18]Nevertheless, the sample period of Kim et al. (2011a) is 1993–2009 and our sample covers 2006–2015. Jiang et al. (2010) find that executives' equity incentives are not positively associated with the magnitude of accruals during the post-SOX period. Therefore, we remain cautious about over interpreting and generalizing this result.

board is only 81 and the number of unique firms with female CFOs on board is only 33, supporting the view that CFOs do not usually serve as the board of directors at their own companies.[19] Furthermore, we examine whether CFO gender has a significant effect on crash risk after controlling for board gender diversity. In columns (7)–(9), we include $Female\_Director_T$ as a control variable in Equation (4). The coefficients of $FemaleCFO_T$ remain negative and statistically significant in columns (7) and (8). When the dependent variable is $Duvol_{T+1}$, the coefficient of $FemaleCFO_T$ is negative with t-statistics being -1.492. We do not find evidence that female independent directors on board have a significant effect on crash risk.

Finally, we control for CFO characteristics, CEO pay slice, and board gender diversity together in columns (10)–(12). Our main results remain robust. In summary, the results in Table 7 indicate that female CFOs moderate firm future crash risk even after controlling for a battery of managerial characteristics and board gender diversity.[20]

5.3. Female CFOs and bad news hoarding

Previous crash risk studies support the view that firm stock price crashes are caused by bad news hoarding. To establish a channel through which female CFOs mitigate future stock price crash risk, this section conducts analyses on the relation between female CFOs and the probability of firm earnings' restatement.[21] One important way that managers hide bad news is to manipulate firms' reported earnings. When the bad news accumulates to a critical level and eventually managers give up, it is likely that firms will restate their earnings to the fundamental value. Therefore, female CFOs may reduce crash risk by limiting misreporting and increasing financial statement quality.

We examine whether firms with female CFOs are less likely to restate their earnings.

[19] According to a 2012 survey study by executive recruitment firm Spencer Stuart, just 19 CFOs of the Fortune 500 companies sit on their boards, dropping from 37 in 2005

[20] Due to the data availability, we cannot formally rule out the possibility that our findings are explained by CFO financial expertise such as previous work experience, education, and certifications.

[21] Huang and Kisgen (2013) and Faccio et al. (2016) provide the evidence of another channel that firms with female executives take less risk than those with male executives.

Our earnings restatement data is collected from Audit Analytics, which covers only events when firms correct their misstated financial statements. We further drop all clerical application errors and include only accounting rule application failures and financial fraud to ensure that our restatement sample includes material generally accepted accounting principles (GAAP) misapplications and not unintentional reporting errors (e.g., Bens et al., 2012). We define $Restatement_{T+1}$ as an indicator variable that equals one if the beginning date of a misstatement period falls within fiscal year $T+1$ and zero otherwise.

Table 8 presents the marginal effects from the probit regression of $Restatement_{T+1}$ on $FemaleCFO_T$. In column (1), we do not include any control variables. In column (2), we add control variables $Size_T$, Mtb_T, $Leverage_T$, OCF_T, $Loss_T$, and $Bigfour_T$. In column (3), we further add control variables related to firm managers: $CFO\_Opt\_Inc_T$, CFO_Age_T, and CFO_Tenure_T. The marginal effects of female CFOs on the likelihood of earnings restatements are negative and statistically significant across all three columns. Using column (3) as an example, a firm run by a female CFO is associated with a 2.0% decrease in the likelihood of earnings restatements, as compared to a firm run by a male CFO. Given that the sample mean of the restatement probability is 6.5%, the effect of female CFOs in reducing the restatement probability is economically significant. Overall, the results in Table 8 provide evidence that female CFOs reduce crash risk by mitigating bad news hoarding and improving financial reporting quality channels.

5.4. Overconfidence vs. risk aversion

We argue that firms with female CFOs are less likely to experience future stock price crashes because female CFOs are less risk averse, less overconfidence, and more compliant with financial reporting regulations. In the previous section, we have shown that firms with female CFOs are less likely to restate their earnings, providing a direct evidence that female CFOs are more compliant with financial reporting regulations. In this section, we focus on the other two traits and examine whether risk aversion or overconfidence is more important in affecting crash risk.

To measure CFO risk aversion, we adopt $Delta$ and $Vega$ of a CFO's stock option portfolio. Following Core and Guay's (2002) one-year approximation method, $Delta$ ($Vega$) is defined as the value increase in a CFO's option portfolio for a 1% increase in the underlying stock price (stock return volatility). Previous studies suggest that large $Delta$ discourages managerial risk taking, while large $Vega$ encourages risk taking. To measure CFO overconfidence, we adopt a CFO stock option proxy following Malmendier and Tate (2005) and Hirshleifer et al. (2012). Specifically, our measure of overconfidence is based on CFOs' revealed beliefs captured by their preference not to exercise deep in-the-money stock options timely. We exploit information about all outstanding options held by CFOs that are directly observable starting in 2006 due to requirements from the FAS 123R. We define an indicator variable, $Overconfidence$, which is equal to one if a CFO, at least once during our sample period, holds an option until the year of expiration, even though the stock option is at least 67% in-the-money entering its final year; and zero otherwise.[22] Next, we run the following two regressions:

$$\text{CFO gender}_{j,T} = \beta_0 + \beta_1 \text{Delta}_{j,T} + \beta_2 \text{Vega}_{j,T} + \theta_i + \mu_T + \epsilon_{j,T} \tag{6}$$

$$\text{CFO gender}_{j,T} = \beta_0 + \beta_1 \text{Overfidence}_{j,T} + \theta_i + \mu_T + \epsilon_{j,T} \tag{7}$$

where θ_i are Fama–French 48 industry fixed effects and μ_T are year fixed effects. The residual term estimated in Equation (6) represents the variation in CFO gender which cannot be explained by CFO's risk aversion. Similarly, the residual term estimated in Equation (7) represents the variation in CFO gender which cannot be explained by CFO's overconfidence. Next, we replace $Executive\ gender_{j,T}$ in Equation (4) by one of these two residual terms. We reestimate Equation (4) and report the regression results in Table 9.

[22] Following Campbell et al. (2011), we compute option moneyness as follows. The realizable value per option is defined as the total realizable value of all unexercised but exercisable options divided by the number of exercisable options held by a CFO. The average strike price is estimated as the fiscal year-end stock price minus the average realizable value per option. We then calculate the average percent moneyness of the options as the per-option realizable value divided by the estimated average exercise price. Since we are interested in exercisable options that CFO can exercise, we only focus on vested options held by CFOs.

In columns (1)–(3), the residual term is estimated in Equation (6) and all of its coefficients are all negative and statistically significant. After we remove the variation in risk aversion from CFO gender, the variation in CFO gender which cannot be explained by risk aversion still has a negative impact on future stock price crash risk. However, the absolute values of these coefficients are less than the absolute values of $FemaleCFO_T$'s coefficients reported in the columns (1)–(3) of Table 2, suggesting that risk aversion does play a certain role in affecting crash risk. In columns (4)–(6), we find that the coefficients of the residual term estimated in Equation (7) are statistically insignificant. After we remove the variation in overconfidence from CFO gender, the variation in CFO gender which cannot be explained by overconfidence is not related to future stock price crash risk. These results suggest that CFO overconfidence is an important the channel through which CFO gender affects crash risk, which is consistent with Kim et al.'s (2016) findings that firms with overconfident CEOs have higher crash risk than firms with nonoverconfident CEOs. Furthermore, comparing the coefficients of $Residual_T$ between columns (1)–(3) and columns (4)–(6), we find that overconfidence is more important than risk aversion in terms of explaining the empirical relation between CFO gender and crash risk.

