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CEO Age and Stock Price Crash Risk*

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Abstract

We show that firms with younger CEOs are more likely to experience stock price crashes, including crashes caused by revelation of negative news in the form of breaks in strings of consecutive earnings increases. Such strings are accompanied by large increases in CEO compensation that do not dissipate with crashes. These findings suggest that CEOs have financial incentives to hoard bad news earlier in their career, which increases future crashes. This negative impact of CEO age effect is strongest in the presence of managerial discretion. Overall, the findings highlight the importance of CEO age for firm policies and outcomes.

JEL classification: G30, G02

Keywords: CEO age, Crash risk, Hoarding of bad news, Agency theory, Managerial discretion

1. Introduction

A considerable body of literature suggests that managers might hide bad operating performance news from investors when faced with adverse outcomes that affect negatively their personal wealth (Gibbons and Murphy, 1992; Bliss and Rosen, 2001). However, if managers withhold and accumulate negative information for an extended period, this eventually leads to bad news stockpiling within the firm and to severe stock overvaluation. When stockpiling reaches a critical threshold level, it becomes too costly for managers or even impossible to continue withholding the accumulated negative information (Baik, Farber, and Lee, 2011). When revealed at one time in the market, the bad news will lead to a substantial revision of investors' expectations about the future prospects of the firm and, inevitably, to a stock price crash (Jin and Myers, 2006).

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The literature generally ascribes stock price crashes to the failure of corporate governance control systems to alleviate agency problems (Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a; Callen and Fang, 2013; Andreou *et al.*, 2016a; Kim and Zhang, 2016). Despite this conceptual interest on agency problems, this literature focuses on firm attributes and ignores agency problems that relate to CEO characteristics. In this study, we suggest that pay-performance sensitivity creates incentives for bad news hoarding. The incentives vary with CEO age and become a source of agency problems that leads to the prediction that firms managed by younger CEOs are more likely to experience stock price crashes.

The study draws motivation from prior literature suggesting that CEOs are highly concerned about firm performance because performance directly affects their current and future personal wealth through executive compensation packages (Gibbons and Murphy, 1992; Bliss and Rosen, 2001; Petrou and Procopiou, 2016). Thus, when the actions of CEOs fail to deliver, concerns about their personal wealth can incentivize them to conceal adverse operating outcomes from shareholders. However, the pay-performance sensitivity of CEOs varies with CEO age. Younger CEOs could secure significant permanent increases in compensation early in their career, which they can enjoy for a longer period. Accordingly, younger CEOs might have more financial incentives to intentionally conceal and accumulate adverse operating outcomes from investors, increasing in this respect the probability of experiencing a stock price crash in the future.

We test these predictions using ExecuComp firms for the period 1995–2013. We measure firm-specific stock price crashes as the presence of an extreme negative firm-specific weekly return (Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a). Controlling for other known determinants of stock price crashes, the results show that firms managed by younger CEOs are more likely to experience a stock price crash. To investigate the mechanism underpinning this relationship, that is, the hoarding of bad news, we focus on stock price crashes triggered by earnings announcements that break previous years' strings of consecutive earnings increases. Myers, Myers, and Skinner (2007) suggest that breaks in strings of consecutive earnings increases emanate from stockpiling of negative news, particularly when the break occurs after a longer string. Thus, breaks in earnings strings that trigger stock price crashes is a manifestation of agency risk pertaining to the practice of bad news hoarding. In addition, the severity of agency risk is positively related to the length of the string. Using these crashes, we still find that firms managed by younger CEOs are more likely to experience a stock price crash, ascertaining that the mechanism of stockpiling of negative information pertaining to adverse operating performance drives this relationship. In corroboration, we find that the length of the string prior to the break is more strongly associated with crashes when a younger CEO leads the company. Next, we investigate CEOs' pay-performance incentives by focusing on the evolution of CEO compensation before (up to 3 years), during, and after (up to 1 year) stock price crashes. Controlling for known determinants of CEO compensation, the results demonstrate large increases in CEO compensation in periods of consecutive earnings increases. Interestingly, CEO compensation does not revert to previous levels during and after the crash. These findings imply that CEOs have strong financial incentives to generate strings of consecutive earnings increases earlier in their career, resulting in a CEO agency problem that drives stock price crashes.

To prevent moral hazard situations, agency theory identifies the board's monitoring role, among others, as a critical control system (Eisenhardt, 1989). Accordingly, we examine two organizational factors which compromise board monitoring and increase managerial discretion, namely, the CEO duality in the governance structure (Jensen, 1993; Dalton *et al.*, 1998) and the degree of corporate diversification (Martin and Sayrak, 2003; Ndofor, Wesley, and Priem, 2013). Our results show that these two factors strengthen the relationship between younger CEOs and future crash risk. This finding raises important considerations for the competence of the board to effectively monitor and control self-interested young CEOs.

Our results are robust to alternative measures of stock price crash risk, such as the negative coefficient of skewness of firm-specific weekly returns (Chen, Hong, and Stein, 2001) and the negative of the worst deviation of firm-specific weekly return (Bradshaw *et al.*, 2010). In addition, the results are robust to potential model misspecifications. Specifically, a propensity score-matching analysis ensures that the CEO age effect is not driven by differences between firms managed by younger or older CEOs among observable: (i) firm characteristics, such as firm size, growth, leverage, profitability, performance, and age, and (ii) CEO characteristics, for instance tenure, turnover, retirement, in the money option holdings and equity holdings.

We also consider a variety of alternative explanations. First, a reverse relationship running from crash risk to CEO age is likely to exist under two conditions: (i) stock price crash risk relates to CEO turnover and firms hire younger CEOs, and (ii) stock price crash risk exhibits persistence. However, we find no statistically significant difference in the age of newly hired CEOs for firms that experience a stock price crash relative to firms that do not. In addition, after examining firms that exhibit more difficulties in handling risk or inherently risky firms, which may require more healthy, flexible, and energetic young CEOs, we find no evidence that the age of newly hired CEOs is significantly different among firms that experience a stock price crash and firms that do not. Hence, crash risk is unlikely to relate to the age of newly hired CEOs. Finally, as a complementary test of the reverse causality explanation, we re-run the main analysis and find qualitatively similar results after excluding the first three years of CEO tenure, which are affected more by persistence in crash risk, and thus potentially may cause a reverse relationship.

Second, physiological and psychological characteristics of the CEO and heterogeneous abilities change with age, and some of these characteristics might provoke stock price crashes. Such characteristics include the effects of ability, power, overconfidence, youthful creativeness, and inexperience with corporate communications. Controlling for CEO demonstrated ability, power, and overconfidence, the results remain unaltered. Youthful creativeness and inexperience with corporate communication are more problematic to control directly because it is difficult to measure them precisely; nevertheless, we can observe their consequences, and hence, we can design appropriate tests to examine their merit as alternative explanations of the CEO age effect. More specifically, youthful creativeness associated with younger CEOs experimenting with novel strategies should predict fat tails generally, not only one-sided exposure to crashes. In contrast to such an explanation, we find no relationship between CEO age and the probability of a positive jump in the firm-specific weekly returns. Thus, CEO age appears to predict only negative jumps, that is, stock price crashes. Similarly, inexperience of younger CEOs in corporate communication could lead them to portray optimistic earnings expectations to analysts. In response, younger CEOs might hoard bad news to meet or beat analyst earnings forecasts, increasing in this respect future stock price crash risk. Excluding crashes that likely result from setting inappropriate earnings expectations from the main analysis does not affect the CEO age effect.

Finally, we examine the possibility that the CEO age effect reflects unobservable habitual CEO characteristics (Graham, Li, and Qiu, 2012) that affect disproportionately younger CEOs. Specifically, such characteristics can have implications for stock price crashes and can lead to CEO turnover, particularly younger CEOs who are less reputable, creating a sample selection bias that affects mostly younger CEOs. Nevertheless, this explanation does not gain support because we still find CEO age effect for the subsample of firms with CEOs that avoid turnover for at least 5 years. In this subsample, habitual CEO characteristics should affect a firm's crash risk similarly over a long period.

This study contributes to the literature on stock price crashes by showing that compensation incentives create CEO-level variation in agency problems that increase the likelihood of firms with younger CEOs to experience future stock price crashes due to hoarding of bad news. Prior literature finds that crash risk relates to accounting opacity (Hutton, Marcus, and Tehranian, 2009), tax avoidance (Kim, Li, and Zhang, 2011b), accounting conservatism (Kim and Zhang, 2016), equity-based compensation (Kim, Li, and Zhang, 2011a), and inefficient governance (Callen and Fang, 2013; Andreou *et al.*, 2016a). However, what motivates managers to conceal bad news largely remained unexplored in the literature. This study's main contribution fills this gap by providing novel evidence that CEOs have financial incentives to pursue bad news hoarding activities earlier in their career, which subsequently lead to stock price crashes.

In addition, the study contributes to the emerging literature that links heterogeneous CEO characteristics to firm policies and outcomes (Bertrand and Schoar, 2003). In this vein, recent studies find that CEO age significantly affects corporate investments. For instance, Yim (2013) finds that financial incentives motivate younger CEOs to make more acquisitions, whereas Serfling (2014) provides evidence that older CEOs invest less in research and development, make more diversifying acquisitions and maintain lower operating leverage, resulting in lower firm risk. Our perspective is different and links CEO age to future stock price crashes. This perspective has important implications for corporate governance policies by raising concerns about the role of boards in monitoring and incentivizing CEOs. Specifically, the findings of our study should probe boards to devise appropriate governance mechanisms that combat agency problems that emerge from CEO age.

The rest of the study is organized as follows. Section 2 develops our hypotheses and outlines the testable predictions. Section 3 describes the research design. Section 4 presents the empirical results. Section 5 presents the robustness analysis results. Section 6 presents results on alternative explanations of the findings. Finally, Section 7 concludes the study.

2. Hypotheses Development

2.1 CEO Age and Crash Risk

Gibbons and Murphy (1992) argue that the "labor market uses a worker's current output to update its belief about the worker's ability and then base future wages on these updated beliefs". Accordingly, superior performance affects a manager's value in the labor market and results in future compensation increases. Because of that relationship, younger CEOs should have strong financial incentives to deliver superior (or to hide poor) performance to gain early rises in compensation, which they will enjoy for a longer period. Consistent with this argument, Yim (2013) finds that younger CEOs are more likely to pursue acquisitions and that CEOs are rewarded as much as $300,000 in additional annual compensation for each sizable acquisition they make. Similarly, Boschen *et al.* (2003) show that excess performance has a positive effect on the cumulative financial gain of CEOs. Such evidence suggests that younger CEOs might be more sensitive about firm performance and that similar performance achievements have more wealth-related value for younger CEOs.

Drawing on agency theory (Jensen and Meckling, 1976), we suggest that different levels of CEO pay for performance sensitivity, which depend upon CEOs' ages, should create different responses to adverse operating outcomes. For instance, disclosure of negative information about performance should harm the personal wealth of younger CEOs more because the labor market will use this information to update beliefs about their abilities and set a corresponding (lower) level of compensation (Gibbons and Murphy, 1992), which, when accumulated across a CEO's career, is more costly for younger CEOs. Therefore, these CEOs have more incentives to hide negative information to avoid personal wealth consequences, hoping that poor current performance will be offset by stronger future performance. Hiding and accumulating bad news, however, is unsustainable in the long run; eventually, bad news will spill out in the market when strong future performance does not materialize (Jin and Myers, 2006; Bleck and Liu, 2007). Investors' response to unexpected bad news is fierce, leading to an abrupt downward revision of their expectations about the firm's long-term prospects, which triggers a stock price crash (Jin and Myers, 2006; Callen and Fang, 2015). The abovementioned discussion leads us to the following hypothesis:

Hypothesis 1. Firms managed by younger CEOs are associated with higher levels of future stock price crash risk.

2.2 The Moderating Effect of Management Discretion

CEOs are more prone to engage in moral hazard situations when they have discretion, which they might use to compromise the effectiveness of the boards' monitoring function (Finkelstein and Hambrick, 1989; Ocasio, 1994). Such opportunities emerge in the presence of two organizational characteristics: the existence of CEO duality in the governance structure and the degree of corporate diversification.

A CEO-Chair can acquire significant influence over the board, thereby weakening the board's ability to effectively monitor and control management decisions (Hambrick and Finkelstein, 1987; Jensen, 1993; Dalton *et al.*, 1998). This influence can be achieved in a number of ways. First, CEO-Chairs, who nominate board directors, can select directors who are loyal to them (Westphal and Zajac, 1995). Second, the duality structure can enable CEOs to root themselves in the organization by creating norms of not questioning management effectiveness (Finkelstein and D'aveni, 1994). Finally, these CEOs might control the board's distribution of attention to organizational matters, purposely discouraging adequate attention to monitoring (Tuggle *et al.*, 2010). Consequently, when the CEO-Chair position is held by younger CEOs who are more sensitive to adverse changes in firm performance, it is more likely to suppress the board's monitoring function to facilitate hoarding of bad news from shareholders. Effectively, such behavior makes firms more prone to future stock price crash risk. Consequently, we expect that:

Hypothesis 2. The relationship between CEO age and future stock price crash risk is stronger in the presence of a CEO-Chair position.