5.5. Powerful CEOs

In our paper, we find that the impact of CFO gender on crash risk is statistically significant while the impact of CEO gender on crash risk is not. Our result is consistent with the results of Kim et al. (2011a) that CFO equity incentives are strongly associated with higher firm crash risk, while the relation between CEO equity incentives and crash risk is much weaker. Feng et al. (2011) document that CFOs may involved in material accounting manipulations because they succumb to pressure from CEOs. While we cannot directly observe the interactions between CEOs and CFOs to explain why CFOs become involved in bad news hoarding activities, we provide indirect evidence to identify whether our main finding is due to CFO acquiescing to CEO pressure. To explore the interactive relationship between CEOs and CFOs, we follow Feng et al. (2011) and classify powerful

CEOs as those who are both a firm's CEO and chairman of the board. Untabulated results suggest that the impact of CFO gender on crash risk is statistically significant for the firms with non-dual-role CEOs, while the impact of CEO gender on crash risk is not statistically significant for the firms with dual-role CEOs. Our results support our prediction that CEOs may overpower the influence of CFOs on crash risk.

5.6. Alternative crash risk measures

In this section, we explore the alternative crash risk definitions in the previous studies. First, we follow Kim et al. (2011b) and identify crash weeks in fiscal year T for firm j as those weeks during which the firm-specific weekly return $W_{j,t}$ is 3.20 standard deviations below the average firm-specific weekly returns over the fiscal year T. Then we redefine $Crash_{T+1}$ as $Crash\_3.20_{T+1}$ using 3.20 as the threshold. Second, we follow Callen and Fang (2015) and estimate firm-specific weekly returns by adding Fama–French 10 industry returns in Equation (1). Then we redefine $Ncsckew_{T+1}$ and $Duvol_{T+1}$ as $Ncsckew\_FF10_{T+1}$ and $Duvol\_FF10_{T+1}$ using the firm-specific weekly returns estimated by the expanded market and industry index model. Third, we redefine $Crash_{T+1}$ as $Crash\_3.20\&FF10_{T+1}$ using both 3.20 as the threshold and the firm-specific weekly returns estimated by the expanded market and industry index model. Fourth, we follow Hutton et al. (2009) and define $Count_{T+1}$ as the number of firm-specific weekly returns exceeding 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year. Finally, we follow Kim et al. (2011b) and extend our measurement interval of future crash risk into two- and three-year-ahead forecast windows.[23] We use all these alternative crash risk measures as the dependent variables in Equation (4). Untabulated results suggest that the estimated coefficients of $FemaleCFO_T$ are all negative and statistically significant. Our results remain robust for these alternative definitions of crash risk.

[23] If firm managers withhold bad news for extended periods, then the effect of bad news hoarding on stock price will persist for a longer period of time. Given an average tenure of female CFOs as 4.7 years in our sample, it is likely that female CFOs may influence crash risk for more than one year in the future.

5.7. Discussion

In this paper, we argue that female executives' behavioral traits, such as risk aversion, lack of self-confidence, and the tendency for compliance, affect their decisions and firm stock price crash risk. We caution, however, that social norms may be a potential driver of our results. The expectations by society about what is appropriate for women to do (Altonji and Blank, 1999; Akerlof and Kranton, 2000), may affect not only a woman's intention to work, but also her choice of occupations (CEO or CFO). Due to the invisible yet unavoidable glass ceiling, female firm managers who reach the top echelon of the corporate hierarchy may be more competent and work harder than their male peers (e.g., Green et al., 2009; Kumar, 2010). Given the data available to us, we cannot empirically rule out this competency story as the alternative explanation of our results. However, the competency concern is mitigated to a certain degree given that previous studies fail to draw a conclusion that teams with female members perform better than those with male members (e.g., Adams and Ferreira, 2009). Furthermore, some firms may have a target for their executive gender diversity ratios. If these firms do not find enough female executive candidates in the labor market, then the competence of their female executives would be actually lower than that of male executives.

Previous stock price crash risk studies have applied an agency theory framework to explore the firm side explanations of stock price crashes. The rational explanations of managerial bad news hoarding activities include (but are not limited to) limited investor protection (Jin and Myers, 2006), opaqueness in financial reports (Hutton et al., 2009), executive compensation incentive (Kim et al., 2011a), corporate tax avoidance (Kim et al., 2011b), International Financial Reporting Standards (DeFond et al., 2015), and auditor–client relationship (Callen and Fang, 2017). These studies assume that managers are rational and can make managerial decisions accurately based on firm inside information. The agency conflicts that managers try to benefit themselves at the costs of shareholders lead to the managerial bad news hoarding activities.

Our paper suggests that executive gender is an alternative behavioral explanations of stock price crashes. Among the three behavioral traits related to executive gender, the tendency for compliance is directly related to the agency conflicts, while risk aversion and overconfidence are beyond the scope of the rational explanations in the previous crash risk literature. Baker and Wurgler (2012) describe irrational managerial behaviors in the behavioral finance theories as those departing from rational expectations and expected utility maximization of the manager. Risk loving and overconfident managers fall into the situations where a manager believes that he is actually maximizing firm value but is, in fact, deviating from the optimal equilibrium (Baker et al., 2007; Baker and Wurgler, 2012). Both the degree of risk aversion and overconfidence level are naturally related to managerial risk-taking activities. The documented association between CFO gender and stock price crash risk, as an explanation based on behavioral corporate finance, complements prior stock price crash theories.

6. Conclusions

In this paper, we focus on the ongoing debate about gender diversity and its impact on stock returns. We examine whether executive gender has an impact on asset prices by reducing firm future stock price crash risk. Using a large sample of US public firms during 2006–2015, we find a negative association between female CFOs and future crash risk than those with male CFOs, while CEO gender does not contribute to crash risk. Our main results are robust after controlling for the endogeneity between executive gender and crash risk. These results are consistent with the view that female CFOs are less aggressive in making business and finance decisions and are more cautious in the disclosure of firm information. We further find that the empirical relation between CFO gender and crash risk is more pronounced for firms with weaker corporate governance, less product market competition, lower financial analyst coverage, and higher firm leverage. These findings enrich our understanding of the influence of executive gender on crash risk and shed light on how firm internal governance, external monitoring mechanisms, as well as risk profiles interact with executive gender to mitigate the agency problem.

We contribute to the literature by examining the implication of executive gender on firm stock returns, a previously unexplored area. Our findings complement prior studies that examine the impact of executive gender on corporate decision making activities and document the different roles of CEOs and CFOs in firm operations. Our findings suggest that female and male executives make corporate decisions differently, which affects firm asset returns in a higher moment. Our study also has two important implications for legislators and regulators. First, it may be beneficial for firms to run by a gender diversified management team. Second, our evidence that firm CFOs have a substantial impact on firm crash risk caused by bad news hoarding activities supports the current Sarbanes-Oxley requirement that a firm's CEO and CFO need to file individual certifications about the firm's financial statements.

Highlights

- Female CFOs curb bad news hoarding and affect stock return distribution.
- Firms with female CFOs experience lower future stock price crash risk.
- The impact of female CEOs on crash risk is not statistically significant.

Appendix A

Table A1. Variable definitions

This table provides variable definitions and corresponding data sources. CRSP refers to the Centre for Research in Security Prices, ExecuComp refers to Standard and Poor's Executive Compensation database, ISS refers to the Institutional Shareholder Services (formerly RiskMetrics), I/B/E/S refers to the Institutional Brokers' Estimate System, s34 files refer to the Thomson Reuters 13F Database, and Bushee's website refers to http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.

Variable	**Definition**	**Source**
$Crash_{T+1}$	An indicator variable that equals one if a firm experiences one or more firm-specific weekly returns exceeding 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year and zero otherwise, with 3.09 chosen to generate frequencies of 0.1% in a normal distribution (Hutton et al., 2009).	CRSP
$Ncskew_{T+1}$	The negative coefficient of skewness of firm-specific weekly returns over the fiscal year (Chen et al., 2001).	CRSP
$Duvol_{T+1}$	The natural logarithm of the ratio of the standard deviation of firm-specific weekly returns for the "down-week" sample to the standard deviation of firm-specific weekly returns for the "up week" sample over the fiscal year (Chen et al., 2001).	CRSP
$FemaleCFO_T$	An indicator variable that equals one if a CFO is female and zero otherwise.	ExecuComp
$FemaleCEO_T$	An indicator variable that equals one if a CEO is female and zero otherwise.	ExecuComp
$Dturn_T$	The difference between the average monthly share turnover over fiscal year $T-1$ and the average monthly share turnover over fiscal year T, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding over the month (Kim et al., 2011a).	CRSP
$Sigma_T$	The standard deviation of firm-specific weekly returns over the fiscal year (Kim et al., 2011a).	CRSP
$Return_T$	The mean of firm-specific weekly returns over the fiscal year, times 100 (Kim et al., 2011a).	CRSP
$Size_T$	The natural logarithm of market capitalization at the end of the fiscal year (Kim et al., 2011a).	Compustat
Mtb_T	The ratio of the market value of equity to the book value of equity measured at the end of the fiscal year (Kim et al., 2011a).	Compustat

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Table A1 - continued from previous page

Variable	Definition	Source
$Leverage_T$	The ratio of long-term debt to total assets measured at the end of the fiscal year (Kim et al., 2011a).	Compustat
Roa_T	The ratio of income before extraordinary items divided by lagged total assets (Kim et al., 2011a), measured at the end of the fiscal year.	Compustat
$Accm_T$	The prior three years' moving sum of the absolute value of discretionary accruals, where discretionary accruals are estimated from the modified Jones's (1991) model (Dechow et al., 1995).	Compustat
$Litigationrisk_T$	An indicator variable that equals one for firms in the biotechnology (4-digit SIC codes 2833–2836 and 8731–8734), computer (4-digit SIC codes 3570–3577 and 7370–7374), electronics (4-digit SIC codes 3600–3674), and retail (4-digit SIC codes 5200–5961) industries, and zero otherwise (Francis et al., 1994).	Compustat
$Eindex_T$	An entrenchment index composed of the six most important provisions in the *G-index* (Bebchuk et al., 2009).	ISS
$Analyst_T$	The natural logarithm of one plus the number of following analysts who issue earnings forecasts during the fiscal year.	I/B/E/S
$Competition_T$	The Herfindahl-Hirschman index estimated by firms' total sales over the fiscal year within the same industry.	Compustat
Dio_T	The percentage of shares outstanding held by dedicated and quasi-index institutional investors at the end of the fiscal year (Bushee, 1998).	s34 files & Bushee's website
$CFO\_Opt\_Inc_T$	The incentive ratio for CFO option holdings, which is calculated as Onepct_Opt/(Onepct_Opt+Salary+Bonus). The variable Onepct_Opt is the dollar change in the value of CFO option holdings resulting from a 1% increase in the firm's stock price (Kim et al., 2011a).	ExecuComp
CFO_Age_T	The CFO age.	ExecuComp
CFO_Tenure_T	The number of years in a CFO post with a particular firm.	ExecuComp
$CFOTransition$	An indicator variable that equals one if a firm is a male-to-female CFO transaction firm and zero if a firm is a male-to-male CFO transaction firm (Huang and Kisgen, 2013).	ExecuComp
$CFOPost_{T+1}$	An indicator variable that equals one if firm–years are after the CFO transition and zero otherwise (Huang and Kisgen, 2013).	ExecuComp
$CEO\_Payslice_T$	The ratio of a CEO's annual compensation to the sum of top five executives' annual compensation.	ExecuComp
$Female\_Director_T$	The ratio of female independent director number to the board size (Chen et al., 2017).	ISS

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Table A1 - continued from previous page

Variable	Definition	Source
$Restatement_{T+1}$	An indicator variable that equals one if a firm restates its earnings and zero otherwise.	Audit Analytics
OCF_T	The operating cash flow scaled by total assets.	Compustat
$Loss_T$	An indicator variable that equals one if a firm's earnings are negative and zero otherwise.	Compustat
$Bigfour_T$	An indicator variable that equals one if a firm is audited by a Big Four auditor and zero otherwise.	Compustat

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Table 1. Summary statistics

This table reports summary statistics of stock price crash risk variables, executive gender variables, and the other variables used in our empirical tests. Our main sample consists of 12,745 firm–year observations covered by ExecuComp over the period 2006–2015 with available CFO gender and other variable information. The number of observations, mean, standard deviation, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentile are reported from left to right, in sequence for each variable. Detailed definitions of all variables are described in Appendix A.

Variables	**Obs.**	**Mean**	**S.D.**	**p5**	**p25**	**Median**	**p75**	**p95**
Crash risk measures								
$Crash_{T+1}$	12,745	0.254	0.435	0.000	0.000	0.000	1.000	1.000
$Ncskew_{T+1}$	12,745	0.098	0.866	-1.174	-0.375	0.051	0.511	1.555
$Duvol_{T+1}$	12,745	0.004	0.380	-0.596	-0.247	-0.006	0.245	0.643
CEO & CFO gender variables								
$FemaleCEO_T$	13,018	0.034	0.181	0.000	0.000	0.000	0.000	0.000
$FemaleCFO_T$	12,745	0.089	0.284	0.000	0.000	0.000	0.000	1.000
Other variables								
$Dturn_T$	12,745	0.001	0.101	-0.130	-0.036	0.000	0.034	0.134
$Ncskew_T$	12,745	0.095	0.832	-1.132	-0.366	0.040	0.483	1.518
$Sigma_T$	12,745	0.040	0.020	0.017	0.026	0.036	0.049	0.077
$Return_T$	12,745	-0.097	0.128	-0.290	-0.115	-0.062	-0.032	-0.014
$Size_T$	12,745	7.727	1.508	5.437	6.621	7.603	8.741	10.410
Mtb_T	12,745	2.844	2.333	0.834	1.437	2.174	3.419	7.140
$Leverage_T$	12,745	0.203	0.163	0.000	0.048	0.192	0.318	0.496
Roa_T	12,745	0.057	0.075	-0.063	0.024	0.054	0.095	0.180
$Accm_T$	12,745	0.146	0.215	0.029	0.064	0.108	0.181	0.376
$Litigationrisk_T$	12,745	0.283	0.451	1.000	0.000	0.000	1.000	1.000
$Eindex_T$	9,776	2.726	1.251	1.000	2.000	3.000	4.000	5.000
$Analyst_T$	12,745	1.964	0.974	0.000	1.386	2.197	2.708	3.258
Dio_T	12,745	0.523	0.234	0.000	0.442	0.574	0.675	0.814
$Competition_T$	12,745	0.120	0.103	1.000	0.066	0.093	0.137	0.282
$CFO\_Opt\_Inc_T$	12,745	0.072	0.096	1.000	0.006	0.039	0.100	0.261
CFO_Age_T	12,015	51.021	6.584	40	46	51	56	62
CFO_Tenure_T	12,015	4.723	3.426	1	2	4	7	11
$CEO\_Payslice_T$	12,671	0.396	0.115	0.203	0.332	0.401	0.461	0.574
$Female\_Director_T$	10,172	0.122	0.098	0	0	0.111	0.200	0.300
$Restatement_{T+1}$	12,745	0.065	0.247	0	0	0	0	1
OCF_T	12,745	0.099	0.075	0	0.056	0.096	0.140	0.224
$Loss_T$	12,745	0.131	0.338	0	0	0	0	1
$Bigfour_T$	12,745	0.918	0.274	0	1	1	1	1