Likewise, in diversified firms, there is greater organizational complexity, which can compromise in many ways the effectiveness of board monitoring (McKendall and Wagner, 1997; Martin and Sayrak, 2003; Ndofor, Wesley, and Priem, 2013). First, due to decentralized controls embedded in diversified firms, management decisions are based on information originating from multiple units operating in different segments. This makes the verification and the assessment of management decisions by board members more difficult. Second, in such complex organizational setting, the correctness of the CEO's judgment is difficult to challenge because people in that position are expected to have the most knowledge and information about the subject of the decision. Finally, CEOs have the chance to control what information is disclosed, in particular, information relating to the efficiency of their actions. Consequently, such deficiencies limit investors' capacity to collect and interpret important information, which in turn can impede material input from being timely incorporated into firm valuations (Cohen and Lou, 2012). Because of that, younger CEOs in the presence of organizational complexity are more likely to hide bad news relating to poor performance from shareholders, which increases the probability of a stock price crash. Consequently, we expect that:

Hypothesis 3. The relationship between CEO age and future stock price crash risk is stronger in more-highly diversified firms.

3. Research Design

3.1 Sample

To construct our sample, we use several data sources. First, we estimate crash risk measures using firms listed in the Center for Research in Security Prices (CRSP). Similar to earlier research, we exclude financial service firms (SIC 6000-6999) and utilities (SIC 4900-4999) because the financial characteristics in these industries are not the same as in other industries (Kim, Li, and Zhang, 2011a). In addition, we exclude firm-years with a stock price less than \$2.5 at the end of the fiscal year and firm-years with fewer than 26 weeks of stock returns in a fiscal year (Hutton, Marcus, and Tehranian, 2009). For the remaining firms, we gather CEO-related information from ExecuComp. We also collect firm-related information from Industrial Segment and Compustat Industrial Annual databases. The final sample with complete information covers the period 1995–2013 and consists of 18,649 firm-year observations, which correspond to 2,255 firms from various industries.

3.2 Dependent Variables

Because the aim of this study is to investigate the effect of CEO age on stock price crashes, we first estimate firm-specific weekly returns using the following index model regression:

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

where $r_{j,w}$ is the return on stock j in week w, and $r_{m,w}$ is the CRSP value-weighted market index in that week. Consistent with Dimson (1979), we include lead and lag variables for the market index to allow for non-synchronous trading. This regression is useful to separate firm returns into two components: (i) returns due to market-wide movements, as measured by the fitted value of the regression; and (ii) firm-specific returns as captured by the residuals of the regression. Our focus is on the residuals of the regression. Following the literature, we define the firm-specific weekly returns for firm j in week w ($W_{j,w}$) as the natural logarithm of 1 plus the residual (i.e., $W_{j,w} = \ln[1 + \varepsilon_{j,w}]$). This approach is necessary because the residuals of the regression are skewed. We use the residuals to estimate three measures of crash risk. The primary crash risk measure is a binary variable that equals 1 when firm j experiences at least one crash week during the fiscal year t, and zero otherwise ($\text{CRASH}_{j,t}$). A crash week is identified when the firm-specific weekly return is 3.2 standard deviations below the average firm-specific weekly returns for the entire fiscal year (3.2 is chosen to generate a frequency of 0.1% in the normal distribution).[1]

As an alternative measure of crash risk, we also employ the negative coefficient of skewness (NCSKEW), which equals the negative of the third moment of firm-specific weekly returns for each firm in a year divided by the standard deviation of firm-specific weekly returns raised to the third power (Chen, Hong, and Stein, 2001). Specifically, for a given firm in a fiscal year t, we calculate NCSKEW as follows:

$$\text{NCSKEW}_{j,t} = \frac{-\left[n(n-1)^{\frac{3}{2}} \sum W_{j,w}^{3}\right]}{(n-1)(n-2)\left(\sum W_{j,w}^{2}\right)^{\frac{3}{2}}}, \tag{2}$$

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

The third measure of crash risk is the extreme sigma (EXTR_SIGMA). EXTR_SIGMA is the negative of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns (Bradshaw *et al.*, 2010). In particular, for a given firm j in a fiscal year t, we compute EXTR_SIGMA as follows:

$$\text{EXTR\_SIGMA}_{j,t} = -\text{Min}\left[\frac{W_{j,w} - \bar{W}}{\sigma_W}\right], \tag{3}$$

where $\bar{W}$ is the mean and σ_W is the standard deviation of the firm-specific weekly returns over the fiscal year t. For both NCSKEW and EXTR_SIGMA, larger values signify greater crash risk.

3.3 Main Explanatory Variables

Our main explanatory variable is the CEO age (AGE_{t-1}).[2] In addition, we measure CEO duality (DUALITY_{t-1}) using a binary variable which equals 1 when the positions of CEO and Chairman are held by the same person, and zero otherwise (Davidson *et al.*, 2004). Furthermore, a firm's degree of diversification is measured using a sales-based Herfindahl index (HERFINDAHL_{t-1}). A smaller Herfindahl index indicates a greater degree of firm diversification. All explanatory and control variables are described in the Appendix.

1 Similar to Kim, Li, and Zhang (2011a), we use 3.2 standard deviations below the average firm-specific weekly returns of the entire fiscal year as a reasonable benchmark to define extremely negative returns. Our findings are qualitatively similar using alternative benchmarks, such as 3.09 standard deviations below the average firm-specific weekly returns of the entire fiscal year (Hutton, Marcus, and Tehranian, 2009).

2 Note that in our regression tests, all of the explanatory/control variables are measured during the period $t-1$ with respect to the crash risk. Thus, we model the probability of a stock price crash at time t given all information at time $t-1$. In this respect, we require that the CEO remains in the position during the period from $t-1$ to t.

3.4 Control Variables

We use a set of control variables that are deemed potential predictors of stock price crash risk. These variables include CEO characteristics, firm characteristics, investor characteristics, and industry/year effects. Concerning CEO characteristics, we control for CEO firm-specific experience (Hambrick and Fukutomi, 1991) using CEO tenure (TENURE_{t-1}). Uncertainty concerning the ability of short-tenured CEOs to lead the firm due to deficient firm-specific knowledge and experience (Simsek, 2007) creates pressure for such CEOs to defend their job, for instance by hiding bad news. In that case, tenure should be inversely related to future stock price crashes. We measure CEO tenure using the natural logarithm of the number of years in a CEO post with a particular company (Henderson, Miller, and Hambrick, 2006). We also control for departing CEOs who might overstate earnings, using two binary variables that equal 1 when there is a change in a firm's CEO in either the leading 1 or 2 years, respectively, and zero otherwise ($\mathrm{CEO\_CHANGE}_{t-1}$ and $\mathrm{CEO\_CHANGE}_{t-2}$). Overstatement of earnings could be more severe when the CEO change is known ex-ante, as in the case of CEO retirements (Ali and Zhang, 2015). Accordingly, we additionally control for CEO retirement using a binary variable that equals 1 when the CEO age is close to retirement (i.e., CEO age is 64–65 years), and zero otherwise ($\mathrm{RETIREMENT}_{t-1}$). Generally, during periods of CEO departures, it is possible that CEOs use accounting and/or investment decisions to increase performance-based compensation in their final years at the expense of future earnings or to cover up the firm's deteriorating performance that threatens their position (Murphy and Zimmerman, 1993). Both decisions might lead to a stock price crash during either the pre- or the post-CEO departure period, depending upon when bad news is revealed in the market.[3] Finally, we control for CEO equity-based compensation using the intrinsic value of the vested and unvested in-the-money options held by CEOs ($\mathrm{ITM\_OPTION\_HOLDINGS}_{t-1}$) and CEO equity holdings ($\mathrm{EQUITY\_HOLDINGS}_{t-1}$) using the natural logarithm of the market value of shares held by CEOs.[4] Kim, Li, and Zhang (2011a) find that equity incentives relate positively to the firm's future stock price crash risk.

Concerning firm characteristics, following Chen, Hong, and Stein (2001) and Hutton, Marcus, and Tehranian (2009), we include standard control variables such as past firm size, defined as the natural logarithm of the market value of equity ($\mathrm{Log}(\mathrm{SIZE}_{t-1})$); firm growth ($\mathrm{MB}_{t-1}$), defined as the ratio of the market value to the book value of equity; firm leverage (LEV_{t-1}), defined as the firm's total liabilities scaled by total assets; and firm operating performance, defined as income before extraordinary items to equity (ROE_{t-1}). Small, high growth, highly leveraged and less-profitable firms are expected to exhibit more stock price crashes. Also, Chen, Hong, and Stein (2001) find that firms with high past returns are more prone to crash. Therefore, we control for past firm financial performance using the average firm-specific weekly returns (RETURN_{t-1}). In addition, we control for firm age using the number of years that the firm is covered in COMPUSTAT ($\mathrm{FIRM\_AGE}_{t-1}$). More-experienced firms should be better at handling risk than less

3 If the reason for CEO departure is poor performance and firms hire younger CEOs, then assuming persistence in crash risk, CEO changes could induce a spurious CEO age effect on stock price crashes. In Section 6, we explicitly test this alternative explanation and show that it does not affect our findings.

4 According to Efendi, Srivastava, and Swanson (2007), intrinsic holding values capture information on both possible equity overvaluation and price sensitivity.

experienced firms. Thus, firm age should negatively relate to stock price crashes. Furthermore, we control for the firms' operational opacity using goodwill to total assets ($GOODWILL_{t-1}$), research and development to total assets ($R\&D_{t-1}$), and a binary variable that equals 1 when the firm belongs to the technology industry ($TECHNOLOGY_{t-1}$).[5] According to Jin and Myers (2006), opaque firms are more likely to crash. Finally, we control for the firm's degree of competitiveness ($COMPETITIVENESS_{t-1}$) using the Lerner index, measured as industry-adjusted firm operating profit to sales, and default risk ($PR\_DEFAULT_{t-1}$), using Merton (1974) probability-to-default model as in Andreou (2015). Pressure to deliver performance and inherent riskiness that characterizes such firms' operations can make them more prone to crash. Concerning investor characteristics, we control for investor heterogeneity or the difference of opinions among investors using the de-trended average weekly stock trading volume ($DTURN_{t-1}$). Chen, Hong, and Stein (2001) find that firms with high turnover are more likely to crash in the future.

In the regression, we also include industry effects to cover for idiosyncratic differences between industries that can make it easier/more difficult for managers to hide bad news (Finkelstein and Hambrick, 1989). We control for industry fixed effects by including industry binary variables, using the forty-eight-industry classification suggested by Fama and French (1997). Similarly, we include year fixed effects to control for the unobserved year characteristics omitted from the analysis. Finally, as a mean of addressing concerns about dynamic endogeneity, we use past values of the dependent variable in our regressions. Given that crash risk is a binary variable, we use a continuous variable, the negative coefficient of skewness ($NCSKEW_{t-1}$).

4. Empirical Results

4.1 Summary Statistics

Table I presents yearly information about the incidence and magnitude of crashes. Based on the definition of crashes, and assuming that firm-specific returns are normally distributed, we would expect to observe 0.1% of the firms crashing in any week. Accordingly, the likelihood of a crash during a year would be $1 - (1 - 0.001)^{52} = 5.07\%$. Interestingly, consistent with Kim, Li, and Zhang (2011a) and Hutton, Marcus, and Tehranian (2009), it seems that crashes are more prevalent than would have been expected under normality of firm-specific returns. In particular, the sample consists of 18,649 firm-year observations, of which 3,573 firm-years or 19.16% are classified as crashes. This finding is in line with prior evidence showing that simple returns are not normal but exhibit negative skewness (Harvey and Siddique, 2000; Chen, Hong, and Stein, 2001; Theodossiou, 2015). Finally, the average weekly return of crashes throughout the period of investigation is substantial and equals −18%. Both the prevalence and the magnitude of the crashes indicate that stock price crashes are events with substantial consequences for the shareholders of a firm.

Table II displays descriptive statistics. The average CEO age is 55.04 years. In addition, the 25th and 75th percentiles are 50 and 60 years, respectively, implying that there is sufficient variation in CEO age to investigate the effect of CEO age on stock price crash risk. Concerning the moderator variables, 57.80% of the firm-year observations consist of

5 Technology industry is defined by the following four-digit SIC codes: 2833-2836 (drugs), 3570-3577 (computers), 3600-3674 (electronics), 3810-3845 (precise measurement instruments), 7371-7379 (programming), and 8731-8734 (R&D services).