Table 2. Female executives and stock price crash risk

This table reports the panel regression results of the impact of female executives on future stock price crash risk. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. The dependent variables are three measures of stock price crash risk: $Crash_{T+1}$, $Ncskew_{T+1}$, and $Duvol_{T+1}$. The independent variables of interests are CFO and CEO gender indicators: $FemaleCFO_T$ and $FemaleCEO_T$. We use logit regressions in columns (1), (4), and (7), and OLS regressions in columns (2)–(3), (5)–(6), and (8)–(9). The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO sample			CEO sample			CFO & CEO		
Variables	**(1)** $Crash_{T+1}$	**(2)** $Ncskew_{T+1}$	**(3)** $Duvol_{T+1}$	**(4)** $Crash_{T+1}$	**(5)** $Ncskew_{T+1}$	**(6)** $Duvol_{T+1}$	**(7)** $Crash_{T+1}$	**(8)** $Ncskew_{T+1}$	**(9)** $Duvol_{T+1}$
$FemaleCFO_T$	-0.155**	-0.057**	-0.023*				-0.158**	-0.058**	-0.024**
	(-2.083)	(-2.132)	(-1.948)				(-2.120)	(-2.172)	(-1.993)
$FemaleCEO_T$				0.087	0.042	0.022	0.110	0.046	0.023
				(0.764)	(0.919)	(1.117)	(0.957)	(0.992)	(1.177)
$Dturn_T$	-0.010	0.020	0.004	0.242	0.085	0.029	-0.008	0.021	0.004
	(-0.045)	(0.269)	(0.102)	(1.013)	(1.163)	(0.834)	(-0.037)	(0.279)	(0.112)
$Ncskew_T$	0.027	0.025**	0.009**	0.041	0.027***	0.010**	0.026	0.025**	0.009**
	(1.067)	(2.337)	(2.001)	(1.644)	(2.586)	(2.231)	(1.058)	(2.328)	(1.990)
$Sigma_T$	25.296***	5.373***	1.652***	11.393***	3.046**	0.862	25.284***	5.365***	1.648***
	(5.461)	(3.989)	(2.969)	(2.677)	(2.456)	(1.575)	(5.454)	(3.982)	(2.961)
$Return_T$	2.814***	0.516***	0.179**	1.557**	0.361**	0.126*	2.813***	0.515***	0.179**
	(3.571)	(2.758)	(2.345)	(2.199)	(2.231)	(1.683)	(3.566)	(2.753)	(2.340)
$Size_T$	0.061***	0.020***	0.011***	0.013	0.010	0.007**	0.061***	0.020***	0.011***
	(3.334)	(3.027)	(3.585)	(0.700)	(1.504)	(2.403)	(3.339)	(3.030)	(3.588)
Mtb_T	-0.015	-0.001	0.000	-0.011	-0.002	-0.000	-0.015	-0.002	0.000

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Table 2 - continued from previous page

	CFO sample			CEO sample			CFO & CEO		
Variables	**(1)** $Crash_{T+1}$	**(2)** $Ncskew_{T+1}$	**(3)** $Duvol_{T+1}$	**(4)** $Crash_{T+1}$	**(5)** $Ncskew_{T+1}$	**(6)** $Duvol_{T+1}$	**(7)** $Crash_{T+1}$	**(8)** $Ncskew_{T+1}$	**(9)** $Duvol_{T+1}$
	(-1.441)	(-0.345)	(0.046)	(-1.124)	(-0.469)	(-0.035)	(-1.465)	(-0.362)	(0.025)
$Leverage_T$	-0.027	-0.067	-0.053**	-0.047	-0.067	-0.053**	-0.027	-0.066	-0.053**
	(-0.185)	(-1.203)	(-2.154)	(-0.322)	(-1.231)	(-2.195)	(-0.179)	(-1.189)	(-2.138)
Roa_T	1.498***	0.675***	0.318***	1.193***	0.623***	0.303***	1.503***	0.677***	0.319***
	(4.705)	(5.562)	(5.887)	(3.792)	(5.160)	(5.711)	(4.717)	(5.573)	(5.900)
$Accm_T$	0.127	0.068*	0.033**	0.198**	0.088**	0.038**	0.128	0.068*	0.033**
	(1.461)	(1.710)	(2.138)	(2.364)	(2.372)	(2.563)	(1.469)	(1.719)	(2.149)
$Litigationrisk_T$	-0.053	-0.050	-0.017	-0.050	-0.052	-0.017	-0.051	-0.050	-0.017
	(-0.573)	(-1.234)	(-0.999)	(-0.544)	(-1.286)	(-1.020)	(-0.552)	(-1.216)	(-0.978)
Intercept	-1.999***	-0.235	-0.107	-1.237***	-0.087	-0.056	-1.999***	-0.235	-0.107
	(-4.551)	(-1.485)	(-1.503)	(-2.875)	(-0.565)	(-0.804)	(-4.551)	(-1.484)	(-1.502)
Observations	12,745	12,745	12,745	13,018	13,018	13,018	12,745	12,745	12,745
Pseudo/Adjusted-R^2	0.025	0.013	0.015	0.021	0.011	0.014	0.025	0.013	0.015
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Executive gender and crash risk: Propensity score matching estimators

Panel A. Pre-match propensity score regressions and post-match diagnostic regressions. This panel reports the parameter estimates from the probit model used to estimate the propensity scores. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. The dependent variables are CFO gender indicators, $FemaleCFO_T$, in columns (1)–(2), and CEO gender indicators, $FemaleCEO_T$, in columns (3)–(4). The independent variables are all the firm characteristics included in our panel regression analyses. We use one-to-one match and require that the difference between the propensity score of the firm run by a female executive and its matching peer does not exceed 0.5% in absolute value. Columns (1) and (3) report the pre-match propensity score regressions. Columns (2) and (4) report the post-match diagnostic regressions. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO sample		**CEO sample**	
	Pre-match	Post-match	Pre-match	Post-match
	(1)	**(2)**	**(3)**	**(4)**
Variables	$FemaleCFO_T$	$FemaleCFO_T$	$FemaleCEO_T$	$FemaleCEO_T$
$Dturn_T$	-0.106	0.011	-0.251	-0.281
	(-0.656)	(0.038)	(-1.221)	(-0.446)
$Ncskew_T$	-0.031	-0.005	0.032	-0.009
	(-1.619)	(-0.144)	(1.130)	(-0.181)
$Sigma_T$	3.453	-0.792	4.928	-6.199
	(1.613)	(-0.171)	(1.285)	(-0.685)
$Return_T$	0.115	0.027	0.800	-0.707
	(0.414)	(0.043)	(1.377)	(-0.477)
$Size_T$	0.048***	-0.011	-0.018	-0.001
	(3.311)	(-0.461)	(-0.875)	(-0.019)
Mtb_T	-0.026***	0.014	0.027***	-0.014
	(-2.957)	(0.844)	(2.777)	(-0.898)
$Leverage_T$	-0.517***	0.345	-0.177	0.038
	(-4.437)	(1.629)	(-1.158)	(0.111)
Roa_T	0.601**	0.427	-0.770**	-0.190
	(2.343)	(0.913)	(-2.340)	(-0.258)
$Accm_T$	-0.610***	-0.308	-0.373*	0.502
	(-3.966)	(-0.998)	(-1.690)	(1.058)
$Litigationrisk_T$	0.122*	-0.043	-0.172*	-0.107
	(1.649)	(-0.301)	(-1.793)	(-0.484)
Intercept	-1.607***	0.296	-1.703***	0.033
	(-7.821)	(0.764)	(-7.086)	(0.072)
Observations	12,504	2,240	11,340	872
Pseudo R^2	0.037	0.010	0.095	0.017
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Panel B. Differences in firm characteristics. This panel reports the univariate comparisons of firm characteristics between treatment and control groups. In columns (1)–(2) and (5)–(6), we report the mean value of firm characteristics. In columns (3) and (7), we report the differences between the treatment and control groups. In columns (4) and (8), we report the t-statistics of the univariate comparisons. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO sample				**CEO sample**			
	Female CFO (N=1,120) **(1)**	Male CFO (N=1,120) **(2)**	Difference **(3)**	T-stat **(4)**	Female CEO (N=436) **(5)**	Male CEO (N=436) **(6)**	Difference **(7)**	T-stat **(8)**
$Dturn_T$	-0.001	0.000	-0.001	-0.143	-0.004	-0.001	-0.003	-0.494
$Ncskew_T$	0.071	0.078	-0.007	-0.206	0.128	0.147	-0.018	-0.300
$Sigma_T$	0.039	0.040	-0.001	-1.480	0.038	0.039	-0.001	-0.819
$Return_T$	-0.094	-0.101	0.007	1.293	-0.086	-0.092	0.006	0.797
$Size_T$	7.803	7.760	0.043	0.666	7.823	7.801	0.023	0.204
Mtb_T	2.798	2.717	0.081	0.948	3.516	3.537	-0.021	-0.086
$Leverage_T$	0.180	0.171	0.009	1.432	0.211	0.205	0.006	0.509
Roa_T	0.065	0.062	0.003	1.021	0.059	0.060	-0.002	-0.344
$Accm_T$	0.131	0.135	-0.005	-1.043	0.129	0.124	0.005	0.608
$Litigationrisk_T$	0.342	0.365	-0.023	-1.149	0.335	0.358	-0.023	-0.711

Panel C. Propensity score matching estimator. This panel reports the average treatment effects. The dependent variables include $Crash_{T+1}$, $Ncskew_{T+1}$, and $Duvol_{T+1}$. In columns (1)–(2) and (5)–(6), we report the mean value of crash risk. In columns (3) and (7), we report the differences between the treatment and control groups. In columns (4) and (8), we report the t-statistics of the univariate comparisons. $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO sample				**CEO sample**			
	Female CFO (N=1,120) **(1)**	Male CFO (N=1,120) **(2)**	Difference **(3)**	T-stat **(4)**	Female CEO (N=436) **(5)**	Male CEO (N=436) **(6)**	Difference **(7)**	T-stat **(8)**
$Crash_{T+1}$	0.238	0.285	-0.046**	-2.502	0.271	0.245	0.025	0.851
$Ncskew_{T+1}$	0.060	0.159	-0.099***	-2.721	0.130	0.135	-0.006	-0.090
$Duvol_{T+1}$	-0.011	0.030	-0.041**	-2.549	0.026	0.020	0.006	0.219

Table 4. Executive gender and crash risk: High-dimensional fixed effects

This table reports the high-dimensional fixed effects model estimation results of the impact of female executives on future stock price crash risk. Columns (1)–(3) report the analyses in the CFO sample and columns (4)–(6) report the analyses in the CEO sample. In columns (1) and (4), we control for the firm and year fixed effects. In columns (2)–(3) and (5)–(6), we control for the firm and interacted industry-year fixed effects. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO sample			**CEO sample**		
Variables	**(1)** $Crash_{T+1}$	**(2)** $Ncskew_{T+1}$	**(3)** $Duvol_{T+1}$	**(4)** $Crash_{T+1}$	**(5)** $Ncskew_{T+1}$	**(6)** $Duvol_{T+1}$
$FemaleCFO_T$	-0.302**	-0.120**	-0.050**			
	(-2.158)	(-2.437)	(-2.317)			
$FemaleCEO_T$				-0.160	-0.023	0.009
				(-0.714)	(-0.285)	(0.257)
$Dturn_T$	0.104	0.089	0.032	0.515**	0.179**	0.064*
	(0.454)	(1.027)	(0.856)	(2.211)	(2.067)	(1.694)
$Ncskew_T$	-0.176***	-0.095***	-0.042***	-0.148***	-0.088***	-0.039***
	(-6.549)	(-9.315)	(-9.520)	(-5.552)	(-8.746)	(-8.950)
$Sigma_T$	18.342***	4.521***	1.410**	-3.789	0.392	0.082
	(3.567)	(2.922)	(2.087)	(-0.820)	(0.240)	(0.115)
$Return_T$	1.628**	0.291	0.058	0.099	0.102	0.009
	(2.207)	(1.590)	(0.724)	(0.160)	(0.510)	(0.104)
$Size_T$	0.720***	0.402***	0.200***	0.560***	0.374***	0.190***
	(9.588)	(14.790)	(16.831)	(7.713)	(14.104)	(16.413)
Mtb_T	-0.052**	-0.013*	-0.007**	-0.035*	-0.015**	-0.008***
	(-2.563)	(-1.811)	(-2.351)	(-1.874)	(-2.142)	(-2.645)
$Leverage_T$	0.399	0.068	0.013	0.369	0.102	0.025
	(1.227)	(0.569)	(0.243)	(1.169)	(0.877)	(0.494)
Roa_T	0.260	0.027	0.013	0.034	0.045	0.021
	(0.571)	(0.160)	(0.178)	(0.077)	(0.274)	(0.294)
$Accm_T$	0.143	0.085	0.044	0.320	0.137*	0.057*
	(0.746)	(1.150)	(1.362)	(1.554)	(1.886)	(1.801)
Observations	10,878	12,594	12,594	11,151	12,864	12,864
Pseudo/Adjusted-R^2	0.027	0.068	0.079	0.023	0.067	0.078
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	No	Yes	No	No
Industry×Year fixed effects	No	Yes	Yes	No	Yes	Yes