Table I. Yearly incidence and magnitude of stock price crashes

Year	Number of observations	Number of crashes	Percentage of crashes	Average returns during crashes	Standard deviation of returns during crashes
1995	886	142	16.03	−0.18	0.08
1996	914	135	14.77	−0.20	0.09
1997	946	135	14.27	−0.18	0.08
1998	982	144	14.66	−0.22	0.08
1999	1,016	182	17.91	−0.26	0.09
2000	940	164	17.45	−0.29	0.10
2001	897	155	17.28	−0.23	0.09
2002	950	214	22.53	−0.23	0.11
2003	963	170	17.65	−0.18	0.09
2004	1,037	194	18.71	−0.16	0.07
2005	973	237	24.36	−0.15	0.06
2006	966	221	22.88	−0.14	0.05
2007	994	177	17.81	−0.16	0.06
2008	1,027	216	21.03	−0.22	0.08
2009	1,050	179	17.05	−0.19	0.08
2010	1,057	193	18.26	−0.14	0.06
2011	1,049	215	20.50	−0.15	0.06
2012	1,004	260	25.90	−0.15	0.07
2013	998	240	24.05	−0.13	0.06
Totals	18,649	3,573	19.16	−0.18	0.09

CEOs who also serve as Chairman of the board; the average Herfindahl index is approximately 0.81.[6]

4.2 CEO Age and Crashes

To investigate our hypotheses, we begin by plotting in Figure 1 the percentage of stock price crashes across firm-years based on CEO age quartiles. CEOs with age less than 51 years are included in the youngest age cohort (AGE_GROUP_I). CEOs with ages between 51 and 55 (56 and 60) years are included in AGE_GROUP_II (AGE_GROUP_III) while CEOs with age greater than 60 years are included in the oldest age cohort (AGE_GROUP_IV). The percentage of stock price crashes in AGE_GROUP_I is 20.60% and declines monotonically to 17.10% in AGE_GROUP_IV. In addition, a Chi-square test indicates that the percentage of stock price crashes in AGE_GROUP_I and AGE_GROUP_II is statistically significantly different compared with crashes in AGE_GROUP_IV. Finally, relative to the unconditional average of stock price crashes, which equals 19.16%, firms managed by CEOs that belong in the youngest (oldest) age cohort exhibit 7.51% (10.75%) greater (lower) likelihood of a stock price crash.

To formalize this evidence in a multivariate setting, we employ a logit regression analysis. The dependent variable is the stock price crash in year t, whereas the main

6 Untabulated correlation analysis reveals that most variables, including CEO age, correlate with stock price crashes and exhibit the expected sign. None of the cross correlations is sufficiently high to raise concerns over multicollinearity.

Table II. Descriptive statistics

This table presents descriptive statistics for key variables. All variables are defined in the Appendix.

	Mean	Std	Q1	Median	Q3
$CRASH_t$	0.192	0.394	0.000	0.000	0.000
AGE_{t-1}	55.041	7.376	50.000	55.000	60.000
$DUALITY_{t-1}$	0.578	0.494	0.000	1.000	1.000
$HERFINDAHL_{t-1}$	0.809	0.282	0.500	1.000	1.000
$TENURE_{t-1}$	7.975	7.470	2.752	5.659	10.669
CEO_CHANGE_{t-1}	0.110	0.312	0.000	0.000	0.000
CEO_CHANGE_{t-2}	0.103	0.304	0.000	0.000	0.000
$RETIREMENT_{t-1}$	0.040	0.197	0.000	0.000	0.000
$ITM\_OPTIONS\_HOLDINGS_{t-1}$ \$MM	10.839	23.641	0.281	2.552	10.042
$EQUITY\_HOLDINGS_{t-1}$ \$MM	51.398	168.287	2.052	6.983	24.242
$SIZE_{t-1}$	7.185	1.526	6.057	7.011	8.164
MB_{t-1}	3.253	2.846	1.599	2.404	3.781
LEV_{t-1}	0.480	0.195	0.334	0.494	0.620
ROE_{t-1}	0.110	0.199	0.058	0.122	0.187
$RETURN_{t-1}$	−0.137	0.138	−0.170	−0.091	−0.049
$FIRM\_AGE_{t-1}$	24.408	16.324	11.000	19.000	38.00
$GOODWILL_{t-1}$	0.111	0.138	0.000	0.055	0.182
$R\&D_{t-1}$	0.032	0.051	0.000	0.003	0.044
TECHNOLOGY	0.217	0.412	0.000	0.000	0.000
$COMPETITIVENESS_{t-1}$	−0.053	0.201	−0.182	−0.026	0.065
$BANKRUPTCY_{t-1}$	0.004	0.029	0.000	0.000	0.000
$DTURN_{t-1}$	1.354	19.278	−5.888	0.652	7.762
$NCSKEW_{t-1}$	0.094	0.728	−0.336	0.042	0.449

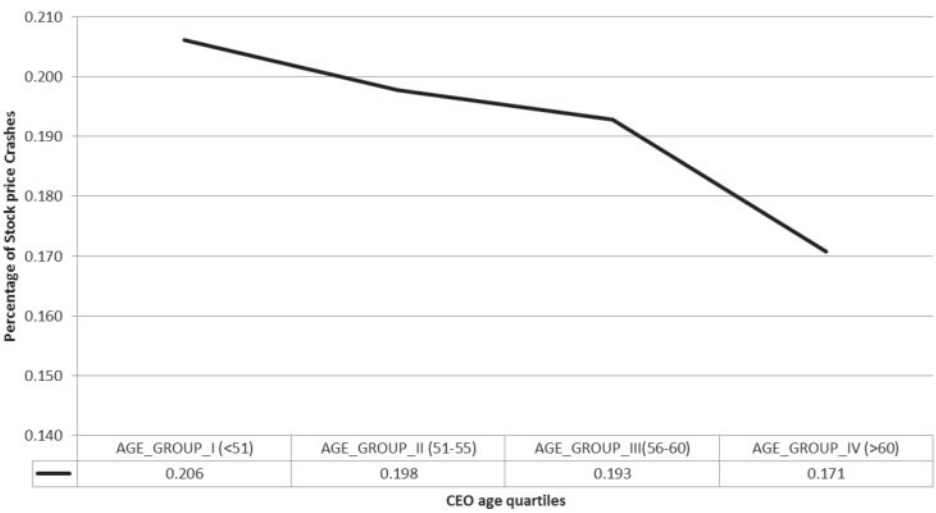

Figure 1. Percentage of stock price crashes across CEO age quartiles.
This figure displays the percentage of stock price crashes across CEO age quartiles. For each age quartile, the percentage of stock price crashes is the number of firm-year crashes divided by the total number of firm-year observations in that quartile.

explanatory variable is the CEO age in year $t-1$. In addition, the regression includes control variables for CEO characteristics, firm characteristics, investor characteristics, and industry/year fixed effects. All of the continuous explanatory variables are standardized to have a mean of 0 and standard deviation of 1. Such standardization is useful to avoid potential influences attributed to scaling differences.[7] Furthermore, to ease interpretation of the results, the models report odds ratios, that is, the exponential of each coefficient estimate. When all other variables are held constant, an odds ratio that equals 1 indicates no relationship between the variable and crash risk. In contrast, an odds ratio greater (less) than 1 shows how much the probability of a crash risk increases (decreases). In addition, given that our data include multiple observations for the same firm, we use a clustering procedure that accounts for potential within-firm dependence to prevent biased standard error estimates that can arise when the residuals of a firm are correlated over time.

Consistent with Hypothesis 1, the results in model 2 of Table III show that firms employing younger CEOs are more likely to experience a future stock price crash. In terms of economic importance, one standardized unit decrease of CEO age increases the probability of a stock price crash by approximately 7.60% ($p < 0.01$). In model 3, we present the effect of CEO age utilizing binary variables based on the quartile groupings of age (AGE_GROUP_I < 51, AGE_GROUP_II = 51–55, AGE_GROUP_III = 56–60, omitted AGE_GROUP_IV > 61). The coefficient estimates are greater than 1 and decline monotonically across the CEO age groups, suggesting that the probability of a stock price crash for the younger CEO groups is increasing relative to older CEO groups. In model 4, we present the effect of age in an alternative way, which is relevant for subsequent analysis in Section 5, using a binary variable that equals 1 if the CEO age is less than the median value (YOUNG_CEO). The coefficient estimate shows that firms managed by young CEOs exhibit approximately 11.20% greater probability of a stock price crash ($p < 0.05$) relative to older CEOs.

Turning next to the control variables, the results in model 1 show that most variables affect the probability of a stock price crash significantly. Specifically, concerning CEO-characteristics, CEO tenure decreases the probability of crash risk ($p < 0.10$) in line with the view that pressure to deliver performance incentivizes short-tenured CEOs to defend their jobs using methods that induce future crashes. Furthermore, the results show that changes in a firm's CEO in either the leading 1 or 2 years are positively related to crashes ($p < 0.01$ and $p < 0.01$, respectively), suggesting that CEOs overstate earnings when they are close to a departure. In addition, consistent with Kim, Li, and Zhang (2011a), in-the-money options increase the probability of crashes ($p < 0.01$), indicating that stock options can motivate managers to hide bad news to increase stock option benefits. Concerning firm characteristics, firm size decreases the probability of crashes ($p < 0.01$), whereas firm performance, goodwill, and the competitive status of the firm increase the probability of crashes ($p < 0.10$, $p < 0.01$, and $p < 0.01$, respectively). Consistent with these results, Chen, Hong, and Stein (2001) also find that past firm performance relates positively to stock price crashes. Similarly, Jin and Myers (2006) show that opaque stocks are more likely to crash. Concerning investor characteristics, investor heterogeneity increases the likelihood of crash risk ($p < 0.01$), consistent with the view that investor heterogeneity and short-sale constraints prevent bearish investors from participating in the market, leading to

7 Nevertheless, note that the results are robust to using unstandardized variables.

Table III. The impact of CEO age on stock price crashes

This table reports the results of logit regressions where the dependent variable is the firm-specific stock price crash dummy (CRASH). Coefficients are reported as odds ratios. All models include a constant, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Log($TENURE_{t-1}$)	0.954*	0.976	0.976	0.965
	(0.024)	(0.026)	(0.025)	(0.025)
CEO_CHANGE_{t-1}	1.206***	1.238***	1.252***	1.223***
	(0.059)	(0.059)	(0.059)	(0.059)
CEO_CHANGE_{t-2}	1.237***	1.266***	1.278***	1.255***
	(0.061)	(0.061)	(0.061)	(0.061)
$RETIREMENT_{t-1}$	1.102	1.193*	1.288**	1.148
	(0.094)	(0.096)	(0.100)	(0.095)
Log($ITM\_OPTIONS\_HOLDINGS_{t-1}$)	1.101***	1.095***	1.095***	1.098***
	(0.023)	(0.023)	(0.023)	(0.023)
Log($EQUITY\_HOLDINGS_{t-1}$)	1.004	1.006	1.009	1.005
	(0.025)	(0.025)	(0.025)	(0.025)
$SIZE_{t-1}$	0.877***	0.878***	0.875***	0.879***
	(0.028)	(0.028)	(0.028)	(0.028)
MB_{t-1}	1.005	1.000	1.001	1.003
	(0.023)	(0.023)	(0.023)	(0.023)
LEV_{t-1}	1.024	1.024	1.022	1.023
	(0.025)	(0.025)	(0.025)	(0.025)
ROE_{t-1}	1.021	1.023	1.022	1.022
	(0.024)	(0.024)	(0.024)	(0.024)
$RETURN_{t-1}$	1.047*	1.054*	1.051*	1.049*
	(0.028)	(0.028)	(0.028)	(0.028)
Log($FIRM\_AGE_{t-1}$)	0.971	0.983	0.981	0.977
	(0.026)	(0.026)	(0.026)	(0.026)
$GOODWILL_{t-1}$	1.072***	1.071***	1.070***	1.070***
	(0.023)	(0.023)	(0.023)	(0.023)
$R\&D_{t-1}$	1.006	1.004	1.001	1.003
	(0.028)	(0.028)	(0.028)	(0.028)
TECHNOLOGY	1.104	1.100	1.104	1.102
	(0.073)	(0.073)	(0.072)	(0.073)
$COMPETITIVENESS_{t-1}$	1.114***	1.113***	1.114***	1.113***
	(0.031)	(0.031)	(0.031)	(0.031)
$PR\_DEFAULT_{t-1}$	1.000	1.000	1.000	1.000
	(0.023)	(0.023)	(0.023)	(0.023)
$DTURN_{t-1}$	1.049**	1.050**	1.050**	1.050**
	(0.020)	(0.020)	(0.020)	(0.020)
$NCSKEW_{t-1}$	1.072***	1.070***	1.070***	1.071***
	(0.020)	(0.020)	(0.020)	(0.020)
$DUALITY_{t-1}$	1.064	1.082*	1.084*	1.075
	(0.045)	(0.045)	(0.045)	(0.045)

(continued)

Table III. Continued

	(1)	(2)	(3)	(4)
HERFINDAHL$_{t-1}$	1.035	1.032	1.033	1.033
	(0.023)	(0.023)	(0.023)	(0.023)
Log(AGE$_{t-1}$)		0.924***		
		(0.023)		
AGE_GROUP_I (<51)			1.277***	
			(0.064)	
AGE_GROUP_II (51–55)			1.270***	
			(0.066)	
AGE_GROUP_III (56–60)			1.248***	
			(0.059)	
YOUNG_CEO				1.112**
				(0.044)
−2 Log likelihood	17,766.81	17,754.18	17,745.55	17,760.36
Wald Chi-square	383.7***	394.6***	405.9***	392.0***
Max-rescaled R^2	0.039	0.040	0.040	0.039
Number of observations	18,649	18,649	18,649	18,649

overvalued equity and subsequent stock price crashes (Hong and Stein, 2003). Finally, past negative conditional skewness increases the likelihood of crash risk ($p < 0.01$).