Table 5. Executive gender and crash risk: Difference-in-differences regressions

This table reports the difference-in-differences regression results of the impact of female executives on future stock price crash risk. The sample covers firm–year observations three years before and three years after an executive transition, excluding the year of the transition. The sample period is 2006–2015. Following Huang and Kisgen (2013), we require that firms have at least two years of non-missing data for all variables before the executives' transition. The dependent variables are three measures of stock price crash risk: $Crash_{T+1}$, $Ncskew_{T+1}$, and $Duvol_{T+1}$. $CFOTransition_T$ ($CEOTransition_T$) is an indicator variable for whether a firm is a male-to-female CFO (CEO) transition firm. $CFOPost_{T+1}$ ($CEOPost_{T+1}$) is an indicator variable for whether year $t+1$ is after the CFO (CEO) transition. In columns (1)–(6), the data sample includes all male-to-male and male-to-female executive turnovers. In columns (7)–(12), the data sample only includes exogenous executive turnovers. Columns (1)–(3) and (7)–(9) report the analyses in the CFO transition sample, and columns (4)–(6) and (10)–(12) report the analyses in the CEO transition sample. We use logit regressions in columns (1) and (4), and OLS regressions in columns (2)–(3) and (5)–(6). The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Full Turnover Sample						**Exogenous Turnover sample**					
	CFO sample			**CEO sample**			**CFO sample**			**CEO sample**		
Variables	**(1)** *Crash*	**(2)** *Ncskew*	**(3)** *Duvol*	**(4)** *Crash*	**(5)** *Ncskew*	**(6)** *Duvol*	**(7)** *Crash*	**(8)** *Ncskew*	**(9)** *Duvol*	**(10)** *Crash*	**(11)** *Ncskew*	**(12)** *Duvol*
$CFOPost_{T+1}$	-0.044	-0.035	-0.012				-0.041	-0.022	-0.005			
	(-0.262)	(-0.583)	(-0.470)				(-0.217)	(-0.321)	(-0.185)			
$CFOTransition_T \times CFOPost_{T+1}$	-0.665***	-0.171**	-0.061*				-0.471*	-0.153*	-0.051			
	(-2.784)	(-2.085)	(-1.717)				(-1.787)	(-1.678)	(-1.284)			
$CEOPost_{T+1}$				0.015	0.059	0.024				0.036	0.112	0.045
				(0.082)	(0.939)	(0.881)				(0.161)	(1.537)	(1.405)
$CEOTransition_T \times CEOPost_{T+1}$				-0.284	-0.031	-0.001				-0.261	0.052	0.034
				(-0.882)	(-0.272)	(-0.026)				(-0.679)	(0.405)	(0.590)
$Dturn_T$	0.314	0.181	0.060	0.094	0.153	0.029	0.145	0.131	0.038	-1.173	-0.222	-0.195*
	(0.659)	(1.048)	(0.806)	(0.178)	(0.869)	(0.372)	(-0.273)	(-0.690)	(-0.457)	(-1.550)	(-0.885)	(-1.766)
$Ncskew_T$	-0.166***	-0.109***	-0.044***	-0.153***	-0.089***	-0.038***	-0.158***	-0.084***	-0.035***	-0.131**	-0.091***	-0.043***
	(-3.323)	(-5.724)	(-5.316)	(-2.812)	(-4.438)	(-4.347)	(-2.827)	(-3.951)	(-3.801)	(-2.039)	(-3.968)	(-4.243)

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Table 5 - continued from previous page

	Full Turnover Sample						Exogenous Turnover sample					
	CFO sample			CEO sample			CFO sample			CEO sample		
Variables	**(1)** *Crash*	**(2)** *Ncskew*	**(3)** *Duvol*	**(4)** *Crash*	**(5)** *Ncskew*	**(6)** *Duvol*	**(7)** *Crash*	**(8)** *Ncskew*	**(9)** *Duvol*	**(10)** *Crash*	**(11)** *Ncskew*	**(12)** *Duvol*
$Sigma_T$	22.656*	4.646*	1.944*	-5.270	1.479	0.586	28.174**	6.354**	2.585**	-10.463	2.285	0.910
	(1.921)	(1.762)	(1.700)	(-0.641)	(0.487)	(0.439)	(-2.110)	(-2.182)	(-2.032)	(-1.026)	(0.663)	(0.597)
$Return_T$	2.051	0.149	0.030	-0.814	0.026	-0.067	3.266	0.298	0.084	-0.899	0.132	-0.026
	(1.053)	(0.541)	(0.252)	(-0.969)	(0.077)	(-0.446)	(-1.459)	(-1.051)	(-0.677)	(-0.825)	(0.351)	(-0.155)
$Size_T$	0.841***	0.408***	0.210***	0.527***	0.367***	0.191***	0.827***	0.442***	0.228***	0.394*	0.322***	0.165***
	(5.553)	(7.504)	(8.902)	(3.180)	(6.419)	(7.591)	(-4.821)	(-7.100)	(-8.378)	(1.930)	(4.722)	(5.466)
Mtb_T	-0.075**	-0.019	-0.013**	-0.039	-0.022	-0.010	-0.052	-0.006	-0.009	-0.029	-0.029	-0.013
	(-2.000)	(-1.397)	(-2.176)	(-0.750)	(-1.246)	(-1.250)	(-1.269)	(-0.391)	(-1.304)	(-0.463)	(-1.429)	(-1.426)
$Leverage_T$	1.369**	0.465**	0.184*	1.220*	0.262	0.048	1.202	0.308	0.135	1.140	0.212	0.001
	(2.079)	(1.961)	(1.788)	(1.718)	(1.014)	(0.424)	(-1.627)	(-1.154)	(-1.156)	(1.362)	(0.717)	(0.009)
Roa_T	1.055	0.146	0.105	0.548	0.197	0.091	0.408	-0.276	-0.028	0.473	0.163	0.079
	(1.101)	(0.439)	(0.730)	(0.593)	(0.595)	(0.624)	(-0.362)	(-0.708)	(-0.162)	(0.412)	(0.419)	(0.460)
$Accm_T$	-0.327	-0.120	-0.072	0.026	0.117	0.045	-0.579	-0.060	-0.060	-0.739	0.007	-0.004
	(-0.549)	(-0.565)	(-0.784)	(0.039)	(0.554)	(0.489)	(-0.846)	(-0.244)	(-0.563)	(-0.867)	(0.027)	(-0.033)
Intercept		-3.399***	-1.758***		-2.894***	-1.527***		-3.770***	-1.943***		-2.552***	-1.335***
		(-7.588)	(-9.046)		(-6.155)	(-7.391)		(-7.255)	(-8.560)		(-4.552)	(-5.385)
Observations	2,951	3,842	3,842	2,536	3,311	3,311	2,410	3,125	3,125	1,902	2,524	2,524
Pseudo/Adjusted-R^2	0.041	0.045	0.053	0.020	0.034	0.042	0.037	0.040	0.050	0.020	0.043	0.034
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Differential impact of CFO gender on crash risk: Sub-sample analyses

This table reports the cross-sectional relation between CFO gender, governance monitoring mechanisms, and future stock price crash risk. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. In Panel A–E, we divide our main sample into two sub-samples based on the medians of $Eindex_T$, Dio_T, $Competition_T$, $Analyst_T$, and $Leverage_T$, respectively. The high (low) sub-samples include firm–year observations with above(below)-median corresponding variables. We use logit regressions in columns (1) and (2), and OLS regressions in columns (3)–(6). The coefficients of all the control variables as in Table 2, Fama–French 48 industry fixed effects, and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$Crash_{T+1}$		$Ncskew_{T+1}$		$Duvol_{T+1}$	
Variables	**(1) High**	**(2) Low**	**(3) High**	**(4) Low**	**(5) High**	**(6) Low**
Panel A. $Eindex_T$**: Managerial entrenchment**						
$FemaleCFO_T$	-0.333**	-0.087	-0.105**	-0.038	-0.043*	-0.010
	(-2.210)	(-0.880)	(-1.986)	(-1.032)	(-1.869)	(-0.646)
Observations	3,532	6,221	3,546	6,230	3,546	6,230
Pseudo/Adjusted-R^2	0.028	0.031	0.011	0.019	0.014	0.020
Panel B. Dio_T**: Monitoring institutional ownership**						
$FemaleCFO_T$	-0.091	-0.218*	-0.017	-0.092**	0.000	-0.046***
	(-0.894)	(-1.945)	(-0.438)	(-2.390)	(0.024)	(-2.742)
Observations	6,364	6,351	6,370	6,375	6,370	6,375
Pseudo/Adjusted-R^2	0.026	0.032	0.012	0.013	0.014	0.016
Panel C. $Competition_T$**: Product market competition**						
$FemaleCFO_T$	-0.123	-0.187*	0.003	-0.113***	-0.000	-0.045***
	(-1.153)	(-1.781)	(0.074)	(-3.017)	(-0.003)	(-2.696)
Observations	6,347	6,369	6,376	6,369	6,376	6,369
Pseudo/Adjusted-R^2	0.028	0.032	0.018	0.011	0.021	0.014
Panel D. $Analyst_T$**: Analyst coverage**						
$FemaleCFO_T$	-0.103	-0.200*	-0.038	-0.075**	-0.015	-0.030*
	(-0.974)	(-1.847)	(-0.992)	(-1.983)	(-0.885)	(-1.793)
Observations	6,110	6,615	6,110	6,635	6,110	6,635
Pseudo/Adjusted-R^2	0.032	0.032	0.016	0.015	0.018	0.018
Panel E. $Leverage_T$**: Financial leverage**						
$FemaleCFO_T$	-0.263**	-0.109	-0.098**	-0.032	-0.040**	-0.012
	(-2.306)	(-1.092)	(-2.566)	(-0.856)	(-2.329)	(-0.708)
Observations	6,241	6,479	6,256	6,489	6,256	6,489
Pseudo/Adjusted-R^2	0.030	0.028	0.012	0.016	0.013	0.019

Table 7. Managerial characteristics and board gender diversity

This table reports the regression results of the impact of female CFOs on stock price crash risk, controlling for CFO characteristics, CEO pay slice, and board gender diversity. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. The dependent variables are three measures of stock price crash risk: $Crash_{T+1}$, $Ncskew_{T+1}$, and $Duvol_{T+1}$. The independent variable of interest is $FemaleCFO_T$, a CFO gender indicator variable. In columns (1)–(3), we control for $CFO\_Opt\_Inc_T$ (the incentive ratio for CFO option holdings (Kim et al., 2011a)), CFO_Age_T, and CFO_Tenure_T. In columns (4)–(6), we control for CEO pay slice. In columns (7)–(9), we control for board gender diversity, $Female\_Director_T$. In columns (10)–(12), we include all these additional control variables together. We use logit regressions in columns (1), (4), (7), and (10), and OLS regressions in columns (2)–(3), (5)–(6), (8)–(9), and (11)–(12). The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	CFO characteristics			CEO pay slice			Board gender			All together		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Variables	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$
$FemaleCFO_T$	-0.169**	-0.062**	-0.026**	-0.156**	-0.056**	-0.023*	-0.182**	-0.054*	-0.019	-0.196**	-0.057*	-0.021
	(-2.199)	(-2.230)	(-2.081)	(-2.088)	(-2.103)	(-1.935)	(-2.245)	(-1.895)	(-1.492)	(-2.243)	(-1.921)	(-1.585)
$CFO\_Opt\_Inc_T$	0.054	0.139	0.062							0.022	0.127	0.047
	(0.217)	(1.426)	(1.463)							(0.078)	(1.217)	(1.023)
CFO_Age_T	-0.004	-0.001	-0.001							-0.004	-0.000	-0.001
	(-1.038)	(-0.683)	(-1.141)							(-1.007)	(-0.259)	(-0.848)
CFO_Tenure_T	0.001	-0.001	-0.000							0.003	-0.000	-0.000
	(0.150)	(-0.470)	(-0.298)							(0.350)	(-0.061)	(-0.009)
$CEO\_Payslice_T$				0.384**	0.092	0.053*				0.373*	0.070	0.033
				(2.121)	(1.336)	(1.750)				(1.771)	(0.885)	(0.948)
$Female\_Director_T$							0.192	-0.091	-0.048	0.168	-0.107	-0.058
							(0.749)	(-0.904)	(-1.106)	(0.617)	(-1.068)	(-1.298)
$Dturn_T$	0.023	0.027	0.005	-0.014	0.015	0.001	0.008	0.057	0.010	-0.022	0.048	0.005
	(0.105)	(0.355)	(0.149)	(-0.063)	(0.199)	(0.019)	(0.032)	(0.644)	(0.239)	(-0.080)	(0.522)	(0.117)
$Ncskew_T$	0.029	0.027**	0.010**	0.025	0.024**	0.009*	0.032	0.031**	0.011**	0.033	0.033**	0.012**
	(1.121)	(2.443)	(2.197)	(1.015)	(2.249)	(1.942)	(1.125)	(2.549)	(2.086)	(1.126)	(2.575)	(2.225)