4.3 CEO Age and Crashes: The Role of Bad News Hoarding

According to our perspective, the mechanism underpinning the relationship between CEO age and stock price crashes is the hoarding of bad news. In this section, we investigate explicitly this idea by focusing on stock price crashes triggered by company earnings announcements that break previous years' strings of consecutive earnings increases. Myers, Myers, and Skinner (2007) suggest that strings of consecutive earnings increases, particularly longer strings, can result from hoarding of bad news. Therefore, a break in strings that triggers a stock price crash represents an ideal setting to investigate explicitly whether bad news hoarding drives the relationship between the CEO age and stock price crashes.

Consistent with this idea, we redefine crashes as follows: (i) CRASH_BREAK_STRING1 equal to 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous year, and zero otherwise; (ii) CRASH_BREAK_STRING2 equal to 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous 2 years, and zero otherwise; and (iii) CRASH_BREAK_STRING3 equal to 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous 3 years, and zero otherwise. We expect that stock price crashes that associate with CRASH_BREAK_STRING1, CRASH_BREAK_STRING2, and CRASH_BREAK_STRING3 are more likely to result from stockpiling of negative news, and this likelihood might increase with the length of the string. Among 3,573 stock price crashes, as exhibited in Table I, 1,055 crashes or 29.53% are triggered by firm earnings that decreased in the current year but increased in the previous year, 710 crashes or 19.87% are triggered by firm earnings that decreased in the current year but increased in the previous 2 years, and 411 crashes or 11.50% are triggered by firm earnings that decreased in the current year but

Table IV. The impact of CEO age on stock price crashes: crashes triggered by breaks in string of consecutive earnings increases

This table reports the results of logit regressions where the dependent variable is firm-specific stock price crashes triggered by breaks in a firm's string of consecutive earnings increases. Coefficients are reported as odds ratios. All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRASH_BREAK_STRING1		CRASH_BREAK_STRING2		CRASH_BREAK_STRING3	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(AGE$_{t-1}$)	0.892***	0.915**	0.919*	1.004	0.853***	1.019
	(0.038)	(0.038)	(0.047)	(0.046)	(0.061)	(0.062)
LEN_STRING$_{t-1}$	1.524***	1.554***	1.964***	2.052***	2.435***	2.603***
	(0.031)	(0.033)	(0.041)	(0.042)	(0.055)	(0.057)
Log(AGE$_{t-1}$) ×		0.935**		0.878***		0.834***
LEN_STRING$_{t-1}$		(0.027)		(0.036)		(0.049)
−2 Log likelihood	7,221.75	7,216.43	5,099.43	5,083.85	3,092.55	3,072.65
Wald Chi-square	516.4***	520.1***	619.6***	641.6***	501.6***	536.0***
Max-rescaled R^2	0.093	0.094	0.147	0.150	0.212	0.218
Number of observations	16,251	16,251	16,251	16,251	16,251	16,251

increased in the previous 3 years. These statistics indicate that breaks in strings of consecutive earnings increases represent an important source of crashes. Using these alternative definitions of crashes as dependent variables, we re-estimate model 2 of Table III after controlling for the length of the earnings string prior to the break (LEN_STRING$_{t-1}$).[8] The results in models 1, 3, and 5 of Table IV continue to show that one standardized unit decrease of CEO age increases the probability of a stock price crash triggered by a break in string of positive earnings increases by 10.80% ($p < 0.01$), 8.10% ($p < 0.01$), and 14.70% ($p < 0.01$), respectively. Furthermore, as expected, in Models 1, 3, and 5 one standardized unit increase in the length of a string increases the probability of a stock price crash triggered by a break in string of consecutive earnings increases by 52.40% ($p < 0.01$), 96.40% ($p < 0.01$), and 143.50% ($p < 0.01$), respectively. To link these two results, we interact CEO age with the length of the string. To the extent that the length of the string, ex-ante, proxies for bad news hoarding and that a break in a string represents the revelation of bad news that trigger crashes, based on our theoretical perspective, CEO age should moderate the relationship between strings and crashes. Indeed, the results in models 2, 4, and 6 show that the relationship between the length of the string and the probability of a stock price crash triggered by a break in strings is more positive for younger CEOs. Note that this moderating effect is becoming more important and significant in (i) model 4 relative to model 2 (the coefficient estimate is 0.878 ($p < 0.01$) and 0.935 ($p < 0.05$), respectively) and (ii) model 6 relative to model 4 (the coefficient estimate is 0.834 ($p < 0.01$) and 0.878 ($p <$

8 Strings of consecutive earnings increases are quite prevalent and endure in our sample. Specifically, the sample comprises 4,093 unique strings that exhibit an average duration of 2.76 years.

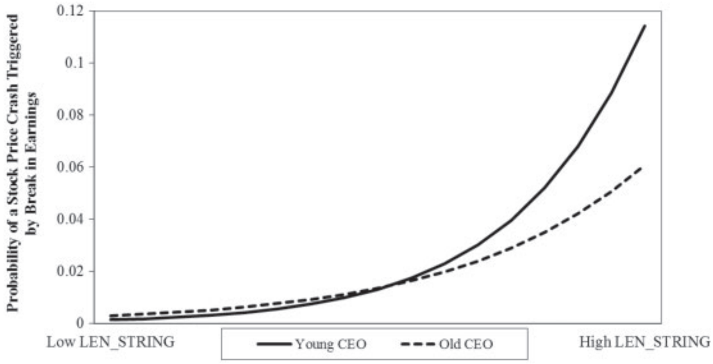

Figure 2. Strings of consecutive earnings increases and crash risk: the moderating effect of CEO age. This figure displays the estimated moderating effect of standardized values of CEO age on the relationship between the standardized values of the length of string of consecutive earnings increases and the likelihood of stock price crashes using model 6 of Table IV. The values of string of consecutive earnings increases range from low length of string (i.e., 1 standard deviation below the mean value) to high length of string (i.e., 1 standard deviation above the mean value) in the cases of both young (solid line) and old (dotted line) CEO age (i.e., 1 standard deviation above or below the mean, respectively).

0.01), respectively). Accordingly, assuming that stock price crashes in models 2, 4, and 6 represent, in an increasing manner, the outcome from revelation of bad news hoarding, these results imply that earnings strings are much more likely to represent stockpiling of negative news when firms are managed by younger CEOs. Finally, Hoetker (2007) suggests that when interpreting interaction terms, it is important to consider not only the coefficient estimates of interaction terms but also the coefficients of each interacted variable and the values of all of the other variables. Therefore, to reinforce our interpretation, we plot in Figure 2 the estimated moderating effect of CEO age on the relationship between the length of the earnings string and the likelihood of stock price crashes using model 6 of Table IV.[9] Consistent with our previous interpretation, the plot shows that the positive effect of the length of the string on the probability of a stock price crash caused by a break is stronger for young than old CEOs. To further examine this moderation effect, we also use the Johnson–Neyman technique to estimate the region of significance, which provides values within the range of CEO age where the relation between the length of the string and the probability of a stock price crash caused by a break is significant at the 5% level. Figure 3 displays the effect of the length of the string given CEO age (measured as deviations from the mean CEO age). The solid line shows the marginal effect of the length of the string while the dotted lines represent the 95% confidence intervals, with the conditional effect to be significant only when both confidence interval bounds lie either below or above zero. Thus, for Figure 3 the marginal effect of the length of the string is significant when CEO age is up to 3.55 standard deviations above the mean CEO age (or equivalently CEO age is below 81 years). For CEO age greater than 3.55 standard deviations above the mean CEO age, the effect is insignificant. These results nuance our previous interpretation.

9 Hoetker (2007) shows that not only the magnitude but also the sign of the interaction effect can change depending on the sign of independent variable coefficients and their coefficient estimates.

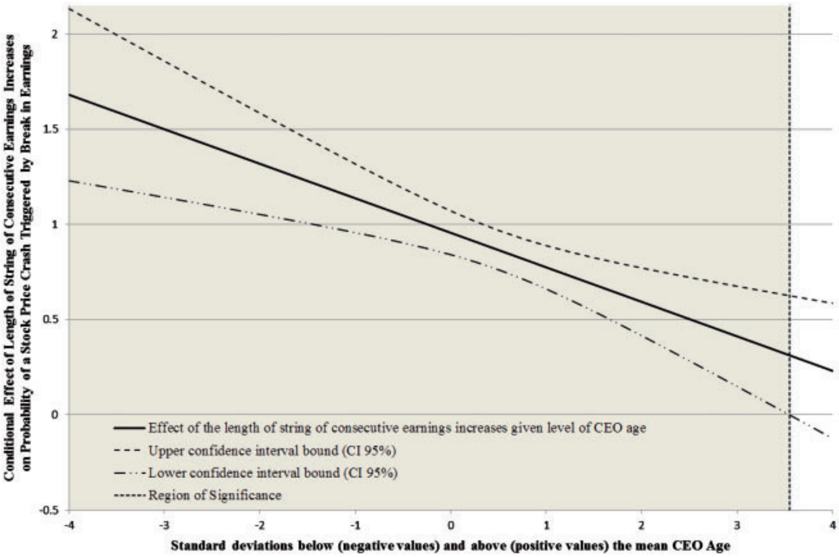

Figure 3. Johnson–Neyman region of significance for the conditional effect of the length of string of consecutive earnings increases given CEO age.

This figure displays the range of standard deviations below and above the mean CEO age where the relation between the length of the string and the probability of a stock price crash caused by a break using model 6 of Table IV is significant at 5% level.

4.4 CEO Compensation Incentives and Crashes

To investigate CEOs' incentives to hide bad news we examine the evolution of CEO compensation before (up to 3 years), during, and after (up to 1 year) the incurrence of stock price crashes. We focus on crashes triggered by revelation of bad news, as captured by CRASH_BREAK_STRING3, because this setting portrays the strongest relationship between strings of consecutive earnings increases and crashes. More specifically, we explore the determinants of CEO compensation using a regression of the natural logarithm of CEO compensation on various firm characteristics. Specifically, our main independent variable is the total CEO compensation (COMP). We also consider CEO salary (SALARY), bonus (BONUS), or equity-based components of compensation (OPTIONS). Firm characteristics include the natural logarithm of total assets ($SIZE_t$), the number of years that the firm is covered in the COMPUSTAT universe ($FIRM\_AGE_t$), the ratio of market value of equity to book value of equity (MB_t), the ratio of net income to total assets (ROA_t), the cumulative monthly returns during the year ($RETURN_t$), and the standard deviation of monthly returns during the year ($STDEV_t$). In addition, we introduce a series of binary variables that denote individual years surrounding the crash year. In this respect, $CRASH\_YR_t$ is the year that the crash occurred; $BEF\_CRASH\_YR_{t-1}$ is the year before the crash; $AFT\_CRASH\_YR_{t+1}$ is the year after the crash; and so forth. All regressions include year and industry binary variables, and standard errors are adjusted for clustering at the firm level. In this specification, the coefficient estimates of $BEF\_CRASH\_YR_{t-3}$ to $BEF\_CRASH\_YR_{t-1}$ represent the (yearly) effect of consecutive earnings increases on CEO compensation before the crash. Similarly, the coefficient estimate of $CRASH\_YR_t$ represents the effect of a stock price crash on CEO compensation, and the estimate of

Table V. CEO compensation, earning strings, and stock price crashes

This table presents the results of OLS regressions where the dependent variables of models 1–4 are, respectively, the log of the CEO's total compensation, salary, bonus, and equity-based compensation (equity-based compensation includes grants of options and restricted stock). All models include a constant, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Log(COMP) (1)	Log(SALARY) (2)	Log(BONUS) (3)	Log(OPTIONS) (4)
$SIZE_t$	0.689***	0.604***	0.113***	0.507***
	(37.13)	(31.55)	(8.94)	(23.28)
Log($FIRM\_AGE_t$)	0.001	0.121***	0.021*	−0.001
	(0.06)	(8.15)	(1.83)	(−0.40)
MB_t	0.131***	−0.041**	0.003	0.101***
	(7.35)	(−2.30)	(0.22)	(5.08)
ROA_t	0.032***	0.021**	0.095***	−0.003
	(3.31)	(2.21)	(10.48)	(−0.30)
$RETURN_t$	0.030***	0.012	0.124***	0.017*
	(3.51)	(1.64)	(15.85)	(1.66)
$STDEV_t$	0.044***	−0.020*	−0.040***	0.037***
	(4.21)	(−1.82)	(4.08)	(3.05)
$BEF\_CRASH\_YR_{t-3}$	0.013	0.067*	0.102**	−0.026
	(0.30)	(1.72)	(2.19)	(−0.50)
$BEF\_CRASH\_YR_{t-2}$	0.078**	0.061*	0.137***	0.077
	(1.97)	(1.76)	(3.35)	(1.64)
$BEF\_CRASH\_YR_{t-1}$	0.118***	0.095***	0.010	0.149***
	(3.16)	(2.68)	(0.25)	(3.68)
$CRASH\_YR_t$	0.011	0.046	−0.177***	0.045
	(0.31)	(1.40)	(−4.46)	(1.10)
$AFT\_CRASH\_YR_{t+1}$	−0.033	0.011	−0.086**	−0.001
	(−0.94)	(0.31)	(−2.49)	(−0.01)
Adjusted R^2	0.523	0.562	0.423	0.328
Number of observations	16,242	16,242	16,242	16,242

$AFT\_CRASH\_YR_{t+1}$ represents the effect on CEO compensation of the year after a stock price crash.

The results in model 1 of Table V show that, controlling for the determinants of CEO compensation, consecutive earnings increases appear to raise CEO total compensation by 11.80% ($p < 0.01$) and 7.80% ($p < 0.05$) 1 and 2 years before the crash, respectively. Interestingly, stock price crashes do not adversely affect CEO compensation because we do not find any statistically significant reductions. Similarly, the year after a stock price crash does not affect CEO compensation. Consequently, increases in CEO compensation during periods of consecutive earnings increases seem to be permanent because compensation does not revert to previous levels during both the year and the year after a firm experiences a stock price crash. This permanence creates strong financial incentives for CEOs to generate strings of consecutive earnings increases earlier in their careers.

Next, we examine which components of CEO compensation drive the increase in compensation prior to a stock price crash. In models 2–4 of Table V, the dependent variable is the natural logarithm of salary, bonus, and equity-based compensation, respectively. The results show that 1 year before the crash, strings of consecutive earnings increases are associated with sizeable increases of 9.50% ($p < 0.01$) and 14.90% ($p < 0.01$) in salary and equity-based compensation, respectively. In addition, 2 years before the crash, consecutive earnings increases relate to an increase of 6.10% ($p < 0.10$) in salary and a significant increase of 13.70% ($p < 0.01$) in bonus. Finally, as expected, bonus appears to fall during the crash year and the year after crash. Nevertheless, the increase in salary and equity-based compensation seems to be largely retained, and the decline in bonus does not affect total compensation in any economically meaningful fashion because the average CEO in the sample receives 50% of compensation in the form of equity-based compensation, 15% in salary, and only 8% in bonus. Overall, these results suggest that equity-based compensation and salary are the primary financial incentives that young CEOs pursue to hoard bad news and create strings of consecutive earnings increases.

4.5 The Moderating Effect of Managerial Discretion

In the previous section, we provide evidence that firms managed by younger CEOs are more likely to experience a stock price crash. This finding supports the view that financial incentives to hoard negative information, which vary across CEO age, create agency problems that drive stock price crashes. Agency theory identifies monitoring, among others, as a critical control system for such problems. Thus, we investigate whether an increase in managerial discretion, which suppresses the effectiveness of the monitoring, could moderate the relationship between CEO age and stock price crashes.

The results in Table VI show coefficient estimates of the moderating effects of duality and Herfindahl index on the relationship between CEO age and stock price crashes. Similarly, Figures 4 and 5 plot the estimated moderating effect of duality and Herfindahl index on the relationship between the standardized values of CEO age and the likelihood of stock price crashes. Consistent with hypotheses 2 and 3, the results show that duality and degree of diversification increase the likelihood of firms managed by young (than old CEOs) to experience a stock price crash. Estimating the region of significance for the moderating effect of duality is meaningless because duality is a binary variable. Nevertheless, we can estimate the significance of the slope when duality equals one or zero, that is, for dual and non-dual CEOs. Untabulated results show that the slope is significant at the 1% level for dual CEOs and insignificant at conventional levels for non-dual CEOs. Regarding the region of significance of the moderating effect of Herfindahl index we estimate it using the Johnson–Neyman technique. Figure 6 plots the effect of CEO age given Herfindahl index. The figure shows that the marginal effect of CEO age is significant when the Herfindahl index is up to 0.60 standard deviations above the mean Herfindahl index (or equivalently Herfindahl index is below 0.97). For Herfindahl index greater than 0.60 standard deviations above the mean, the effect is insignificant. Overall, these findings support the view that younger CEOs are more likely to exploit the CEO-Chair position and organizational complexity to hide bad news, thus increasing stock price crash risk.

5. Additional Analyses

In this section, we perform several additional analyses to assess the robustness of the findings. First, thus far, a crash is defined to represent an extreme negative firm-specific weekly

Table VI. The impact of CEO age on stock price crashes: moderating effects of CEO duality and Herfindahl index

This table reports the results of logit regressions where the dependent variable is the firm-specific stock price crash dummy (CRASH). Coefficients are reported as odds ratios. All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
$DUALITY_{t-1}$	1.067	1.081*	1.068
	(0.045)	(0.045)	(0.045)
$HERFINDAHL_{t-1}$	1.033	1.026	1.027
	(0.023)	(0.023)	(0.023)
$Log(AGE_{t-1})$	0.985	0.912***	0.966
	(0.033)	(0.023)	(0.033)
$Log(AGE_{t-1}) \times DUALITY_{t-1}$	0.899**		0.909**
	(0.042)		(0.042)
$Log(AGE_{t-1}) \times HERFINDAHL_{t-1}$		1.072***	1.068***
		(0.021)	(0.021)
−2 Log likelihood	17,747.00	17,743.10	17,737.39
Wald Chi-square	409.1***	406.0***	418.6***
Max-rescaled R^2	0.040	0.041	0.041
Number of observations	18,649	18,649	18,649

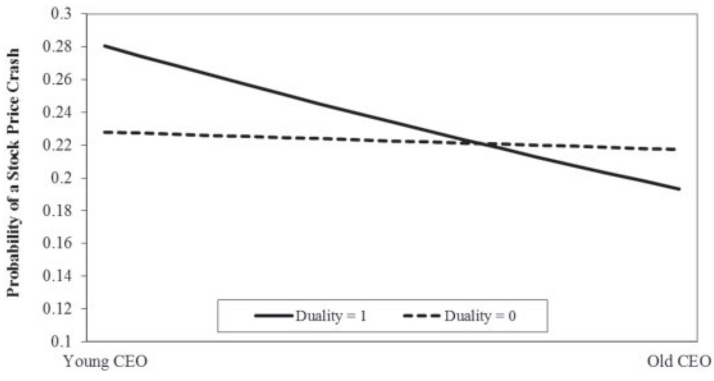

Figure 4. CEO age and crash risk: the moderating effect of duality.
This figure displays the estimated moderating effect of duality on the relationship between the standardized values of CEO age and the likelihood of stock price crashes using model 1 of Table VI. The likelihood of stock price crashes is evaluated for values of CEO age ranging from young CEO (i.e., 1 standard deviation below the mean value) to old CEO (i.e., 1 standard deviation above the mean value) in the cases of dual CEO, that is, duality equals 1 (solid line), and of non-dual CEO, that is, duality equals 0 (dotted line).

return. To alleviate concerns over the definition of extremeness, we re-run the main analysis using alternative measures of crash risk. In particular, we use as dependent variables either the negative coefficient of skewness (Chen, Hong, and Stein, 2001) or extreme sigma (Bradshaw *et al.*, 2010). The advantage of these variables is that they are continuous and they capture the proclivity of a firm toward stock price crashes; not necessarily, however,

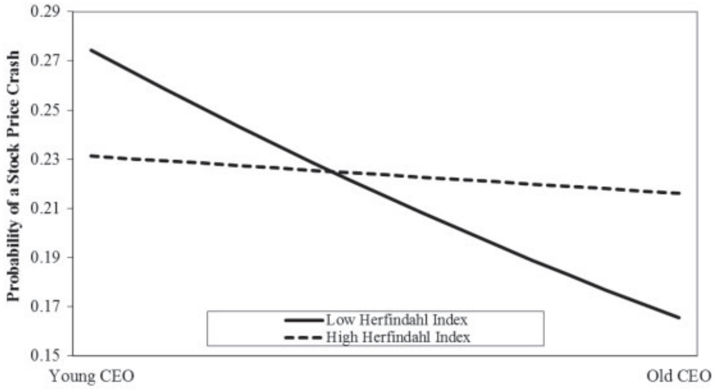

Figure 5. CEO age and crash risk: the moderating effect of the Herfindahl index.
This figure displays the estimated moderating effect of the Herfindahl index on the relationship between the standardized values of CEO age and the likelihood of stock price crashes using model 2 of Table VI. The likelihood of stock price crashes is evaluated for values of CEO age ranging from young CEO (i.e., 1 standard deviation below the mean value) to old CEO (i.e., 1 standard deviation above the mean value) in the cases of a low Herfindahl index. That is, the Herfindahl is set to 1 standard deviation below its mean value (solid line) and 1 standard deviation above its mean value (dotted line).

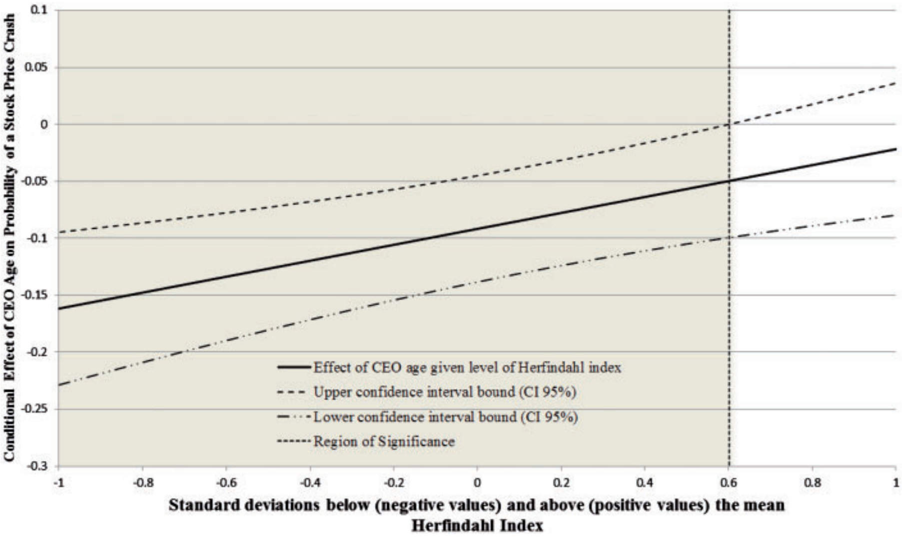

Figure 6. Johnson–Neyman region of significance for the conditional effect of CEO age given Herfindahl index.
This figure displays the range of standard deviations below and above the mean Herfindahl index where the relation between the standardized values of CEO age and the probability of a stock price crash using model 2 of Table VI is significant at 5% level.

the more extreme ones. As shown in Table VII, the results from this analysis are qualitatively similar to those presented above.

Second, it is possible that inappropriate model specification of CEO tenure, which is correlated with CEO age, bias coefficient estimates of CEO age. Table VIII reports results

Table VII. The impact of CEO age on stock price crashes: alternative measures of crash risk

This table presents the results of OLS regressions where the dependent variable of models 1–3 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 4–6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	NCSKEW			EXTR_SIGMA		
	(1)	(2)	(3)	(4)	(5)	(6)
DUALITY_{t-1}	0.003	0.008	0.005	0.010	0.016	0.012
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
HERFINDAHL_{t-1}	0.015**	0.015**	0.013**	0.015**	0.014**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\text{Log}(\text{AGE}_{t-1})$		−0.025***	−0.011		−0.027***	−0.008
		(0.006)	(0.009)		(0.006)	(0.009)
$\text{Log}(\text{AGE}_{t-1}) \times \text{DUALITY}_{t-1}$			−0.027**			−0.036***
			(0.012)			(0.012)
$\text{Log}(\text{AGE}_{t-1}) \times \text{HERFINDAHL}_{t-1}$			0.015***			0.014**
			(0.006)			(0.006)
Adjusted R^2	0.029	0.029	0.030	0.027	0.028	0.029
Number of observations	18,649	18,649	18,649	18,649	18,649	18,649

after controlling for quadratic, cubic, and quartic forms of tenure. The results show that the effect of CEO age on crashes and the moderating effect of duality/Herfindahl index remain robust; therefore, they are not driven by any non-linear effects of tenure.

Third, if the characteristics of firms managed by younger CEOs are different, then the apparent CEO age effect on stock price crashes might be biased when linear control variables employed in the main specification are inadequate. Under this assumption, the CEO age effect might pick up non-linear effects of the control variables on a firm's propensity to experience a stock price crash. Ideally, to alleviate concerns over such functional form misspecification biases, we create two data samples that are comparable across all the control variables but differ only on CEO age. To construct these samples, we use a one-to-one propensity-score matching estimation method. More specifically, the method uses a probit regression to estimate propensity scores, $p(Y=1|X=x)$, based on the probability of receiving a binary treatment, Y, conditional on all the control variables, x. To operationalize the estimation, we transform CEO age into a binary variable based on the median value of 55 (YOUNG_CEO) and we consider having a young CEO as treatment. Then, we estimate the propensity score of having a young CEO using the control variables, as in model 1 of Table III. We then use the resulting estimated propensity scores to find comparable firms that belong in the treatment effects and exhibit comparable scores. That is, for each firm-year with a young CEO we use the propensity scores to find comparable firm-years with an old CEO based on the nearest-neighbor method. To ensure the adequacy of the matching estimation method, we require that the absolute difference in propensity scores among pairs does not exceed 0.01. If there are more firm-years with an old CEO that meet this criterion, we retain the firm-year with the smallest difference in propensity scores. Using this method

Table VIII. The impact of CEO age on stock price crashes: controls for non-linear effects of CEO tenure

This table reports regression results where the dependent variable is a firm-specific stock price crash variable. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRASH		NCSKEW		EXTR_SIGMA	
	(1)	(2)	(3)	(4)	(5)	(6)
Log($TENURE_{t-1}$)	2.627	0.967	−0.003	−0.002	−0.006	−0.005
	(0.772)	(0.043)	(0.013)	(0.013)	(0.012)	(0.012)
Log($TENURE_{t-1}$)^2	0.349	1.091*	0.001	0.001	0.006	0.006
	(0.691)	(0.045)	(0.013)	(0.013)	(0.012)	(0.012)
Log($TENURE_{t-1}$)^3	1.501	1.008	0.002	0.002	0.002	0.002
	(0.249)	(0.016)	(0.004)	(0.004)	(0.004)	(0.004)
Log($TENURE_{t-1}$)^4	0.950*	0.983	0.000	0.000	−0.001	−0.001
	(0.031)	(0.011)	(0.003)	(0.003)	(0.003)	(0.003)
$DUALITY_{t-1}$	1.082*	1.069	0.008	0.006	0.016	0.013
	(0.045)	(0.045)	(0.013)	(0.013)	(0.013)	(0.013)
$HERFINDAHL_{t-1}$	1.121	1.028	0.015**	0.013**	0.014**	0.013**
	(0.081)	(0.023)	(0.006)	(0.006)	(0.006)	(0.006)
Log(AGE_{t-1})	0.582***	0.976	−0.022***	−0.008	−0.024***	−0.005
	(0.171)	(0.033)	(0.006)	(0.009)	(0.006)	(0.009)
Log(AGE_{t-1}) × $DUALITY_{t-1}$		0.904**		−0.027**		−0.036***
		(0.042)		(0.012)		(0.012)
Log(AGE_{t-1}) × $HERFINDAHL_{t-1}$		1.065***		0.015***		0.013**
		(0.021)		(0.006)		(0.006)
Max-rescaled R^2/Adjusted R^2	0.040	0.041	0.029	0.030	0.028	0.029
Number of observations	18,649	18,649	18,649	18,649	18,649	18,649

we obtain 5,803 unique pairs of matched firm-years. Panel A of Table IX displays the average of the control variables for young (below median age) and old (above median age) CEOs for both the unmatched and propensity-score matched samples. For the unmatched sample, it is evident that most of the control variables differ significantly across the two samples. For the propensity-score matched sample, however, all of the control variables are comparable across the two groups; by design, only the CEO age differs.[10] Using this sample, panel B of Table IX reports the results of the main analysis (in the spirit of models 1 and 3 of Table VI) using comparison samples for each treatment effect (e.g., young versus old CEOs). The results remain qualitatively similar, suggesting that the CEO age effect on stock price crashes is not an artifact of functional form misspecification biases.

10 An exception is the $RETIREMENT_{t-1}$ variable that by definition should not vary across young and old CEOs.

Table IX. The impact of CEO age on stock price crashes: subsamples based on CEO age propensity scores

Panel A presents the unmatched and matched covariate means of control variables for young and old CEOs. Panel A1 presents the unmatched sample (i.e., the original sample), and Panel A2 presents the matched sample based on CEO age propensity score matching. Panel B reports regression results where the dependent variable is a firm-specific stock price crash variable. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Covariate means of control variables for young and old CEOs

	A1. Unmatched				A2. Matched			
	YOUNG CEOs	OLD CEOs	Diff	*t*-Stat	YOUNG CEOs	OLD CEOs	Diff	*t*-Stat
$DUALITY_{t-1}$	0.458	0.685	−0.226***	−31.940	0.664	0.651	0.013	1.470
$HERFINDAHL_{t-1}$	0.842	0.779	0.062***	15.260	0.792	0.790	0.002	0.330
$Log(TENURE_{t-1})$	1.684	2.088	−0.404***	−37.020	1.977	1.998	−0.021	−1.600
CEO_CHANGE_{t-1}	0.071	0.144	−0.073***	−16.350	0.119	0.109	0.010	1.650
CEO_CHANGE_{t-2}	0.074	0.130	−0.056***	−12.780	0.114	0.111	0.003	0.530
$RETIREMENT_{t-1}$	0.000	0.077	−0.077***	−28.560	0.000	0.071	−0.071***	−21.110
$Log(ITM\_OPTIONS\_HOLDINGS_{t-1})$	6.794	6.755	0.040	0.780	6.820	6.874	−0.054	−0.840
$Log(EQUITY\_HOLDINGS_{t-1})$	8.391	9.096	−0.705***	−21.120	9.037	8.983	0.054	1.370
$SIZE_{t-1}$	6.978	7.371	−0.393***	−17.780	7.345	7.330	0.015	0.530
MB_{t-1}	3.408	3.114	0.295***	7.010	3.074	3.132	−0.059	−1.200
LEV_{t-1}	0.467	0.493	−0.026***	−9.060	0.491	0.490	0.001	0.340
ROE_{t-1}	0.098	0.120	−0.022***	−7.430	0.117	0.118	−0.002	−0.480
$RETURN_{t-1}$	−0.155	−0.121	−0.034***	−16.680	−0.125	−0.124	−0.001	−0.270
$Log(FIRM\_AGE_{t-1})$	2.852	3.132	−0.281***	−26.940	3.080	3.096	−0.016	−1.230
$GOODWILL_{t-1}$	0.112	0.111	0.001	0.380	0.112	0.112	0.000	−0.130
$R\&D_{t-1}$	0.038	0.027	0.011***	14.560	0.026	0.028	−0.001*	−1.790
TECHNOLOGY	0.253	0.185	0.068***	11.180	0.188	0.193	−0.005	−0.690

(continued)

Table IX. Continued

Panel A: Covariate means of control variables for young and old CEOs

	A1. Unmatched				A2. Matched			
	YOUNG CEOs	OLD CEOs	Diff	*t*-Stat	YOUNG CEOs	OLD CEOs	Diff	*t*-Stat
COMPETITIVENESS$_{t-1}$	−0.046	−0.059	0.013***	4.340	−0.054	−0.055	0.001	0.360
PR_DEFAULT$_{t-1}$	0.005	0.004	0.001***	2.840	0.004	0.004	0.000	0.470
DTURN$_{t-1}$	1.475	1.245	0.230	0.800	1.204	1.154	0.051	0.150
NCSKEW$_{t-1}$	0.113	0.078	0.034***	3.230	0.101	0.087	0.014	1.030
N	8,826	9,823			5,803	5,803		

Panel B: The impact of CEO age on stock price crashes: Matched sample using CEO age propensity scores

	CRASH		NCSKEW		EXTR_SIGMA	
	(1)	(2)	(3)	(4)	(5)	(6)
DUALITY$_{t-1}$	1.077	1.073	0.024	0.022	0.023	0.022
	(0.052)	(0.052)	(0.015)	(0.015)	(0.015)	(0.015)
HERFINDAHL$_{t-1}$	1.033	1.034	0.020***	0.020**	0.013*	0.013*
	(0.027)	(0.027)	(0.008)	(0.008)	(0.007)	(0.007)
Log(AGE$_{t-1}$)	0.929***	0.940	−0.018***	0.001	−0.028***	−0.007
	(0.024)	(0.042)	(0.007)	(0.012)	(0.007)	(0.011)
Log(AGE$_{t-1}$) × DUALITY$_{t-1}$		0.968		−0.032**		−0.033**
		(0.050)		(0.014)		(0.014)
Log(AGE$_{t-1}$) × HERFINDAHL$_{t-1}$		1.061**		0.020***		0.019***
		(0.025)		(0.007)		(0.007)
Max-rescaled R^2/Adjusted R^2	0.037	0.038	0.030	0.031	0.025	0.026
Number of observations	11,606	11,606	11,606	11,606	11,606	11,606

Finally, the literature provides evidence that other variables measuring the severity of agency problems within a firm explain stock price crashes.[11] Specifically, Hutton, Marcus, and Tehranian (2009) find that opaque firms are more prone to stock price crashes. Kim, Li, and Zhang (2011a) find that the sensitivity of CEO and CFO option portfolios value-to-stock price relate positively to stock price crashes. Finally, Andreou *et al.* (2016a) show that inefficient corporate governance, among others, dedicated (transient) institutional ownership relates negatively (positively) to stock price crashes. We re-run the main analysis after controlling for opacity, using the prior 3 years' moving sum of the absolute value of discretionary accruals (OPACITY_{t-1}), CEO and CFO incentive ratios for executive option and stock holdings (CEO_INC_OPT_{t-1}, CFO_INC_OPT_{t-1}, CEO_INC_STK_{t-1}, CFO_INC_STK_{t-1}), and dedicated and transient institutional ownership relative to total shares outstanding ($\text{DED\_INST\_HOLDINGS}_{t-1}$ and $\text{TRA\_INST\_HOLDINGS}_{t-1}$, respectively) as additional control variables.[12] The results in Table X show that the main findings remain robust to the inclusion of these variables.

6. Alternative Explanations

In this section, we explore alternative explanations of our findings. First, whereas the theoretical arguments discussed in Section 2 suggest a causal relationship running from younger CEOs to stock price crash risk, the evidence could also be consistent with alternative explanations that consider reverse causality; that is, stock price crash risk causes CEO firing and the firms hire younger CEOs thereafter. If this implication is true, then, assuming persistence in crash risk, our findings could be spurious and driven by this type of reverse causality. We explicitly investigate this explanation using various approaches. Initially, we compare the CEO age of newly hired CEOs for the sub-samples of firms that experience a stock price crash with those that do not. In Panel A of Table XI, there are 2,093 CEO turnovers; among them, 370 (or 17.68%) coincide with a stock price crash and 1,723 (or 82.32%) do not. However, neither the mean nor the median age of newly hired CEOs is significantly different between the two sub-samples, suggesting that reverse causality is unlikely to drive our findings. We also examine whether this type of reverse causality is more relevant as an explanation among firms that exhibit more difficulties in handling risk and/or firms that exhibit inherent riskiness. Such firms might be more prone to crash risk. At the same time, these firms might need a healthy, flexible, and energetic young CEO that is able to deal with the stress of leadership. Accordingly, if these firms hire younger CEOs, then the CEO age effect could be an artifact of firm risk. To alleviate such concerns, we compare the mean/median age of newly hired CEOs for high-risk firms that experience a stock price crash with those that do not. In particularly, we focus on the sub-samples of less experienced firms (e.g., below the median firm age), more competitive firms (e.g., above the median industry-adjusted firm operating profit to sales), and high default-risk firms (e.g., above the median probability of bankruptcy based on the Merton Distance-to-Default model), which arguably represent riskier firms. The results in Panel A of Table XI show

11 Note that many of these variables, due to data availability, reduce the sample size substantially. Thus, rather than reporting the main analysis using a smaller sample size, we explicitly investigate the effect of these variables on our results in this section.

12 Information about institutional ownership classification into dedicated and transient investors is from Brian Bushee's website.

Table X. The impact of CEO age on stock price crashes: additional control variables

This table reports regression results where the dependent variable is a firm-specific stock price crash variable. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRASH		NCSKEW		EXTR_SIGMA	
	(1)	(2)	(3)	(4)	(5)	(6)
$OPACITY_{t-1}$	1.019	1.019	0.010	0.010	0.011	0.011
	(0.025)	(0.025)	(0.008)	(0.008)	(0.007)	(0.007)
$CEO\_INC\_OPT_{t-1}$	0.950	0.952	−0.023*	−0.022*	−0.003	−0.002
	(0.039)	(0.039)	(0.012)	(0.012)	(0.011)	(0.011)
$CFO\_INC\_OPT_{t-1}$	1.030	1.029	0.017*	0.017*	0.002	0.001
	(0.032)	(0.032)	(0.010)	(0.010)	(0.009)	(0.009)
$CEO\_INC\_STC_{t-1}$	1.053	1.057	0.016	0.017	0.015	0.016
	(0.036)	(0.036)	(0.012)	(0.012)	(0.011)	(0.011)
$CFO\_INC\_STC_{t-1}$	0.969	0.969	−0.005	−0.005	−0.005	−0.005
	(0.025)	(0.025)	(0.007)	(0.007)	(0.007)	(0.007)
$DED\_INST\_HOLDINGS_{t-1}$	0.989	0.988	−0.001	−0.001	−0.007	−0.007
	(0.034)	(0.034)	(0.009)	(0.009)	(0.009)	(0.009)
$TRA\_INST\_HOLDINGS_{t-1}$	1.127***	1.127***	0.055***	0.055***	0.045***	0.045***
	(0.027)	(0.027)	(0.009)	(0.009)	(0.008)	(0.008)
$DUALITY_{t-1}$	1.065	1.048	0.001	−0.001	0.008	0.005
	(0.053)	(0.053)	(0.015)	(0.015)	(0.015)	(0.015)
$HERFINDAHL_{t-1}$	1.057**	1.054**	0.024***	0.022***	0.024***	0.023***
	(0.026)	(0.026)	(0.007)	(0.007)	(0.007)	(0.007)
$\text{Log}(AGE_{t-1})$	0.919***	0.969	−0.024***	−0.016	−0.028***	−0.013
	(0.027)	(0.038)	(0.008)	(0.011)	(0.008)	(0.011)
$\text{Log}(AGE_{t-1}) \times DUALITY_{t-1}$		0.900**		−0.018		−0.028**
		(0.047)		(0.014)		(0.014)
$\text{Log}(AGE_{t-1}) \times HERFINDAHL_{t-1}$		1.061**		0.018***		0.014**
		(0.024)		(0.007)		(0.007)
Max-rescaled R^2/Adjusted R^2	0.042	0.044	0.031	0.031	0.029	0.030
Number of observations	13,265	13,265	13,265	13,265	13,265	13,265

that the mean/median age of newly hired CEOs is not significantly different between risky firms that experience a stock price crash and risky firms that do not, implying that crash risk is not a determinant of the age of newly hired CEOs. As a complementary test of the reverse causality explanation, we also use multivariate regression analysis. Specifically, a prerequisite of the reverse causality explanation is that stock price crash risk shows persistence. Indeed, untabulated results reveal persistence in stock price crash risk that might prevail up to 3 years among the continuous measures of crash risk (i.e., the negative coefficient of skewness and the extreme sigma), rather than the binary indicator measure of

Table XI. The impact of CEO age on stock price crashes: endogeneity tests

Panel A presents univariate analysis of the age of newly hired CEOs of firms that exhibit a stock price crash (CRASH = YES) relative to firms that do not (CRASH = NO). Panels B, C, D, and E report regression results where the dependent variable is a firm-specific stock price crash variable after excluding the first 3 years of CEO tenure for the whole sample, for firms below median value of firm age, for firms with above median competitiveness, and for firms with above median probability of default, respectively. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Univariate analysis

	Full sample		Risky firms					
	Age of newly hired CEOs		Low firm age		Competitive firms		High probability of default	
CRASH	NO	YES	NO	YES	NO	YES	NO	YES
Mean	52.13	52.29	51.14	51.34	51.98	51.70	52.12	52.35
Diff		0.16		0.20		−0.28		0.23
t-stat		0.40		0.34		−0.48		0.41
Median	52	52	51	51	52	52	52	52
Diff		0		0		0		0
z-stat		0.71		0.15		0.65		0.34
N	1,723	370	772	190	808	173	899	193

Panel B: Analysis after excluding the first 3 years of CEO tenure

	CRASH		NCSKEW		EXTR_SIGMA	
Name	(1)	(2)	(3)	(4)	(5)	(6)
$DUALITY_{t-1}$	1.078	1.060	0.006	0.002	0.014	0.009
	(0.050)	(0.050)	(0.014)	(0.014)	(0.014)	(0.014)
$HERFINDAHL_{t-1}$	1.016	1.011	0.012*	0.010	0.011*	0.010
	(0.025)	(0.025)	(0.007)	(0.007)	(0.007)	(0.007)
$Log(AGE_{t-1})$	0.899***	0.937*	−0.029***	−0.016	−0.037***	−0.018*
	(0.026)	(0.038)	(0.007)	(0.010)	(0.007)	(0.011)
$Log(AGE_{t-1}) \times DUALITY_{t-1}$		0.921*		−0.025*		−0.032**
		(0.046)		(0.013)		(0.013)
$Log(AGE_{t-1}) \times HERFINDAHL_{t-1}$		1.065***		0.016**		0.014**
		(0.023)		(0.006)		(0.006)
Max-rescaled R^2/ Adjusted R^2	0.043	0.045	0.030	0.031	0.030	0.030
Number of observations	15,258	15,258	15,258	15,258	15,258	15,258

(continued)

Table XI. Continued

Panel C: Analysis after excluding the first 3 years of CEO tenure for firms below median value of firm age

	CRASH		NCSKEW		EXTR_SIGMA	
Name	(1)	(2)	(3)	(4)	(5)	(6)
$DUALITY_{t-1}$	1.069	1.059	0.006	0.003	0.018	0.014
	(0.064)	(0.064)	(0.019)	(0.019)	(0.019)	(0.019)
$HERFINDAHL_{t-1}$	1.025	1.022	0.015*	0.015	0.012	0.012
	(0.032)	(0.033)	(0.009)	(0.009)	(0.009)	(0.009)
Log(AGE_{t-1})	0.926**	0.982	−0.026***	−0.001	−0.028***	0.004
	(0.033)	(0.050)	(0.010)	(0.014)	(0.010)	(0.014)
Log(AGE_{t-1}) × $DUALITY_{t-1}$		0.908		−0.040**		−0.053***
		(0.061)		(0.017)		(0.018)
Log(AGE_{t-1}) × $HERFINDAHL_{t-1}$		1.033		0.006		0.007
		(0.031)		(0.009)		(0.009)
Max-rescaled R^2/ Adjusted R^2	0.046	0.047	0.032	0.032	0.029	0.030
Number of observations	7,852	7,852	7,852	7,852	7,852	7,852

Panel D: Analysis after excluding the first 3 years of CEO tenure for firms with above median competitiveness

	CRASH		NCSKEW		EXTR_SIGMA	
Name	(1)	(2)	(3)	(4)	(5)	(6)
$DUALITY_{t-1}$	1.092	1.065	0.010	0.003	0.016	0.009
	(0.071)	(0.071)	(0.019)	(0.018)	(0.019)	(0.019)
$HERFINDAHL_{t-1}$	1.034	1.033	0.017*	0.015*	0.012	0.011
	(0.035)	(0.035)	(0.009)	(0.009)	(0.009)	(0.009)
Log(AGE_{t-1})	0.882***	0.954	−0.033***	−0.001	−0.039***	−0.008
	(0.035)	(0.056)	(0.009)	(0.014)	(0.009)	(0.015)
Log(AGE_{t-1}) × $DUALITY_{t-1}$		0.878*		−0.052***		−0.051***
		(0.068)		(0.017)		(0.018)
Log(AGE_{t-1}) × $HERFINDAHL_{t-1}$		1.039		0.015*		0.013
		(0.034)		(0.008)		(0.008)
Max-rescaled R^2/ Adjusted R^2	0.058	0.059	0.035	0.036	0.035	0.036
Number of observations	7,679	7,679	7,679	7,679	7,679	7,679

Panel E: Analysis after excluding the first 3 years of CEO tenure for firms with above median probability of default

	CRASH		NCSKEW		EXTR_SIGMA	
Name	(1)	(2)	(3)	(4)	(5)	(6)
$DUALITY_{t-1}$	1.184**	1.163**	0.013	0.008	0.033	0.029
	(0.074)	(0.075)	(0.021)	(0.021)	(0.020)	(0.020)
$HERFINDAHL_{t-1}$	1.034	1.031	0.008	0.006	0.011	0.011

(continued)

Table XI. Continued

Panel E: Analysis after excluding the first 3 years of CEO tenure for firms with above median probability of default

	CRASH		NCSKEW		EXTR_SIGMA	
Name	(1)	(2)	(3)	(4)	(5)	(6)
	(0.035)	(0.035)	(0.010)	(0.010)	(0.009)	(0.010)
Log(AGE_{t-1})	0.880***	0.915*	−0.037***	−0.019	−0.046***	−0.027*
	(0.035)	(0.053)	(0.010)	(0.015)	(0.010)	(0.015)
Log(AGE_{t-1}) × $DUALITY_{t-1}$		0.930		−0.030		−0.030*
		(0.064)		(0.018)		(0.018)
Log(AGE_{t-1}) × $HERFINDAHL_{t-1}$		1.052		0.019**		0.006
		(0.032)		(0.009)		(0.009)
Max-rescaled R^2/ Adjusted R^2	0.063	0.063	0.042	0.043	0.036	0.036
Number of observations	7,508	7,508	7,508	7,508	7,508	7,508

crash risk. Accordingly, we re-run the main analysis after excluding the first 3 years of CEO tenure using (i) the full sample, and (ii) the sub-samples of riskier firms (i.e., less experienced firms, more-competitive firms, and high default-risk firms). The results in Panels B, C, D, and E of Table XI show that our main findings remain qualitatively similar.[13]

Second, we investigate whether our results could be explained with age-related physiological and psychological characteristics of the CEO and heterogeneous abilities that could provoke stock price crashes. Such characteristics include CEO demonstrated ability, power, risk tendency, youthful creativeness, and inexperience in corporate communication. To rule out CEO demonstrated ability, power, and risk tendency as alternative explanations, we rerun the main analysis after including explicit control variables. As a proxy for CEO demonstrated ability, we use the 5-year historical industry-adjusted return on assets ($IND\_ADJ\_ROA_{t-1}$) (Baik, Farber, and Lee, 2011).[14] Positive values can indicate that the CEO demonstrated greater ability to manage a firm more efficiently and generate greater profitability compared with industry rival firms. As a proxy for CEO power, following Bebchuk, Cremers, and Peyer (2011), we use the fraction of aggregate CEO compensation to the compensation of the top management team (CPS_{t-1}). Greater values indicate the relative importance of the CEO compared with the top management team. We also control for a CEO risk tendency due to overconfidence ($OVERCONFIDENCE_{t-1}$), one of the most prominent behavioral biases (Malmendier and Tate, 2005), using the time-varying press-

13 Note that among high-risk firms, the moderating effect of the Herfindahl index on the relationship between CEO age and stock price crashes is weak. This finding is not surprising because the Herfindahl index exhibits less variation among high-risk firms.

14 In an untabulated analysis, we also use alternative measures of CEO demonstrated ability. In particular, we use 3-year and 7-year historical industry-adjusted returns on assets and the managerial ability measure of Demerjian et al. (2012). Including these measures into our regression analysis does not affect our findings.

Table XII. The impact of CEO age on stock price crashes: controls for heterogeneous CEO abilities

This table reports regression results where the dependent variable is a firm-specific stock price crash variable. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRASH		NCSKEW		EXTR_SIGMA	
	(1)	(2)	(3)	(4)	(5)	(6)
$IND\_ADJ\_ROA_{t-1}$	1.067*	1.065*	−0.002	−0.002	0.013	0.012
	(0.033)	(0.034)	(0.011)	(0.011)	(0.010)	(0.010)
$OVERCONFIDENCE_{t-1}$	0.992	0.992	−0.032	−0.032	−0.015	−0.015
	(0.077)	(0.077)	(0.021)	(0.021)	(0.021)	(0.021)
CPS_{t-1}	1.061**	1.062**	0.019**	0.019**	0.018**	0.018**
	(0.025)	(0.025)	(0.007)	(0.007)	(0.007)	(0.007)
$DUALITY_{t-1}$	1.084	1.065	0.004	0.001	0.018	0.013
	(0.056)	(0.056)	(0.015)	(0.015)	(0.015)	(0.015)
$HERFINDAHL_{t-1}$	1.018	1.013	0.018**	0.015**	0.016**	0.014*
	(0.028)	(0.028)	(0.007)	(0.008)	(0.007)	(0.007)
$Log(AGE_{t-1})$	0.928***	0.977	−0.018**	−0.006	−0.023***	−0.004
	(0.028)	(0.040)	(0.008)	(0.011)	(0.008)	(0.011)
$Log(AGE_{t-1}) \times DUALITY_{t-1}$		0.901**		−0.024*		−0.034**
		(0.049)		(0.014)		(0.014)
$Log(AGE_{t-1}) \times HERFINDAHL_{t-1}$		1.084***		0.022***		0.018***
		(0.025)		(0.007)		(0.007)
Max-rescaled R^2/ Adjusted R^2	0.038	0.040	0.030	0.031	0.025	0.026
Number of observations	12,571	12,571	12,571	12,571	12,571	12,571

based measure from Andreou *et al.* (2016b). The results in Table XII show that our main findings remain unaltered by the inclusion of these additional CEO characteristics.

Concerning youthful creativeness and inexperience with corporate communication, these CEO characteristics are more problematic to control directly because it is difficult to measure them precisely. Nevertheless, we can observe their consequences, which enable us to design appropriate tests to preclude them as alternative explanations of the CEO age effect. Specifically, the CEO age effect could result from (unsuccessful) youthful creativeness. Youthful creativeness, however, could also be successful and this would lead to positive jumps in performance. Accordingly, the CEO age should predict fat tails generally, not only one-sided exposure to crashes. To investigate whether youthful creativeness explains our findings, we define a positive jump symmetrically to a crash, that is, as a 3.2 standard deviation above the average firm-specific weekly returns for the entire fiscal year (JUMP), and

Table XIII. The impact of CEO age on positive stock price jumps and stock price crashes excluding crashes that likely result from inappropriate earnings expectations

This table reports the results of logit regressions where the dependent variable in models 1 and 2 is positive stock price jumps and in models 3 and 4 is the firm-specific stock price crash, excluding crashes that likely result from inappropriate earnings expectations. Coefficients are reported as odds ratios. All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	JUMP		CRASH_EX_MB	
	(1)	(2)	(3)	(4)
DUALITY_{t-1}	1.060	1.061	1.046	1.037
	(0.048)	(0.048)	(0.052)	(0.051)
HERFINDAHL_{t-1}	0.993	0.997	1.010	1.006
	(0.024)	(0.024)	(0.026)	(0.025)
$\text{Log}(\text{AGE}_{t-1})$	1.007	1.011	0.930***	0.959
	(0.024)	(0.035)	(0.025)	(0.037)
$\text{Log}(\text{AGE}_{t-1}) \times \text{DUALITY}_{t-1}$		0.999		0.926
		(0.044)		(0.047)
$\text{Log}(\text{AGE}_{t-1}) \times \text{HERFINDAHL}_{t-1}$		0.972		1.067***
		(0.023)		(0.024)
Max-rescaled R^2	0.039	0.040	0.037	0.038
Number of observations	18,649	18,649	15,254	15,254

repeat our main analysis.[15] Table XIII (Models 1 and 2) shows no evidence of a relationship between CEO age and the probability of a positive jump. Thus, CEO age appears to predict only stock price crashes, and unsuccessful youthful creativeness is unlikely to explain this finding.

Similarly, the CEO age effect could result from young CEOs' lack of experience in corporate communication to set appropriate earnings expectations (Huang, Ena, and Lee, 2012). This effect could motivate young CEOs to hoard bad news to meet or beat analyst earnings forecasts, thus increasing future stock price crash risk. Essentially, this explanation assumes that crashes that result from inexperience in corporate communication drive the CEO age effect. Accordingly, we redefine the binary crash risk variable after excluding these crashes (CRASH_EX_MB). These crashes are expected to coincide (i) with meeting or beating analyst earnings forecasts in the previous year and (ii) missed analyst earnings forecasts in the current year. Using this definition of crashes, we re-run the main analysis. The results in Table XIII (Models 3 and 4) remain qualitatively similar, suggesting that the CEO age effect is not explained by inappropriate earnings expectations.

Finally, we also investigate the robustness of our results to potential unobserved CEO characteristic biases. Specifically, we examine whether the results are driven by habitual CEO characteristics, that is, characteristics stemming from innate abilities, social capital, and personalities that remain constant over time (Graham, Li, and Qiu, 2012). Such habitual CEO characteristics shape managerial style and might have implications for stock price

15 Within our sample, 2,883 firm-years or 15.45% are classified as jumps.

Table XIV. The impact of CEO age on stock price crashes: subsample of CEOs stayed with a firm for at least 5 years

This table reports regression results where the dependent variable is a firm-specific stock price crash variable. The results of models 1 and 2 are odd ratios from logit regressions where the dependent variable is a crash risk dummy (CRASH). Models 3–6 report results of OLS regressions where the dependent variable of models 3 and 4 is the negative coefficient of skewness (NCSKEW) and the dependent variable of models 5 and 6 is the extreme sigma (EXTR_SIGMA). All models include a constant, control variables, year, and industry fixed effects. Standard errors clustered at the firm level are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CRASH		NCSKEW		EXTR_SIGMA	
	(1)	(2)	(3)	(4)	(5)	(6)
$DUALITY_{t-1}$	1.077	1.062	0.003	−0.001	0.011	0.007
	(0.049)	(0.049)	(0.013)	(0.013)	(0.013)	(0.013)
$HERFINDAHL_{t-1}$	1.021	1.015	0.016**	0.014**	0.015**	0.014**
	(0.025)	(0.025)	(0.007)	(0.007)	(0.007)	(0.007)
$Log(AGE_{t-1})$	0.912***	0.950	−0.026***	−0.011	−0.030***	−0.011
	(0.026)	(0.039)	(0.007)	(0.010)	(0.007)	(0.010)
$Log(AGE_{t-1}) \times DUALITY_{t-1}$		0.919*		−0.027**		−0.033***
		(0.047)		(0.013)		(0.013)
$Log(AGE_{t-1}) \times HERFINDAHL_{t-1}$		1.062**		0.012*		0.010
		(0.024)		(0.006)		(0.006)
Max-rescaled R^2/ Adjusted R^2	0.040	0.041	0.030	0.030	0.028	0.029
Number of observations	15,956	15,956	15,956	15,956	15,956	15,956

crashes. Given the association of (extreme negative) stock performance with CEO dismissal, which presumably is greater for younger CEOs because they are less reputable, habitual CEO characteristics should affect disproportionately CEOs with different ages. As a result, if habitual CEO characteristics cause CEO dismissals due to stock price crashes, this will introduce a sample selection bias because younger CEOs are more likely to be dismissed (due to habitual CEO characteristics). This bias could induce a spurious relationship between CEO age and stock price crashes. To control for such potential unobserved CEO characteristic biases, we repeat our main analysis by considering the subsample of CEOs who keep their position for at least 5 years. In this respect, habitual CEO characteristics should affect the firm's crash risk similarly over a long period, regardless of CEO age, which, by definition, varies over time. The results in Table XIV show that using this subsample of long-tenured CEOs, all of our conclusions remain qualitatively unaltered.

7. Conclusions

This study shows that younger CEOs are more likely to associate with future stock price crashes, including crashes resulting from breaks in strings of consecutive earnings increases. This evidence supports the idea that younger CEOs hide bad news relating to adverse operating performance, which subsequently triggers stock price crashes. In addition, this study finds that strings of consecutive earnings increases are accompanied by large permanent increases in CEO compensation that do not dissipate with crashes. Therefore, CEOs have financial incentives to hoard bad news earlier in their career, which subsequently leads to stock price crashes. Such crashes are more likely to occur when younger CEOs enjoy discretion, namely, when they hold a dual position or lead a diversified company. This finding suggests that younger CEOs exploit opportunities relating to (weak) corporate governance to promote their personal interests. Overall, this study suggests that CEO age is an important determinant of stock price crash risk and expands our understanding concerning how CEO age becomes a source of an agency problem.

Our findings have important implications for corporate governance and, more specifically, for the role of boards in selecting, monitoring, and incentivizing CEOs. Boards should consider age when selecting a CEO to lead the company, when deciding about managerial discretion, and when devising monitoring mechanisms or incentivization schemes for CEOs (Carter and Lorsch, 2004).

Appendix A. Definition of variables

Variable	Definition
Main dependent variable:	
CRASH	An indicator variable that equals 1 when a firm experiences at least 1 crash week during the fiscal year, and zero otherwise.
CRASH_BREAK_STRING1	An indicator variable that equals 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous year, and zero otherwise.
CRASH_BREAK_STRING2	An indicator variable that equals 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous 2 years, and zero otherwise.
CRASH_BREAK_STRING3	An indicator variable that equals 1 if a firm experiences a stock price crash and firm earnings decreased in the current year but increased in the previous 3 years, and zero otherwise.
COMP	The value of total compensation that includes Salary, Bonus, Other Annual, Restricted Stock Grants, LTIP Payouts, and Value of Option Grants.
SALARY	The value of base salary earned by the CEO.
BONUS	The value of bonus earned by the CEO.
OPTIONS	The value of equity-based components of compensation.
NCSKEW	The negative of the third moment of firm-specific weekly returns for each firm and year divided by the standard deviation of firm-specific weekly returns raised to the third power.
EXTR_SIGMA	The negative of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns.
JUMP	An indicator variable that equals 1 when a firm experiences at least 1 jump week during the fiscal year, and zero otherwise.

(continued)

Appendix A. Continued

Variable	Definition
CRASH_EX_MB	A binary variable that equals 1 when (i) a firm experiences at least 1 crash week during the fiscal year, and (ii) meet or beat analyst earnings forecasts in the previous fiscal year, and (iii) missed analyst earnings forecasts in the fiscal year, and zero otherwise.
Main explanatory variable:	
AGE	The age of the CEO.
DUALITY	An indicator variable that equals 1 when the positions of the CEO and the chairman of the board are held by the same person, and zero otherwise.
HERFINDAHL	Sales-based Herfindahl index computed as the sum of the squares of each reported segment's sales divided by the firm's total sales in a given fiscal year. Segment sales with the same four-digit SIC code are combined, whereas segment sales with missing SICs or with a description of "Corporate" are proportionately allocated to the remaining segments.
Control variable:	
TENURE	The number of years in a CEO position with a particular company.
CEO_CHANGE	Dummy variable that equals 1 when there is a change in a firm's CEO, and zero otherwise.
RETIREMENT	Dummy variable that equals 1 when the CEO is close to retirement (i.e., CEO age is 64–65 years), and zero otherwise.
ITM_OPTIONS_HOLDINGS	The intrinsic value of the vested and unvested in-the-money options held by CEO.
EQUITY_HOLDINGS	The market value of shares held by CEO.
SIZE	The natural logarithm of total assets at fiscal year-end.
MB	The ratio of market value to book value of equity.
LEV	The ratio of total liabilities to total assets.
ROE	The ratio of income before extraordinary items to equity.
RETURN	Average firm-specific weekly returns during the fiscal year.
FIRM_AGE	The number of years that the firm is covered in the COMPUSTAT universe.
GOODWILL	The ratio of goodwill to total assets. Missing values of goodwill are replaced with zero.
R&D	The ratio of research and development expenses to total assets. Missing values of research and development expenses are replaced with zero.
TECHNOLOGY	Dummy variable that equals 1 if the firm belongs to the following industries as defined by four-digit SIC codes: 2833-2836, 3570-3577, 3600-3674, 3810-3845, 7371-7379, and 8731-8734, and zero otherwise.
COMPETITIVENESS	The industry adjusted price-cost margin (PCM). PCM is defined as the ratio of firm operating profit to sales. Firm operating profit is calculated by subtracting from sales the cost of goods sold and the selling, general, and administrative expenses.
PR_DEFAULT	The firm's default risk estimated using the Merton (1974) probability-to-default model as in Andreou (2015).

(continued)

Appendix A. Continued

Variable	Definition
DTURN	The detrended average weekly stock trading volume during the fiscal year.
Other variables:	
AGE_GROUP_ I	An indicator variable that equals 1 if CEO's age is less than 51 years, and zero otherwise.
AGE_GROUP_II	An indicator variable that equals 1 if CEO's age is between 51 and 55 years, and zero otherwise.
AGE_GROUP_III	An indicator variable that equals 1 if CEO's age is between 56 and 60 years, and zero otherwise.
AGE_GROUP_IV	An indicator variable that equals 1 if CEO's age is greater than 60 years, and zero otherwise.
YOUNG_CEO	An indicator variable that equals 1 if CEO's age is less than 55 years, and zero otherwise.
LEN_STRING	The number of years the company displays consecutive increases in earnings, estimated from the time the CEO joins the company.
STDEV	The standard deviation of monthly returns during the fiscal year.
BEF_CRASH_YR	An indicator variable that equals 1 for the year before the crash, and zero otherwise.
CRASH_YR	An indicator variable that equals 1 for the year of the crash, and zero otherwise.
AFT_CRASH_YR	An indicator variable that equals 1 for the year after the crash, and zero otherwise.
OPACITY	Three-year moving sum of the absolute discretionary accruals estimated from a modified Jones (1991) model.
CEO_INC_OPT	The CEO option holdings incentives ratio estimated as in Bergstresser and Philippon (2006).
CEO_INC_STC	The CEO stock holdings incentives ratio estimated as in Bergstresser and Philippon (2006).
CFO_INC_OPT	The CFO option holdings incentives ratio estimated as in Bergstresser and Philippon (2006).
CFO_INC_STC	The CFO stock holdings incentives ratio estimated as in Bergstresser and Philippon (2006).
DED_INST_HOLDINGS	The ratio of the number of common shares held by dedicated institutional investors (as retrieved from Brian Bushee's website) to the total shares outstanding of the firm.
TRA_INST_HOLDINGS	The ratio of the number of common shares held by transient institutional investors (as retrieved from Brian Bushee's website) to the total shares outstanding of the firm.
IND_ADJ_ROA	The five-year historical industry-adjusted return on assets.
CPS	The fraction of the aggregate CEO compensation to the compensation of the top management team.
OVERCONFIDENCE	The press-based measure of overconfidence from Andreou et al. (2016b).

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