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	CFO characteristics			CEO pay slice			Board gender			All together		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Variables	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$
$Sigma_T$	25.159***	5.122***	1.538***	24.882***	5.227***	1.612***	26.131***	7.964***	2.652***	26.013***	7.606***	2.445***
	(5.252)	(3.768)	(2.755)	(5.347)	(3.937)	(2.937)	(4.572)	(4.484)	(3.388)	(4.385)	(4.101)	(3.001)
$Return_T$	2.837***	0.495***	0.168**	2.726***	0.491***	0.169**	3.105***	1.034***	0.366***	3.013***	0.982***	0.331**
	(3.475)	(2.689)	(2.250)	(3.444)	(2.699)	(2.277)	(3.021)	(3.722)	(2.936)	(2.851)	(3.408)	(2.567)
$Size_T$	0.066***	0.020***	0.011***	0.058***	0.020***	0.010***	0.030	0.017**	0.009***	0.036	0.016*	0.010***
	(3.353)	(2.695)	(3.380)	(3.177)	(2.895)	(3.438)	(1.433)	(2.133)	(2.694)	(1.521)	(1.863)	(2.595)
Mtb_T	-0.016	-0.003	-0.001	-0.015	-0.002	-0.000	-0.010	0.001	0.001	-0.010	-0.001	0.001
	(-1.545)	(-0.717)	(-0.287)	(-1.482)	(-0.439)	(-0.023)	(-0.874)	(0.140)	(0.637)	(-0.819)	(-0.196)	(0.364)
$Leverage_T$	0.001	-0.061	-0.052**	-0.058	-0.076	-0.058**	0.029	-0.054	-0.051*	-0.000	-0.064	-0.058*
	(0.004)	(-1.072)	(-2.066)	(-0.392)	(-1.370)	(-2.326)	(0.169)	(-0.827)	(-1.789)	(-0.001)	(-0.922)	(-1.944)
Roa_T	1.592***	0.689***	0.323***	1.497***	0.681***	0.321***	1.490***	0.610***	0.283***	1.474***	0.598***	0.278***
	(4.857)	(5.503)	(5.817)	(4.689)	(5.615)	(5.940)	(3.837)	(4.031)	(4.253)	(3.637)	(3.656)	(3.986)
$Accm_T$	0.110	0.060	0.028*	0.132	0.069*	0.033**	-0.092	0.039	0.036	-0.153	0.019	0.025
	(1.196)	(1.442)	(1.767)	(1.521)	(1.731)	(2.103)	(-0.438)	(0.497)	(0.972)	(-0.681)	(0.230)	(0.646)
$Litigationrisk_T$	-0.033	-0.034	-0.012	-0.055	-0.050	-0.017	-0.043	-0.062	-0.025	-0.038	-0.051	-0.024
	(-0.343)	(-0.813)	(-0.671)	(-0.591)	(-1.215)	(-1.006)	(-0.415)	(-1.383)	(-1.312)	(-0.361)	(-1.199)	(-1.337)
Intercept	-1.949***	-0.208	-0.086	-2.063***	-0.237	-0.108	-2.091***	-0.325*	-0.144*	-2.042***	-0.313**	-0.109*
	(-3.965)	(-1.162)	(-1.073)	(-4.575)	(-1.455)	(-1.495)	(-4.063)	(-1.743)	(-1.692)	(-5.375)	(-2.259)	(-1.803)
Observations	12,015	12,015	12,015	12,671	12,671	12,671	10,172	10,172	10,172	9,572	9,572	9,572
Pseudo/Adjusted-R^2	0.024	0.013	0.016	0.025	0.012	0.015	0.026	0.012	0.015	0.025	0.012	0.015
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. CFO gender and earnings restatement

This table reports the probit regression results (marginal effect reported) of the impact of female CFOs on firms' future earnings restatement probabilities. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. The dependent variable is $Restatement_{T+1}$, an indicator variable equal to one if a firm restates its earnings in the fiscal year $T+1$. The independent variable of interest is $FemaleCFO_T$, a CFO gender indicator variable. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

Variables	**(1)** $Restatement_{T+1}$	**(2)** $Restatement_{T+1}$	**(3)** $Restatement_{T+1}$
$FemaleCFO_T$	-0.024***	-0.022***	-0.020**
	(-2.83)	(-2.58)	(-2.29)
$Size_T$		-0.001	0.000
		(-0.59)	(0.07)
Mtb_T		-0.011***	-0.010***
		(-3.98)	(-3.32)
$Leverage_T$		0.061***	0.059***
		(3.97)	(3.72)
OCF_T		-0.005**	-0.004**
		(-2.09)	(-2.03)
$Loss_T$		0.012*	0.011*
		(1.79)	(1.67)
$Bigfour_T$		0.010	0.011
		(1.13)	(1.22)
$CFO\_Opt\_Inc_T$			-0.047
			(-1.48)
CFO_Age_T			0.001
			(1.51)
CFO_Tenure_T			-0.001
			(-0.82)
Observations	12,745	12,666	11,941
Pseudo R^2	0.024	0.035	0.034
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Table 9. Risk aversion vs. overconfidence

This table examines whether the empirical relation between CFO gender and future stock price crash risk can be explained by CFO risk aversion or overconfidence. The sample covers firm–year observations with non-missing values for all variables during 2006–2015. The dependent variables are three measures of stock price crash risk: $Crash_{T+1}$, $Ncskew_{T+1}$, and $Duvol_{T+1}$. The independent variables of interests are the residual terms estimated in Equation (6) and (7). We use logit regressions in columns (1) and (4), and OLS regressions in columns (2)–(3) and (5)–(6). The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values and t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Risk aversion (Eq (6))			**Overconfidence (Eq (7))**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Variables	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$	$Crash_{T+1}$	$Ncskew_{T+1}$	$Duvol_{T+1}$
$Residual_T$	-0.044**	-0.016**	-0.006*	-0.017	-0.002	-0.003
	(-2.062)	(-2.091)	(-1.918)	(-0.546)	(-0.171)	(-0.503)
$Dturn_T$	0.005	0.025	0.007	-0.088	-0.017	-0.011
	(0.020)	(0.336)	(0.211)	(-0.331)	(-0.199)	(-0.277)
$Ncskew_T$	0.025	0.024**	0.009*	0.038	0.012	0.003
	(0.980)	(2.257)	(1.910)	(1.291)	(0.942)	(0.552)
$Sigma_T$	25.204***	5.381***	1.645***	24.190***	5.420***	1.691***
	(5.437)	(3.979)	(2.945)	(4.918)	(3.669)	(2.733)
$Return_T$	2.790***	0.515***	0.178**	2.602***	0.487**	0.173**
	(3.551)	(2.754)	(2.332)	(3.248)	(2.571)	(2.193)
$Size_T$	0.061***	0.021***	0.011***	0.072***	0.026***	0.013***
	(3.325)	(3.157)	(3.703)	(3.440)	(3.294)	(3.689)
Mtb_T	-0.015	-0.002	-0.000	-0.020*	-0.001	0.001
	(-1.423)	(-0.524)	(-0.201)	(-1.650)	(-0.159)	(0.299)
$Leverage_T$	-0.024	-0.058	-0.049**	-0.148	-0.100	-0.067**
	(-0.159)	(-1.041)	(-1.985)	(-0.851)	(-1.530)	(-2.324)
Roa_T	1.502***	0.680***	0.320***	1.784***	0.716***	0.333***
	(4.685)	(5.546)	(5.870)	(4.802)	(5.012)	(5.263)
$Accm_T$	0.127	0.069*	0.033**	0.155*	0.090**	0.040***
	(1.450)	(1.756)	(2.167)	(1.840)	(2.348)	(2.632)
$Litigationrisk_T$	-0.053	-0.050	-0.017	0.013	-0.017	-0.006
	(-0.575)	(-1.236)	(-0.997)	(0.117)	(-0.349)	(-0.309)
Intercept	-2.517***	-0.351***	-0.168***	-2.462***	-0.364***	-0.170***
	(-9.658)	(-3.867)	(-4.229)	(-8.289)	(-3.443)	(-3.709)
Observations	12,503	12,503	12,503	9,297	9,297	9,297
Pseudo/Adjusted-R^2	0.015	0.024	0.012	0.018	0.026	0.015
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes