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CEO early-life disaster experience and stock price crash risk

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A B S T R A C T

We study the impact of CEO early-life disaster experience on stock price crash risk. Using a longitudinal sample of U.S. firms, we document that firms led by CEOs with early-life disaster experience have higher stock price crash risk. Our findings are consistent with CEOs who experienced early-life disasters being more risk tolerant, and thus more willing to accept the risks associated with bad news hoarding, engendering formation of stock price crashes. In cross-sectional analyses, we find that the effect of CEO disaster experience is amplified when a CEO has greater equity compensation-based incentives and power over corporate board to hoard bad news. Reinforcing bad news hoarding narrative, we also find that stocks of the firms led by CEOs with early-life disaster experience exhibit stronger asymmetric response to bad versus good news disclosures and are more likely to experience crashes accompanied by breaks in the strings of uninterrupted earnings increases. Further, consistent with early-life disaster experience making CEOs more risk tolerant, we find that firms led by CEOs with early-life disaster experience tend to have higher cash-flow volatility and stock return volatility. Evidence from supplemental analysis suggests that the impact of CEO early-life disaster experience on crash risk varies in a curvilinear manner with the severity of disaster.

1. Introduction

The role of CEO background characteristics—that is, their personal attributes and life experiences—in shaping corporate policies and practices has become a focus of heightened attention for academics and practitioners in recent years (e.g., Malmendier et al., 2011; Hirshleifer et al., 2012; Aktas et al., 2016; Bernile et al., 2017; Shellenbarger, 2019). This research is largely based on upper echelons

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theory (Hambrick and Mason, 1984), which stipulates that background characteristics of a firm's top executives become imprinted on the firm (Bertrand and Schoar, 2003). Consistent with the upper echelons perspective, an emerging stream of research documents that traumatic events—such as adverse economic conditions and natural disasters—early in a CEO's life materially affect the firm's investment and financing policies (Malmendier et al., 2011; Bernile et al. 2017). The current study extends this research stream by examining the influence of CEO early-life natural disaster experience on stock price crash risk.[2]

Prior literature views intentional information management ("bad news hoarding") as the key mechanism underpinning the formation of stock price crashes (e.g., Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011a, 2011b). Managers face a wide range of incentives (e.g., career concerns, compensation contracts, and empire building) to withhold bad news from the market in the hope that in the future firm performance will improve, eliminating the need to disclose unfavourable information (Kothari et al., 2009; Chang et al., 2017). When the amount of withheld bad news accumulates to a critical limit, the news is revealed all at once, causing an abrupt, large-scale drop in the firm's stock price.

CEOs influence corporate financial reporting and disclosure practices by "setting the tone at the top" (Bamber et al., 2010; Feng et al., 2011). Along with bringing current benefits to the CEO, manipulating corporate disclosures to conceal bad news exposes CEO to substantial risks by jeopardizing CEO's prospects in the firm, exposing CEO to shareholder lawsuits, and eroding the value of CEO's wealth tied in the firm if such manipulations are revealed (Skinner, 1994; Bamber and Cheon, 1998; Karpoff et al., 2008a, 2008b). Accordingly, the decision to withhold bad news from the market involves the CEO trading off the current benefits and future risks of hoarding bad news. This implies that the CEO's risk attitudes should materially affect the extent of bad news hoarding, and thus the risk of a stock price crash. Further, prior research provides strong evidence that early-life traumatic experiences—including early-life disaster experiences—have enduring effects on individuals' risk attitudes (Kim and Lee, 2014; Malmendier et al., 2011; Bernille et al. 2017). Collectively, these insights cast CEO early-life disaster experience as potentially important, albeit unexplored, antecedent of stock price crash risk.

Ex ante, it is not clear whether CEO early-life disaster experience engenders or hinders the formation of stock price crashes. On the one hand, experiencing a natural disaster may cause an individual to "perceive the world to be a riskier place" (Lerner and Keltner, 2001). From this perspective, CEOs who experienced an early-life natural disaster would be more sensitized to the consequences of taking risks, and thus be more risk averse. Such CEOs would therefore be more likely to refrain from hoarding bad news, which, in turn, should reduce stock price crash risk. On the other hand, experiencing a natural disaster may increase an individual's willingness to take risks by "making everything else seem pale in comparison" to the experience of natural disaster (e.g., Ben-Zur and Zeidner, 2009; Taylor and Lobel, 1989). In addition, experiencing a natural disaster may elevate an individual's confidence in her ability to handle risky situations (Aldwin, 2007). Taken together, these two perspectives suggest that CEOs who experienced an early-life natural disaster would be more willing to accept the risks associated with hoarding bad news, which, in turn, should increase stock price crash risk. Ultimately, it is an empirical question whether CEO early-life disaster experience increases or decreases stock price crash risk.

We test our research question using a sample of U.S.-born CEOs for whom we were able to collect birth dates, birth city, subsequent places they lived in, and other biographical information. Merging this sample with a comprehensive database of U.S. county-level natural disaster events allows us to identify CEOs who did versus did not experience a natural disaster in their formative years (i.e., ages 5 to 15, as discussed more fully in Section 3). Based on prior literature (Hutton et al., 2009; Kim et al., 2011a, 2011b), we use three measures of crash risk: the likelihood of extremely low stock returns, negative skewness of stock returns, and down-to-up volatility of stock returns.

We provide robust evidence that firms led by CEOs with early-life disaster experience have higher stock price crash risk. The documented effect is economically meaningful: after controlling for known determinants of crash risk, CEO early-life disaster experience is associated, on average, with a 0.069 increase in the likelihood of a stock price crash. Importantly, we control for both (1) stock return volatility and (2) the corporate investment and financing policies that Bernile et al. (2017) find are associated with CEO early-life disaster experience. Accordingly, our results capture the incremental effect of CEO early-life disaster experience on crash risk after controlling for the potential effects of business risk on the tails of stock return distribution and/or volatility of stock returns. These results are consistent with the notion that CEOs with early-life disaster experience, on average, are more prone to hoard bad news, resulting in higher crash risk.

As with prior studies examining the impact of CEO characteristics on corporate practices, endogeneity is a potential issue in our setting. Specifically, the propensity of a CEO with early-life disaster experience to join the focal firm and stock price crash risk could both be driven by some firm- or industry-specific factor (or factors) not accounted for in our analysis. To address this concern, we examine the sensitivity of our baseline results to (1) inclusion of firm- and cohort-fixed effects, (2) estimation using matched sample design, (3) instrumental variable estimation, and (4) difference-in-difference type of analysis using changes in crash risk around CEO turnovers. Our results hold in all these tests, supporting causal interpretation of our findings.

We further explore cross-sectional variation in the documented relation. Prior research suggests that the extent of bad news

[2] Using natural disasters to gauge traumatic experiences provides an appealing research setting for several reasons. First, exposure to natural disasters constitutes an exogenous shock to an individual's life which has been shown to have long-lasting effects on individuals' behaviours (Callen et al., 2014). Second, as opposed to cohort effects—most prominently, the effects of macro-economic shocks examined in prior literature (e.g., Malmendier et al., 2011), our study is not limited to a single cohort since we exploit within-cohort heterogeneity in CEOs' disaster experiences. Third, natural disasters provide an externally validated measure of the occurrence and the intensity of traumatic events as opposed to self-reported traumatic experiences (such as domestic violence, childhood maltreatment, and discrimination) which could be subject to reporting bias (Graham et al., 1993; Schwarz, 1999).

hoarding is a function of managers' incentives and abilities to withhold negative information from outside investors (e.g., Kothari et al., 2009). Hence, if our reasoning is valid, the documented effect of CEO disaster experience on stock price crash risk should be amplified when CEOs have greater incentives and power to withhold bad news. Building on prior research (Armstrong et al., 2013; Laux, 2014; Andreou et al., 2017), we use the sensitivity of CEO compensation to stock return volatility (vega) and CEO-chairman of the board duality to capture CEO incentives and power to hoard bad news, respectively. Consistent with our conjecture, we find that the documented effect of CEO early-life disaster experience on crash risk is amplified in firms with higher CEO vega and firms where the CEO also serves as the chairman of the board.

To provide further evidence on the mechanism behind our findings, we perform four additional sets of tests. First, we explore the nexus between CEO disaster experience and a handful of measures suggested by prior studies to be indicative of bad news hoarding (Kothari et al., 2009; Andreou et al., 2017). Consistent with early-life disaster experience engendering bad news hoarding by CEOs, we find that stocks of the firms led by CEOs with early-life disaster experience (1) are more likely to experience crashes accompanied by earnings announcements that break the strings of uninterrupted earnings increases, and (2) exhibit stronger asymmetric response to bad versus good news disclosures in management earnings forecasts.

Second, we seek to provide evidence to our conjecture that early-life disaster experience makes the CEO more risk tolerant. To that end, we examine the linkage between CEO early-life disaster experience and an array of measures of firm's risk taking suggested in prior literature (e.g., Zhang, 2006; Bernile et al., 2017). Consistent with the view that CEOs with early-life disaster experience, on average, are more willing to take risks, we document that firms led by CEOs with early-life disaster experience tend to have higher cash-flow volatility and stock return volatility.

Third, we examine the relation between stock price crash risk and the severity of CEO disaster experience. We find strong evidence that firms led by CEOs who experienced moderately or marginally severe disasters in their early lives have higher crash risk. At the same time, we find some evidence that firms led by CEOs who experienced extremely severe disasters in their early lives have lower crash risk. These results potentially suggest that the relative importance of the mechanisms through which disaster experience impacts CEO's risk attitudes varies with disaster severity (e.g., Bernile et al., 2017), affecting the sign of CEO disaster experience-crash risk relation.

Lastly, we examine the impact of CEO disaster experience on positive jump risk—the likelihood of sudden but infrequent large stock price increases. Bad news hoarding channel predicts that the effect of CEO early-life disaster experience should be confined to the left tail of the distribution of stock returns, reflecting accumulation of bad news. In contrast, if our findings capture the effect of CEO disaster experience on business risk (Bernile et al., 2017), CEO disaster experience should be positively related to both crash risk and positive jump risk, reflecting a higher spread of firm performance outcomes. Consistent with bad news hoarding channel, we find no evidence of a relation between CEO disaster experience and positive jump risk.

Our study makes several contributions. First, we contribute to the vast literature on the determinants of stock price crash risk (e.g., Hutton et al., 2009; Kim et al., 2011a, 2011b; An and Zhang, 2013; Xu et al., 2014; Yuan et al., 2016; Chang et al., 2017; Chen et al., 2017; Ben-Nasr and Ghouma, 2018; Chen et al., 2018; Jia, 2018; An et al., 2020; Balachandran et al., 2020; Deng et al., 2020; Hu et al., 2020; Ni et al., 2020; Wu and Lai, 2020; Xu et al., 2020). Within this literature, a line of studies explores the impact of CEO attributes, such as CEO gender and CEO power, on the formation of stock price crashes (Li and Zeng, 2019; Al Mamun et al., 2020). Distinct from these studies, which focus on CEO attributes that are either inherent (gender) or organization-specific (power), we document the role of traumatic events experienced by CEO in the early ("formative") age—CEO formative traumatic experience—in the formation of crash risk. Our findings underscore the importance of casting a wider lens on the antecedents of crash risk by considering senior executives' formative experiences.

Second, our study adds to a growing stream of research examining the influence of top managers' background characteristics—including early-life experiences—on corporate policies and practices (e.g., Malmendier and Tate, 2005; Malmendier et al., 2011; Hirshleifer et al., 2012; Aktas et al., 2016; Bernile et al., 2017). Malmendier et al. (2011) and Bernile et al. (2017) find that CEOs' early-life traumatic experiences impact corporate investment and financing policies. We add to this literature by documenting the role of CEO formative experience in shaping corporate practices in the context of bad news hoarding—a pervasive corporate practice (Cohen et al., 2013).

Third, our findings provide important insights for investment practitioners. Identifying antecedents of extreme return outcomes is of considerable importance for portfolio selection, risk management, and option pricing (e.g., Chen et al., 2001; Berkowitz and O'Brien, 2002; Davis and Page, 2013). Our findings suggest that investors should consider CEOs' early-life disaster experiences as important "soft information" when modeling downside equity risk.

2. Related literature and empirical predictions

2.1. Traumatic experiences and risk attitudes

A growing stream of economics research provides compelling evidence that individuals exposed to traumatic experiences have their risk preferences lastingly changed (Callen et al., 2014). Psychology scholars propose several mechanisms through which traumatic experiences may alter individuals' risk preferences. One viewpoint is that exposure to traumatic events causes an individual to "perceive the world to be a riskier place" (Lerner and Keltner, 2001; Cameron and Shah, 2015). Fear arises from and evokes appraisals of uncertainty and lack of individual control, which are two central determinants of risk judgments (Slovic, 1987; Lerner and Keltner, 2001). As Lerner and Keltner (2001, p.148) note, "the sense of uncertainty and lack of control associated with fear should lead fearful individuals to make risk-averse (certainty enhancing) choices." Consequently, individuals exposed to traumatic events are predicted to be more sensitized to the consequences of risk taking, and thus be more risk averse. Consistent with this, several studies provide evidence that exposure to traumatic events increases risk aversion (Callen et al., 2014; Kim and Lee, 2014; Cameron and Shah, 2015; Cassar et al., 2017).[3]

A countervailing argument is that traumatic experience makes an individual less risk averse. Proponents of this viewpoint assert that extreme stress associated with an experience of traumatic event alters a person's construal of the risk by "making everything else seem pale in comparison" (Taylor and Lobel, 1989; Ben-Zur and Zeidner, 2009). When faced with a risky choice, an individual compares an experience of traumatic event with a less ominous experience (i.e., risk taking) (Ben-Zur and Zeidner, 2009). Such comparison decreases perception of loss associated with risk taking, making an individual more prone to make risky choices (Taylor and Lobel, 1989). In addition, surviving though traumatic event may engender risk taking by increasing individual's confidence in her ability to handle risky situations (Aldwin, 2007). Consistent with these arguments, prior research provides evidence that individuals exposed to traumatic events, such as natural disasters and violent conflicts, become more risk tolerant (Eckel et al., 2009; Voors et al., 2012; Page et al., 2014; Hanaoka et al., 2018).[4]

Complementing evidence from economics literature, an emerging stream of finance research shows that early-life traumatic experiences impact individuals' financial investment decisions and corporate policies. Malmendier et al. (2011) find that CEOs who grew up during the Great Depression are averse to debt and lean excessively on internal finance. Bernile et al. (2017) document that CEO's early-life exposure to fatal disasters manifests in corporate policies, such as leverage financing, mergers and acquisitions, and cash holdings. Knüpfer et al. (2017) find that individuals who experienced adverse labour market conditions during Great Finnish Depression of early 90-s are less prone to invest in risky assets.

2.2. Bad news hoarding and stock price crash risk

In this section, we review theories linking bad news hoarding to formation of stock price crashes. For the review of empirical literature on the determinants of stock price crash risk, we refer the reader to supplementary online appendix.

The extent to which managers are forthcoming with bad news disclosures is governed by a variety of incentives which are often not well aligned with those of outside investors (Healy and Palepu, 2001; Kothari et al., 2009). Specifically, considerations such as career concerns, equity-based pay, and the desire to maintain the esteem of peers create incentives for CEO to withhold the disclosure of bad news in the hope that it will ultimately be offset by subsequent improvement in firm performance (Graham et al., 2005; Hermalin and Weisbach, 2007; Kothari et al., 2009). Hermalin and Weisbach (2007) develop a theoretical model showing that investors' tendency to assess the CEO's ability—and thus, CEO's employment prospects—based on firm performance hinders the transparency of corporate disclosures, especially with respect to bad news. CEOs may also incur reduction in bonus payments as a result of the stock price decline following the disclosure of bad news, creating incentives to withhold bad news (Kothari et al., 2009). Further, CEO may withhold bad news in order to avoid interference of the board with the CEO's project choice, as such interference would deprive CEO from private benefits of controlling firm's investment decisions (Adams and Ferreira, 2007).

Bad news hoarding engenders crash risk because the amount of bad news a manager can withhold is limited (Jin and Myers, 2006). As a sufficiently long run of bad news accumulates and reaches a critical threshold, a large amount of negative information is released all at once, resulting in a stock price crash. Jin and Myers (2006) demonstrate that opaqueness of the firm to outside investors enables a manager to capture part of a firm's operating cash flows. In the process, career concerns motivate the manager to hide bad news stemming from temporary bad performance by controlling public access to information about firm's fundamentals. In the limit, if sufficiently long run of bad news is encountered, negative information is released all at once, resulting in a large drop in stock price. Bleck and Liu (2007) show that historical cost accounting regime coupled with accounting value-based compensation (e.g., profit-based bonuses) provides manager with an incentive to keep a bad project for as long as possible in order to derive private benefits from it for longer periods. Consequently, the poor performance of the project accumulates and eventually materializes at its final maturity stage, leading to a stock price crash. Benmelech et al. (2010) show that equity-based compensation induces managers to conceal bad news about future growth options, resulting in inflated stock prices and subsequent crashes.

2.3. CEO early-life disaster experience and stock price crash risk

While managers have a wide range of incentives to withhold bad news, bad news hoarding also exposes managers to substantial risks. Prior research suggests that executives opportunistically manage firms' earnings to withhold negative information from the market (e.g., Burgstahler and Dichev, 1997; Graham et al., 2005; Zhu, 2016). However, if detected, earnings management would lead

[3] For example, Kim and Lee (2014) find that individuals who were in their early childhood during the peak of Korean War were more risk-averse five decades later. Using experimental data from rural Indonesia, Cameron and Shah (2015) find that individuals in villages that suffered a flood or earthquake were less likely to make risky choices compared to individuals in a control group. In a similar vein, Cassar et al. (2017) find that the 2004 tsunami in Thailand led to long-lasting increases in risk aversion among exposed individuals and Callen et al. (2014) report that individuals exposed to violence during Afghan War exhibited an increased preference for certainty.

[4] For example, Page et al. (2014) find that homeowners who were victims of 2011 Australian floods displayed risk-seeking attitudes. Similar findings are reported by Hanaoka et al. (2018) for individuals who experienced the 2011 Great East Japan Earthquake. Eckel et al. (2009) document a strong risk-loving bias among hurricane Katrina evacuees. Using a series of field experiments in rural Burundi, Voors et al. (2012) find that individuals exposed to violent conflicts displayed more risk-seeking behaviour.

to substantial losses in the value of executives' wealth tied in a firm and jeopardize executives' tenure (Karpoff et al., 2008a, 2008b). In a sample of firms targeted by Securities and Exchange Commission (SEC) enforcement actions, Karpoff et al. (2008a, 2008b) find that for each $1 a firm misleadingly inflated its market value, it lost, on average, $4.08 and that 93% of executives identified as responsible parties lost their jobs. Extreme negative stock returns caused by the release of accumulated bad news also expose executives to shareholder lawsuits (Skinner, 1994; Bamber and Cheon, 1998). Shareholders can file class action lawsuits against U.S. companies under SEC Rule lOb-5: upon observing a large stock price decline, plaintiffs typically argue that managers failed to promptly disclose bad news, causing plaintiffs to buy an overvalued security that declined in value after management revealed the material information (Baginski et al., 2002, p.26). Further, large stock price decline can be perceived by firm's stakeholders as a signal of firm's financial distress (Campbell et al., 2008), eroding firm's relations with suppliers and customers (Hui et al., 2012) and, consequently, adversely affecting firm performance and managers' prospects in the firm.

The above discussion suggests that the decision to withhold bad news from the market involves the CEO trading off the current benefits and future risks of hoarding bad news. More specifically, considerable risks associated with bad news hoarding imply that the CEO's personal risk attitudes should materially affect the extent of bad news hoarding. Accordingly, we reason that, ceteris paribus, more risk tolerant (more risk averse) CEOs would be less (more) sensitized to the risks involved in the concealment of bad news from the market and, thus, would engage in more (less) bad news hoarding. As bad news hoarding engenders crash risk (Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2011a, 2011b), it follows that stocks of the firms led by more risk tolerant (more risk averse) CEOs are expected to be more (less) prone to crashes.

As we discuss in Section 2.1, prior research provides compelling evidence that individuals exposed to traumatic experiences have their risk preferences lastingly changed (Callen et al., 2014). At the same time, prior literature offers competing insights as to whether traumatic experiences make individuals more risk tolerant or more risk averse. This, in turn, generates an ex ante tension regarding the impact of CEO early-life disaster experience on crash risk. One viewpoint is that individuals exposed to traumatic events become more sensitized to the consequences of risk taking, and thus are more risk averse. Consistent with this perspective, several studies provide evidence that exposure to traumatic events makes individuals more risk averse (Callen et al., 2014; Kim and Lee, 2014; Cameron and Shah, 2015; Cassar et al., 2017). Under this scenario, CEOs with early-life disaster experience, on average, will be more sensitized to the risks of—and thus, will refrain from—bad news hoarding, which, in turn, should reduce crash risk. A alternative perspective suggests that traumatic experience decreases perception of loss associated with risk taking and increases individual's confidence in her ability to handle risky situations, making an individual more risk tolerant (Taylor and Lobel, 1989; Aldwin, 2007). Supporting this view, a line of studies documents that individuals who experienced traumatic events become more risk tolerant (Eckel et al., 2009; Voors et al., 2012; Page et al., 2014; Hanaoka et al., 2018). This perspective suggests that CEOs with early-life disaster experience, on average, will be more willing to accept risks associated with bad news hoarding, which, in turn, should increase crash risk. Ultimately, it distils to an empirical question as to whether CEO early-life disaster experience engenders or hinders the formation of stock price crashes.

3. Data and variables

3.1. Sample selection

We obtain the data from multiple sources. We collect CEOs' basic biographical information from ExecuComp and BoardEx. We search for CEOs' birth and grow up places from the following sources: official publications containing biographical information (books, such as Steve Jobs by Isaacson and online resources, such as Encyclopedia, NNDB), obituary, university websites (such as distinguished alumni interviews, university foundation board of directors introductions, etc.), local and national newspapers (from ProQuest historical newspapers archive), magazines, company official websites, and other sources such as award-winning introductions (e.g., Franklin Institute awards), and official publications of academic and industrial societies. We obtain information on natural disasters from the following sources: The University of Virginia County and City Data Books service, The U.S. Census Bureau, The U.S. National Geophysical Data Center, Wikipedia.org, The U.S. Geological Survey (USGS), National Weather Service (NWS) of the National Oceanic and Atmospheric Administration, GenDisasters, the U.S. National Climatic Data Center (NCDC), and The International Emergency Disasters Database (EMDAT). The detailed description of databases used to identify disaster events is provided in Appendix A. We obtain firms' financial data from Compustat, stock return data from the Center for Research in Security Prices (CRSP), CEO compensation data from ExecuComp, corporate governance data from RiskMetrics, and mergers and acquisitions data from Thomson One.

Following prior studies (Kim et al., 2011a, 2011b; Chang et al., 2017), we apply the following screening criteria to our sample. First, we exclude observations with negative book value of equity, year-end stock prices less than $1, or fewer than 26 weeks of stock return data. Second, we exclude observations with insufficient information for constructing the crash risk measures, CEO disaster experience measure, or control variables. Third, we exclude financial firms (SIC codes 6000–6999), because the financial characteristics of financial firms are different from firms in other industries (Andreou et al., 2017). Our final sample consists of 3744 firm-year observations for the period 1992–2015. To mitigate the effects of outliers, we winsorize all non-binary variables at both the upper and lower one percentiles of their distributions.

3.2. Crash risk measures

Following prior literature (Hutton et al., 2009; Kim et al., 2011a, 2011b), we employ the following measures of stock price crash risk: the crash dummy variable (*CRASH*), negative skewness (*NSKEW*), and down-to-up volatility (*DUVOL*). To construct our crash risk measures, we first calculate firm-specific weekly returns based on the following regression specification

$$r_{i,t} = \beta_0 + \beta_1 r_{mkt,t-1} + \beta_2 r_{ind,t-1} + \beta_3 r_{mkt,t} + \beta_4 r_{ind,t} + \beta_5 r_{mkt,t+1} + \beta_6 r_{ind,t+1} + \varepsilon_{i,t} \tag{1}$$

In this regression, $r_{i,\ t}$ denotes the return on stock *i* in week *t*, $r_{mkt,\ t}$ and $r_{ind,\ t}$ are the returns on the CRSP value weighted index and the Fama and French's value weighted industry index in week *t*, respectively, and $\varepsilon_{i,\ t}$is the idiosyncratic error term. Following Hutton et al. (2009), we include the lead and lag returns on the market and industry indices to control for potential effects of nonsynchronous trading. We calculate the firm-specific weekly return, $W_{i,\ t}$, as the natural logarithm of 1 plus the regression residual.

We construct a crash dummy (*CRASH*) as a dummy variable equal to one if a firm experiences one or more crash weeks over the fiscal year, and zero otherwise. Consistent with Hutton et al. (2009), we define crash weeks as those when a firm experiences firm-specific weekly returns that are 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year. We calculate negative skewness (*NSKEW*) as the ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by −1. The calculation method is as follows:

$$NSKEW_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^3\right] \Big/ \left[(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{3/2}\right] \tag{2}$$

We calculate down-to-up volatility (*DUVOL*) as the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Following prior literature, for each stock *i* over a fiscal year period *t* we separate firm-specific weekly returns into two groups: "down" weeks when the returns are below the annual mean, and "up" weeks when the returns are above the annual mean. The standard deviation of firm-specific weekly returns is calculated separately for each of these two groups.

3.3. CEO early-life disaster experience

Consistent with prior literature (e.g., Bernile et al., 2017), we define CEO early-life disaster experience as an experience of the disaster that happened during the period of the CEO's formative years, which is 5 to 15 years of age. We focus on this period in the CEO's early life as enduring childhood memories are thought to begin forming from the 5th year and the 15th year is viewed as a natural endpoint for the early-adolescence formative period (Nelson, 1993; Gathercole et al., 2004). We first collect the names, gender, and company information of CEOs in Fortune 500 firms from the ExecuComp database.[5] Then, we cross-check the information from ExecuComp with information from Boardex and collect some further information from Boardex, such as the CEO's accomplishments and education background. To obtain the CEO's birth and grow up places, we manually search for the bios of the CEOs using the sources listed in Section 3.1 and cross-validate the bio information whenever possible. As a result of this process, we were able to identify the exact birth place for all 598 CEOs from the Fortune 500 list and the grow up place for 72% of CEOs in our sample (429 CEOs). For 28% of CEOs for whom we were unable to identify the exact grow up place, we follow Bernile et al. (2017) and use their birth place instead. Further, among the 429 CEOs that we were able to obtain both their birth place and grow up place, 103 CEOs (24%) moved to another place in their childhood and 326 CEOs grew up in their birth place. The detailed description of the search process is provided in Appendix B.

Next, we search for disaster events that happen in the grow-up county of CEOs during their formative years. The disaster events include earthquakes, volcanic eruptions, tsunamis, hurricanes, tornadoes, severe storms, floods, landslides, extreme temperature, wildfires and other miscellaneous accidents (e.g., coal mine explosions) that had a large death toll and severe economic losses. We define the CEO disaster experience (*DISASTER*) as a dummy variable equal to one if the CEO resided in the county where natural disaster happened at least once during his/her formative years, and zero otherwise.

3.4. Control variables

As discussed, we argue that CEO early-life disaster experience affects stock price crash risk by influencing CEO's propensity to engage in bad news hoarding. Bernile et al. (2017) show that CEO early-life disaster experience affects corporate investment and financing policies. Hence, in our setting it is important to control for the firm's business risk—that is, corporate policies which could impact the tails of stock return distribution and/or volatility of stock returns. Accordingly, we control for corporate policies that Bernile et al. (2017) find are associated with CEO early-life disaster experience by including firm's cash holdings (*CASH*), leverage financing (*LEV*) and acquisition activity (*ACQ*). We calculate *CASH* as cash and short-term investment divided by total assets, *LEV* as the ratio of total long-term debt over total assets and *ACQ* as a dummy variable equal to 1 if a firm announces merger or acquisition in year *t*, and 0 otherwise.

The selection of other control variables follows prior literature. Chen et al. (2001) and Hutton et al. (2009) show that large firms and firms with high growth rate tend to have higher stock price crash risk. Accordingly, we control for firm size (*SIZE*), calculated as the natural logarithm of market value of equity, and market-to-book ratio (*MB*), calculated as the ratio of market value of equity over book value of equity. Following Hutton et al. (2009), we control for firm's profitability by including return on assets (*ROA*), calculated

[5] We focus on CEOs in Fortune 500 firms—large and well-established firms—because CEOs in these firms receive more media exposure, which makes their bio information more comprehensive and reliable.

as the income before extraordinary items divided by total assets. We also include change in share turnover (*DTURN*), calculated as the average monthly share turnover in year *t* minus the average monthly share turnover in year *t*-1, to control for the divergence of opinion among investors (Chen et al., 2001). Further, we control for stock performance (*RET*) and stock return volatility (*SIGMA*) as prior research shows that these two variables are positively associated with stock price crash risk (Chen et al., 2001; Chang et al., 2017). We calculate *RET* and *SIGMA* as the mean and standard deviation of firm-specific weekly returns in year *t-1*, respectively. We also include financial reporting opacity (*OPAQUE*), calculated as the prior three years' moving sum of the absolute value of discretionary accruals, and lagged negative skewness (Chen et al., 2001; Hutton et al., 2009). In addition, we control for CEO characteristics which could influence CEO's propensity to hoard bad news by including CEO age (*AGE*), the square of CEO age (AGE^2), and CEO gender (*GENDER*) (Andreou et al., 2017). We define *GENDER* as a dummy variable equal to one if the CEO is female, and zero otherwise.

3.5. Descriptive statistics

Table 1 shows the sample distribution of our explanatory variable of interest (*DISASTER*). Panel A shows the distribution of CEOs with early-life disaster experience by industry based on the Fama and French 12 industry classification. In our sample, firms in the oil, gas, and coal extraction and products industry have the largest proportion of CEOs with early-life disaster experience, whereas firms in the utilities industry have the smallest proportion. Panel B shows the annual distribution of observations with CEOs with early-life disaster experience. The panel shows that the proportion of CEOs with early-life disaster experience is the highest in year 1999 (16.49%) and the lowest in year 2014 (10.13%) with no discernible clustering patterns.

Tables 2 and 3 report the summary statistics and correlation coefficients of the variables, respectively. The mean value of *DISASTER* is 0.133, suggesting that 13.3% of the observations in our sample have CEOs with early-life disaster experience. The mean value of *CRASH* is 0.211, the mean value of *NSKEW* is 0.121 and the mean value of *DUVOL* is 0.086.[6] All three crash risk measures are positively correlated with *DISASTER*. The correlations of crash risk measures with control variables are broadly consistent with prior literature.

4. Empirical results

4.1. Univariate analysis

We begin with a univariate analysis of the relation between CEO early-life disaster experience and stock price crash risk. For each of the three crash risk measures, we estimate its mean value separately for (1) firms led by CEOs with early-life disaster experience and (2) firms led by CEOs without early-life disaster experience and compare the two estimates. We report the results of this analysis in Fig. 1 which shows that the mean values of all three crash risk measures are significantly higher for the firms led by CEOs with early-life disaster experience. These findings provide preliminary evidence that CEO early-life disaster experience engenders crash risk. Next, we explore whether this result holds in a multivariate regression setting.

4.2. Regression analysis

We use the following regression model to examine the relation between CEO early-life disaster experience and stock price crash risk:

$$\begin{aligned} &CRASH_{i,t+1}/NSKEW_{i,t+1}/DUVOL_{i,t+1} = \beta_0 + \beta_1 DISASTER_{i,t} + \beta_2 NSKEW_{i,t} + \beta_3 SIZE_{i,t} \\ &+\beta_4 LEV_{i,t} + \beta_5 MB_{i,t} + \beta_6 ROA_{i,t} + \beta_7 DTURN_{i,t} + \beta_8 RET_{i,t} + \beta_9 SIGMA_{i,t} + \beta_{10} OPAQUE_{i,t} \\ &+\beta_{11} CASH_{i,t} + \beta_{12} ACQ_{i,t} + \beta_{13} AGE_{i,t} + \beta_{14} AGE^2_{i,t} + \beta_{15} GENDER_{i,t} + \sum FE + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

where *i* denotes the firm, *t* denotes the year, $\sum FE$ denotes industry fixed effects based on 2-digit SIC codes and year fixed effects, and $\varepsilon_{i,t+1}$ is the error term. When the dependent variable is *CRASH*, we estimate Eq. (3) using the logit model to accommodate the binary nature of the dependent variable. When the dependent variables are *NSKEW* and *DUVOL*, we estimate Eq. (3) using ordinary least squares (OLS). Both *z*- and *t*-statistics are computed using standard errors adjusted for heteroscedasticity and clustering at the firm level.

We report the results of this estimation in Table 4. Column (1) of the table shows that the coefficient of *DISASTER* in the *CRASH* regression is positive and statistically significant (*z*-statistic = 3.979), suggesting that stocks of the firms led by CEOs with early-life disaster experience, on average, are more likely to experience crashes. The marginal effect of CEO early-life disaster experience (evaluated at the mean values of the explanatory variables) is 0.069, suggesting that CEO early-life disaster experience, on average, is

[6] The sample means of *NSKEW* and *DUVOL* measures in our paper are larger than those reported in prior studies (e.g., Callen and Fang, 2015a, 2015b; Chang et al., 2017) because (1) our sample consists of Fortune 500 firms (large firms) and (2) crash risk increases with firm size (Callen and Fang, 2015a, 2015b; Chang et al., 2017). It important to emphasize that these discrepancies reflect differences in the means of the *unconditional* distributions of the *NSKEW* and *DUVOL* measures. In the multivariate regressions (which model conditional means of *NSKEW* and *DUVOL*), these differences will be reflected in larger intercepts of the regression models. In contrast, there is no obvious reason to expect that these unconditional differences in means will impact the sign and/or the magnitude of the slopes of the regression models (i.e., *conditional* effects of the covariates of interest on crash risk).

Table 1
Sample distribution.

Panel A: Distribution by industry

Industry	Obs. with CEOs having early life disaster experience	Total Obs.	% with CEOs having early life disaster experience
Consumer Non-Durables	32	348	9.20%
Consumer Durables	10	127	7.87%
Manufacturing	92	638	14.42%
Oil, Gas, and Coal Extraction and Products	46	183	25.14%
Chemicals and Allied Products	29	212	13.68%
Business Equipment	103	488	21.11%
Telephone and Television Transmission	15	211	7.11%
Utilities	13	375	3.47%
Wholesale, Retail, and Some Services	94	649	14.48%
Healthcare, Medical Equipment, and Drugs	23	199	11.56%
Other	42	314	13.38%

Panel B: Distribution by year

Year	Obs. with CEOs having early life disaster experience	Total Obs.	% with CEOs having early life disaster experience
1992	23	179	12.85%
1993	26	205	12.68%
1994	23	200	11.50%
1995	26	208	12.50%
1996	28	210	13.33%
1997	34	215	15.81%
1998	34	207	16.43%
1999	31	188	16.49%
2000	26	180	14.44%
2001	19	170	11.18%
2002	23	175	13.14%
2003	21	177	11.86%
2004	24	165	14.55%
2005	19	150	12.67%
2006	20	146	13.70%
2007	17	142	11.97%
2008	18	134	13.43%
2009	16	126	12.70%
2010	16	115	13.91%
2011	15	121	12.40%
2012	15	108	13.89%
2013	9	83	10.84%
2014	8	79	10.13%
2015	8	61	13.11%

This table presents the industry and year distribution of observations with CEOs with early-life disaster experience.

associated with 0.069 increase in one-year ahead probability of stock price crash. Given that the sample mean of *CRASH* is 0.211, we conclude that the effect of CEO early-life disaster experience on crash risk is material. Columns (2,3) of the table report the results for the *NSKEW* and *DUVOL* regressions, respectively and show that the coefficient of *DISASTER* is significantly positive in both regressions (smallest t-statistic = 2.500). These results suggest that stock returns of firms led by CEOs with early-life disaster experience, on average, are more negatively skewed and have higher down-to-up volatility. The coefficient estimates suggest that CEO disaster experience, on average, is associated with an increase of 0.105 (0.063) in one year-ahead negative skewness (down-to-up volatility).

Collectively, the results reported in Table 4 corroborate our findings from the univariate analysis, suggesting that firms led by CEOs with early-life disaster experience, on average, have higher stock price crash risk. These results are consistent with the view that CEOs with early-life disaster experience, on average, are more prone to hoard bad news, thus engendering formation of stock price crashes.

4.3. Sensitivity tests

To assess the robustness of our baseline results, we carry out an array of sensitivity tests. We report the results of these tests in Table 5. Panel A of Table 5 shows the results of tests using alternative crash risk measures. First, we consider alternative firm-specific thresholds to identify crash weeks to address the possibility that the results are driven by the choice of 3.09 standard deviations threshold in defining the *CRASH* variable. To examine this issue, we define crash weeks as those having firm-specific weekly returns that are 3.5 or 4 standard deviations below the mean firm-specific returns. Second, we examine the sensitivity of our baseline results to using a general instead of firm-specific threshold in constructing the *CRASH* variable. To that end, we define crash weeks as the weeks

Table 2
Summary statistics

Variable	Mean	S.D.	Median	P5	P25	P75	P95
$CRASH_{t+1}$	0.211	0.408	0.000	0.000	0.000	0.000	1.000
$NSKEW_{t+1}$	0.121	0.710	−0.954	−0.280	0.078	0.471	1.349
$DUVOL_{t+1}$	0.086	0.470	−0.654	−0.242	0.072	0.380	0.899
$DISASTER_t$	0.133	0.340	0.000	0.000	0.000	0.000	1.000
$NSKEW_t$	0.136	0.683	−0.864	−0.266	0.085	0.467	1.323
$SIZE_t$	9.163	1.369	7.025	8.172	9.064	10.051	11.706
LEV_t	0.222	0.124	0.022	0.130	0.221	0.309	0.427
MB_t	3.732	3.890	1.043	1.720	2.590	4.074	10.193
ROA_t	0.054	0.054	−0.023	0.027	0.051	0.084	0.143
$DTURN_t$	0.006	0.043	−0.056	−0.010	0.003	0.019	0.078
RET_t	−0.069	0.079	−0.223	−0.081	−0.043	−0.024	−0.011
$SIGMA_t$	0.034	0.017	0.015	0.022	0.030	0.041	0.067
$OPAQUE_t$	0.186	0.156	0.032	0.083	0.138	0.240	0.496
$CASH_t$	0.074	0.090	0.003	0.014	0.039	0.099	0.262
ACQ_t	0.539	0.499	0.000	0.000	1.000	1.000	1.000
AGE_t	56.771	6.209	46.000	53.000	57.000	61.000	66.000
$GENDER_t$	0.017	0.128	0.000	0.000	0.000	0.000	0.000
Obs.	3744						

This table presents the summary statistics of the variables used in our baseline analysis. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. All non-binary variables are winsorized at the 1st and 99st percentiles.

that experience firm-specific weekly returns below −10% or − 15%. Third, we use the number of crash weeks in a fiscal year instead of a crash dummy to capture crash risk. Neither of these alternative specifications has a material impact on our findings.

Panel B of Table 5 shows the results of regression models modified to include additional control variables. In the first test, we control for an array of CEO attributes suggested in prior literature (Kim et al., 2016; Al Mamun et al., 2020), including CEO overconfidence (*OVERCONF*), CEO tenure (*TENURE*), CEO educational attainment (*EDUCATION*), CEO ability (*ABILITY*), CEO ownership (*OWNERSHIP*), CEO option incentives (*OPTINCT*), and CEO power (*FOUNDER, CEOFEPCB, CEOPRCH,* and *DUAL*). Detailed definitions of these variables are presented in Appendix C. Despite a sizable reduction in sample size stemming from limited availability of data used to construct these controls, our baseline results continue to hold. In addition, the coefficient of *OVERCONF* is positive and significant in all regressions, consistent with Kim et al. (2016) findings that stocks of the firms led by overconfident CEOs are more likely to experience crashes. The coefficient of *ABILITY* is negative and significant in the *NSKEW* regression, consistent with the view that managerial ability improves earnings quality (Demerjian et al., 2013), which in turn reduces crash risk. Interestingly, the coefficient of *EDUCATION* is positive and marginally significant in the *DUVOL* regression, suggesting that firms led by CEOs with higher education, on average, have higher crash risk.

In the second test, we include a number of determinants of crash risk documented by prior studies (e.g., Kim et al., 2014; Callen and Fang, 2015a; Andreou et al., 2016; Li et al., 2017), including CSR (*CSR*), social capital (*SCAPITAL*), local religious norms (*RELIGION*), transient institutional ownership (*TRAIO*), board size (*BSIZE*), board ownership (*BOWNERSHIP*), and tax avoidance (*ETRdiff*). Detailed definitions of these variables are presented in Appendix C. Despite a material reduction in sample size, our baseline results continue to hold. The coefficient of *SCAPITAL* is negative and marginally significant in the *CRASH* regression, consistent with Li et al. (2017) findings that higher social capital is associated with lower crash risk. The coefficient of *TRAIO* is positive and significant in the *DUVOL* regression, consistent with Andreou et al. (2016) findings that crash risk is higher when the firm has greater transient institutional ownership.[7]

Panel C of Table 5 shows the results for alternative sample period. Specifically, we exclude the dot-com bubble (2000−2001) and the global financial crisis (2007–2008) periods to verify that our findings are not driven by excess market volatility during these periods. Exclusion of these time periods has no material impact on our findings.

In the baseline analysis, we follow prior studies by excluding financial firms because the financial characteristics of these firms are different from firms in other industries. As a robustness check, we repeat our analyses after including financial firms in our sample. The results of this estimation are reported in Panel D of Table 5 and show that inclusion of financial firms in our sample has no material impact on our core findings.

As discussed earlier, for 72% CEOs in our sample, we were able to obtain biographical information on where the CEO grew up. For the remaining 28%, we take the CEO's birth place as the place where they grew up (Bernile et al., 2017). We consider the possibility that some of these CEOs moved from their birth place during their early-life, introducing noise into our *DISASTER* measure.[8] Of the

[7] In an untabulated analysis, we include both groups of additional control variables in the same regression. Despite a further attrition in sample size, our core results remain intact.

[8] Notably, such a noise would bias against finding significant effect of CEO early-life disaster experience on crash risk.

Table 3
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)$CRASH_{t+1}$	1.000																
(2)$NSKEW_{t+1}$	0.628	1.000															
(3)$DUVOL_{t+1}$	0.489	0.880	1.000														
(4)$DISASTER_t$	0.065	0.053	0.050	1.000													
(5)$NSKEW_t$	0.059	0.061	0.058	0.068	1.000												
(6)$SIZE_t$	0.023	0.054	0.060	−0.030	0.013	1.000											
(7)LEV_t	0.033	0.032	0.033	−0.070	0.048	−0.199	1.000										
(8)MB_t	0.031	0.063	0.042	0.053	−0.021	0.284	−0.049	1.000									
(9)ROA_t	0.008	0.019	0.018	0.021	−0.029	0.402	−0.381	0.357	1.000								
(10)$DTURN_t$	0.017	0.040	0.038	0.004	0.068	−0.091	0.041	−0.029	−0.075	1.000							
(11)RET_t	−0.025	−0.038	−0.037	−0.117	−0.145	0.290	−0.022	−0.018	0.277	−0.235	1.000						
(12)$SIGMA_t$	0.027	0.046	0.044	0.126	0.154	−0.329	0.013	0.017	−0.267	0.239	−0.963	1.000					
(13)$OPAQUE_t$	0.039	0.014	0.016	0.095	0.025	0.116	−0.132	0.122	0.045	−0.022	−0.227	0.240	1.000				
(14)$CASH_t$	0.005	−0.035	−0.027	0.112	−0.013	0.220	−0.394	0.189	0.278	−0.048	−0.172	0.180	0.264	1.000			
(15)ACQ_t	0.007	0.000	0.004	−0.005	0.000	0.186	−0.170	0.068	0.181	0.011	0.048	−0.044	0.066	0.100	1.000		
(16)AGE_t	−0.040	−0.024	−0.012	−0.043	−0.008	0.011	0.113	−0.071	0.004	−0.039	0.181	−0.190	−0.168	−0.147	−0.001	1.000	
(17)$GENDER_t$	0.041	0.027	0.036	0.005	0.050	0.051	0.010	0.020	−0.019	−0.004	0.018	−0.021	0.012	0.016	0.015	−0.036	1.000

This table presents the correlation matrix of the variables used in our baseline analysis. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. All non-binary variables are winsorized at the 1st and 99st percentiles.

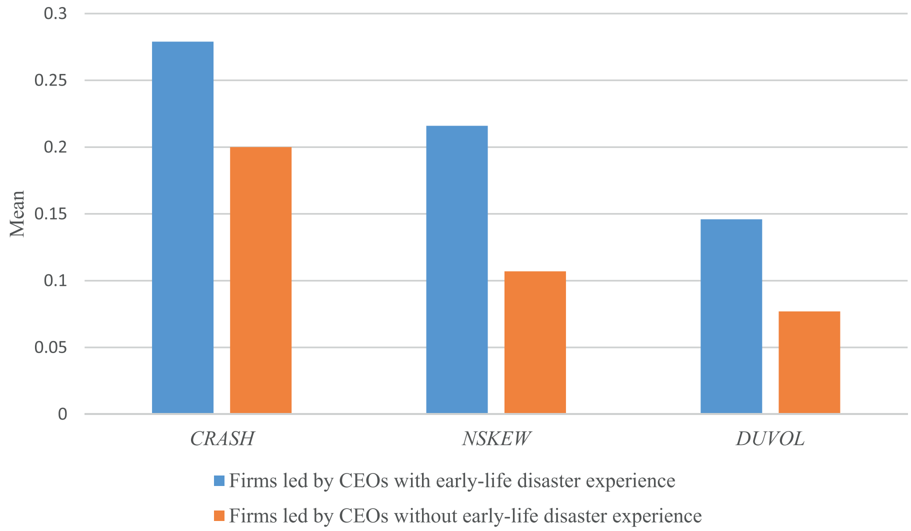

Fig. 1. Univariate analysis.
The figure presents the average value of the crash risk variables for firms lead by CEO with and without early-life disaster experiences. *DISASTER* is a dummy variable equal to one if a firm has CEO with early life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks.

CEOs for whom we have data on where they grew up, 24% moved from the county where they were born during their early-life. This suggests that the default assumption that CEOs grew up in the county where they were born introduces noise into approximately 6.7% (i.e., 24% × 28%) of our sample. To further examine this issue, in an untabulated analysis we use a common econometric technique by coding observations where data on CEO grow-up place is missing as '1' and including this indicator variable as an additional control in our baseline model. This approach allows us to preserve observations while removing any potential bias associated with the default assumption that the CEOs grew up in the county where they were born (Greene, 1993). Adopting this approach leaves our core findings intact.

4.4. Potential endogeneity issues

It is possible that our results are driven by some factor (or factors) not accounted for in our analysis, which influence both the propensity of a CEO with early-life disaster experience to join the focal firm and crash risk. To assuage this endogeneity concern, we conduct four tests.

In the first test, we re-estimate our baseline model (Eq. (3)) with firm, CEO grow-up state, and CEO birth year fixed effects. By including firm fixed effect, our analysis captures the relation between CEO early-life disaster experience and stock price crash risk within a focal firm, thereby controlling for any potential conflating effects of firm-level enduring attributes (both observable and unobservable). Inclusion of CEO birth year fixed effects controls for any cohort-related effects in our sample. Inclusion of CEO grow-up state fixed effects absorbs time-invariant factors at the state level, such as regional differences in exposure to natural disasters, economic conditions, and educational level. The results of this estimation are reported in Table 6 and show that the coefficient of *DISASTER* remains significantly positive for all three crash risk measures.

In the second test, we examine the relation between CEO early-life disaster experience and crash risk using matched sample design. We consider two alternative approaches: (1) matching based on CEO grow-up county and (2) matching based on firm characteristics. In the first approach, we define treatment group as firms led by CEOs who grew up in counties that experienced disaster (affected counties), and control group as firms led by CEOs without disaster experience who grew up in the neighbouring counties located within 100 miles from affected counties. This procedure helps further alleviate concern that our results are spuriously driven by non-disaster related regional characteristics. In the second approach, for each firm led by CEO with disaster experience, we find a matched firm that has the closest propensity score but does not have a CEO with disaster experience. The propensity score is calculated using all the control variables in Eq. (3). The purpose of this test is to further allay potential concern that the documented effect is driven by the differences in firms' characteristics between the firms led by CEOs with early-life disaster experience versus firms led by CEOs with no such experience. The results are reported in Table 7 and show that, despite a drastic reduction in sample size, the coefficient of *DISASTER* remains significantly positive for all three crash risk measures.

In the third test, we estimate our baseline model using an instrumental variable (IV) approach. The instrumental variable we adopt is headquarter disaster (*HQ_DISASTER*), defined as the historical average number of disasters in the firm's headquarter state divided by the state's average population. Prior research provides evidence that firms tend to employ local CEOs (e.g., Yonker, 2017).

Table 4
CEO early-life disaster experience and stock price crash risk.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
$DISASTER_t$	0.433***	0.105**	0.063**
	(3.979)	(2.500)	(2.299)
$NSKEW_t$	0.107*	0.027	0.015
	(1.752)	(1.263)	(1.154)
$SIZE_t$	0.059	0.058***	0.036***
	(1.295)	(4.386)	(4.069)
LEV_t	0.754	0.117	0.051
	(1.630)	(0.853)	(0.576)
MB_t	0.009	0.009**	0.003
	(0.956)	(2.480)	(1.576)
ROA_t	0.965	0.292	0.180
	(1.062)	(1.012)	(0.905)
$DTURN_t$	0.812	0.492	0.266
	(0.754)	(1.575)	(1.243)
RET_t	2.365	1.342**	0.814**
	(1.117)	(2.308)	(2.040)
$SIGMA_t$	12.807	8.808***	5.482**
	(1.116)	(2.797)	(2.539)
$OPAQUE_t$	0.529*	0.077	0.070
	(1.918)	(0.837)	(1.178)
$CASH_t$	−1.208*	−0.653***	−0.303**
	(−1.764)	(−3.040)	(−2.209)
ACQ_t	0.020	0.005	0.009
	(0.224)	(0.203)	(0.540)
AGE_t	0.076	0.021	0.015
	(0.708)	(0.844)	(0.928)
AGE^2_t	−0.001	−0.000	−0.000
	(−0.775)	(−0.871)	(−0.898)
$GENDER_t$	0.473**	0.123	0.109**
	(1.961)	(1.362)	(2.041)
Constant	−3.572	−1.194	−0.958**
	(−1.183)	(−1.618)	(−2.031)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3728	3744	3744
Pseudo/Adjusted R^2	0.048	0.044	0.043

This table presents the effect of CEO early-life disaster experience on stock price crash risk. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in the regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

Accordingly, we reason that the more historical disasters occurred in a firm's headquarter state, the more likely that the firm has a CEO with early-life disaster experience because the CEO is likely to be from the same geographic area, suggesting a positive relation between headquarter disaster and CEO early-life disaster experience. At the same time, there is no ex ante reason to expect that historical disasters in a firm's headquarter state have a direct effect of firm's crash risk. Accordingly, we reason that *HQ_DISASTER* meets both the relevance and exclusion criteria, making this variable a valid instrument (Larcker and Rusticus, 2010). We report the results of IV estimation in Table 8. Column (1) reports the results of the first-stage regression and shows that the coefficient of *HQ_DISASTER* is positive and highly significant. The partial *F*-statistic of the exclusion test of *HQ_DISASTER* is 50.53, which is above the critical value of 8.96 (Stock et al., 2002), suggesting that the weak instrument problem does not pose a concern. Columns (2) to (4) report the results of the second-stage regression and show that the coefficient of instrumented *DISASTER* is significantly positive for all three crash risk measures.[9]

Lastly, we gauge the causal effect of CEO early-life disaster experience on crash risk by examining the changes in crash risk measures around CEO turnover events. We first identify CEO turnover events based on CEO change in the ExecuComp database. We drop turnover events that do not involve change in CEO early-life disaster experience (i.e., turnover events where CEO with disaster

[9] In an untabulated analysis, we estimate our baseline model using latent IV approach (Lewbel, 2012). The results show that the coefficient of *DISASTER* remains significantly positive for all three crash risk measures.

Table 5
Robustness tests.

Panel A: Alternative crash dummy definitions

	3.5 S.D. below the mean	4 S.D. below the mean	Firm-specific return below −10%	Firm-specific return below −15%	No. of crash weeks
	$CRASH_{t+1}$	$CRASH_{t+1}$	$CRASH_{t+1}$	$CRASH_{t+1}$	$CRASH_{t+1}$
	(1)	(2)	(3)	(4)	(5)
$DISASTER_t$	0.570***	0.279***	0.363***	0.464***	0.085***
	(3.687)	(3.009)	(3.010)	(3.018)	(4.000)
$NSKEW_t$	0.040	0.072	−0.032	0.092	0.019*
	(0.491)	(1.363)	(−0.402)	(0.929)	(1.720)
$SIZE_t$	−0.014	0.032	−0.218***	−0.159**	0.008
	(−0.224)	(0.770)	(−4.429)	(−2.531)	(1.067)
LEV_t	0.512	0.324	−0.753	0.682	0.138*
	(0.793)	(0.793)	(−1.584)	(1.051)	(1.736)
MB_t	0.019	0.011	0.025	0.038**	0.003
	(1.546)	(1.287)	(1.641)	(2.210)	(1.558)
ROA_t	1.239	0.167	−0.451	−2.674**	0.166
	(0.960)	(0.196)	(−0.435)	(−2.095)	(0.988)
$DTURN_t$	2.507*	0.530	−0.620	1.315	0.148
	(1.845)	(0.656)	(−0.592)	(0.945)	(0.799)
RET_t	6.392**	4.155**	12.616***	9.083***	0.429
	(2.199)	(2.288)	(5.469)	(3.549)	(1.179)
$SIGMA_t$	23.887	19.858**	125.360***	94.454***	2.303
	(1.536)	(2.124)	(9.711)	(6.124)	(1.178)
$OPAQUE_t$	0.804**	0.318	0.899***	0.953***	0.083
	(2.366)	(1.341)	(3.073)	(2.615)	(1.624)
$CASH_t$	−2.540***	−2.268***	0.595	0.714	−0.218*
	(−2.642)	(−3.152)	(0.871)	(0.874)	(−1.956)
ACQ_t	0.129	−0.067	0.092	0.019	0.010
	(1.145)	(−0.943)	(0.870)	(0.150)	(0.644)
AGE_t	−0.025	0.013	−0.095	−0.024	0.015
	(−0.187)	(0.165)	(−1.003)	(−0.203)	(0.975)
AGE^2_t	0.000	−0.000	0.001	0.000	−0.000
	(0.142)	(−0.147)	(0.888)	(0.114)	(−1.035)
GENDERt	0.470**	0.311	0.573**	1.166***	0.119*
	(2.062)	(1.463)	(2.242)	(2.585)	(1.938)
Constant	−0.759	−2.559	1.328	−2.966	−0.220
	(−0.193)	(−1.131)	(0.474)	(−0.868)	(−0.488)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	3714	3580	3744	3636	3744
Pseudo/Adjusted R^2	0.070	0.085	0.329	0.318	0.030

Panel B: Additional control variables

(1) Control for other CEO attributes

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
$DISASTER_t$	0.751***	0.162**	0.098**
	(5.418)	(2.597)	(2.520)
$NSKEW_t$	0.170**	0.039	0.023
	(2.016)	(1.166)	(1.129)
$SIZE_t$	−0.030	0.083***	0.061***
	(−0.439)	(3.836)	(4.403)
LEV_t	0.571	0.110	0.112
	(0.819)	(0.555)	(0.843)
MB_t	−0.000	0.008	0.004
	(−0.014)	(1.602)	(1.417)
ROA_t	1.730	0.279	0.104
	(1.140)	(0.616)	(0.335)
$DTURN_t$	2.375	0.805	0.467
	(1.525)	(1.642)	(1.459)
RET_t	1.720	1.193	0.574
	(0.605)	(1.483)	(1.024)
$SIGMA_t$	6.977	7.747*	3.941
	(0.436)	(1.677)	(1.278)
$OPAQUE_t$	0.534	0.135	0.050

(continued on next page)

Table 5 (*continued*)

Panel B: Additional control variables

(1) Control for other CEO attributes

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
	(1.308)	(1.010)	(0.598)
$CASH_t$	−0.422	−0.706**	−0.397*
	(−0.468)	(−2.478)	(−1.969)
ACQ_t	−0.111	0.003	0.027
	(−0.869)	(0.076)	(1.007)
AGE_t	0.052	0.017	−0.006
	(0.337)	(0.453)	(−0.242)
AGE^2_t	−0.001	−0.000	0.000
	(−0.411)	(−0.487)	(0.307)
$GENDER_t$	0.551*	0.016	0.091
	(1.655)	(0.148)	(1.447)
$TENURE_t$	−0.017	0.012	0.001
	(−0.206)	(0.473)	(0.079)
$OVERCONF_t$	0.246*	0.096**	0.073**
	(1.714)	(2.122)	(2.439)
$EDUCATION_t$	0.080	0.045	0.031*
	(0.824)	(1.542)	(1.693)
$ABILITY_t$	−0.228	−0.309**	−0.154
	(−0.545)	(−2.186)	(−1.609)
$OWNERSHIP_t$	−1.296	0.102	−0.325
	(−0.506)	(0.149)	(−0.804)
$OPTINCT_t$	0.801**	0.101	0.001
	(2.085)	(0.989)	(0.021)
$FOUNDER_t$	−0.372	−0.114	−0.050
	(−0.408)	(−0.839)	(−0.591)
$CEOFEPCB_t$	0.479	0.185	0.100
	(0.528)	(1.497)	(1.414)
$CEOPRCH_t$	−0.033	−0.033	−0.015
	(−0.259)	(−0.833)	(−0.547)
$DUAL_t$	−0.034	0.003	0.009
	(−0.159)	(0.052)	(0.216)
Constant	−2.684	−1.344	−0.550
	(−0.624)	(−1.220)	(−0.769)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	1783	1796	1796
Pseudo/Adjusted R^2	0.065	0.031	0.035

(2) Control for CSR, social trust, corporate governance, and tax avoidance

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
$DISASTER_t$	0.604***	0.189***	0.131***
	(4.013)	(3.134)	(3.596)
$NSKEW_t$	0.115	−0.002	−0.011
	(1.418)	(−0.057)	(−0.542)
$SIZE_t$	0.086	0.068***	0.049***
	(1.331)	(4.143)	(4.232)
LEV_t	−0.138	−0.056	−0.076
	(−0.217)	(−0.334)	(−0.637)
MB_t	0.022	0.010**	0.005
	(1.620)	(1.985)	(1.528)
ROA_t	−0.276	−0.444	0.168
	(−0.082)	(−0.486)	(0.240)
$DTURN_t$	2.274	0.739*	0.393
	(1.430)	(1.894)	(1.415)
RET_t	0.855	0.397	0.283
	(0.261)	(0.502)	(0.504)
$SIGMA_t$	2.178	3.737	2.798
	(0.121)	(0.821)	(0.860)
$OPAQUE_t$	0.632	0.153	0.079
	(1.643)	(1.329)	(1.022)
$CASH_t$	−1.035	−0.492*	−0.315*
	(−0.940)	(−1.816)	(−1.788)
ACQ_t	0.066	0.019	0.015
	(0.522)	(0.499)	(0.615)

(*continued on next page*)

Table 5 (*continued*)

Panel B: Additional control variables

(1) Control for other CEO attributes

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
AGE_t	0.155	0.042	0.017
	(0.990)	(1.144)	(0.631)
AGE^2_t	−0.002	−0.000	−0.000
	(−1.103)	(−1.174)	(−0.578)
$GENDER_t$	0.796***	0.128	0.097
	(2.642)	(1.250)	(1.595)
CSR_t	−0.011	−0.005	−0.005
	(−0.620)	(−0.821)	(−1.330)
$SCAPITAL_t$	−0.166*	0.006	0.008
	(−1.693)	(0.279)	(0.547)
$RELIGION_t$	−0.105	0.017	0.062
	(−0.265)	(0.138)	(0.729)
$TRAIO_t$	0.130	0.427	0.421*
	(0.130)	(1.197)	(1.836)
$BSIZE_t$	0.329	−0.032	0.003
	(1.254)	(−0.480)	(0.064)
$BOWNERSHIP_t$	−0.020	0.008	0.004
	(−0.504)	(0.770)	(0.603)
$ETRdiff_t$	0.523	0.471	0.024
	(0.212)	(0.770)	(0.051)
Constant	−5.413	−1.955*	−1.041
	(−1.240)	(−1.894)	(−1.417)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	1904	1913	1913
Pseudo/Adjusted R^2	0.088	0.041	0.041

Panel C: Excluding dot-com bubble and Global Financial Crisis periods

	(1)	(2)	(3)
	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
$DISASTER_t$	0.460***	0.114**	0.063**
	(3.944)	(2.432)	(2.016)
$NSKEW_t$	0.138*	0.028	0.016
	(1.872)	(1.186)	(1.154)
$SIZE_t$	0.046	0.055***	0.033***
	(0.843)	(3.756)	(3.419)
LEV_t	1.652***	0.227	0.103
	(3.087)	(1.495)	(1.042)
MB_t	0.008	0.010**	0.005*
	(0.715)	(2.304)	(1.850)
ROA_t	2.130*	0.483	0.308
	(1.929)	(1.533)	(1.427)
$DTURN_t$	0.917	0.681*	0.395
	(0.723)	(1.940)	(1.596)
RET_t	−0.032	1.357*	0.904*
	(−0.012)	(1.858)	(1.809)
$SIGMA_t$	−0.301	7.833**	5.286**
	(−0.022)	(2.118)	(2.098)
$OPAQUE_t$	0.878***	0.106	0.056
	(2.828)	(1.050)	(0.879)
$CASH_t$	−2.029***	−0.841***	−0.376**
	(−2.710)	(−3.615)	(−2.527)
ACQ_t	0.012	0.008	0.016
	(0.116)	(0.314)	(0.876)
AGE_t	0.085	0.015	0.008
	(0.764)	(0.553)	(0.432)
AGE^2_t	−0.001	−0.000	−0.000
	(−0.842)	(−0.655)	(−0.491)
GENDERt	0.396*	0.106	0.090
	(1.698)	(1.041)	(1.477)
Constant	−4.038	−0.622	−0.557
	(−1.252)	(−0.766)	(−1.043)

(*continued on next page*)

Table 5 (*continued*)

Panel C: Excluding dot-com bubble and Global Financial Crisis periods

	(1)	(2)	(3)
	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	3096	3118	3118
Pseudo/Adjusted R^2	0.052	0.032	0.026

Panel D: Including financial firms

	(1)	(2)	(3)
	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
$DISASTER_t$	0.420***	0.103***	0.055**
	(4.048)	(2.604)	(2.183)
$NSKEW_t$	0.063	0.018	0.010
	(1.117)	(0.930)	(0.862)
$SIZE_t$	0.075*	0.059***	0.034***
	(1.782)	(4.799)	(4.307)
LEV_t	0.921**	0.224*	0.121
	(2.182)	(1.799)	(1.483)
MB_t	0.008	0.010**	0.004*
	(0.788)	(2.525)	(1.807)
ROA_t	0.750	0.221	0.141
	(0.821)	(0.775)	(0.726)
$DTURN_t$	0.883	0.438	0.213
	(0.945)	(1.471)	(1.078)
RET_t	2.820	1.596***	0.893**
	(1.378)	(2.838)	(2.362)
$SIGMA_t$	16.261	9.996***	5.781***
	(1.456)	(3.312)	(2.849)
$OPAQUE_t$	0.465*	0.074	0.054
	(1.768)	(0.867)	(0.992)
$CASH_t$	−0.523	−0.263	−0.077
	(−0.977)	(−1.472)	(−0.679)
ACQ_t	0.032	0.001	0.008
	(0.377)	(0.057)	(0.538)
AGE_t	0.079	0.029	0.024
	(0.818)	(1.262)	(1.647)
AGE^2_t	−0.001	−0.000	−0.000
	(−0.868)	(−1.277)	(−1.615)
GENDERt	0.332	0.113	0.094*
	(1.533)	(1.261)	(1.799)
Constant	−4.000	−0.231	−0.245
	(−1.470)	(−0.340)	(−0.566)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs	4205	4230	4230
Pseudo/Adjusted R^2	0.045	0.040	0.039

This table presents results of the robustness checks. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in all regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

experience is replaced by another CEO with disaster experience or where CEO without disaster experience is replaced by another CEO without disaster experience). We also exclude turnover events with insufficient data to construct crash risk measures over the five-year window around the events (i.e., t-2 to $t + 2$). Our final sample consists of 79 CEO turnover events, of which 39 events are about changing from CEO without disaster experience to CEO with disaster experience, and 40 events are about changing from CEO with disaster experience to CEO without disaster experience. We calculate the average crash risk measures for the pre-CEO change window (i.e., t-2 to t-1) and the post-CEO change window (i.e., $t + 1$ to $t + 2$), separately. Then, we calculate the changes in the average values between the two windows.

The results of this analysis are reported in Panel A of Table 9. The panel shows that crash risk increases when a firm changes its CEO from one without disaster experience to one with disaster experience, and crash risk decreases when a firm changes its CEO from one

Table 6
Firm and cohort fixed effects estimation.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
$DISASTER_t$	0.802***	0.173**	0.093*
	(3.577)	(2.358)	(1.815)
$NSKEW_t$	−0.088	−0.060***	−0.037***
	(−1.419)	(−2.825)	(−2.741)
$SIZE_t$	0.631***	0.241***	0.141***
	(4.679)	(6.568)	(5.828)
LEV_t	1.282*	−0.032	−0.075
	(1.723)	(−0.149)	(−0.529)
MB_t	−0.016	0.004	0.000
	(−1.141)	(0.823)	(0.124)
ROA_t	−0.702	0.055	0.134
	(−0.597)	(0.143)	(0.504)
$DTURN_t$	1.437	0.809***	0.426*
	(1.186)	(2.644)	(1.961)
RET_t	1.739	1.211*	0.964**
	(0.741)	(1.705)	(1.983)
$SIGMA_t$	7.834	6.591*	5.247**
	(0.607)	(1.680)	(1.984)
$OPAQUE_t$	0.265	0.109	0.080
	(0.729)	(1.009)	(1.076)
$CASH_t$	−0.689	−0.729**	−0.314
	(−0.604)	(−2.377)	(−1.501)
ACQ_t	−0.001	−0.004	0.007
	(−0.010)	(−0.129)	(0.348)
AGE_t	0.565***	0.189***	0.095***
	(2.739)	(3.606)	(2.837)
AGE^2_t	−0.003**	−0.001**	−0.000
	(−2.393)	(−2.506)	(−1.459)
$GENDER_t$	0.366	0.144	0.144**
	(1.199)	(1.500)	(2.296)
Constant		−9.008***	−4.783***
		(−4.715)	(−4.070)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Grow-up State FE	Yes	Yes	Yes
Birth Year FE	Yes	Yes	Yes
Obs.	3385	3744	3744
Pseudo/Adjusted R^2	0.077	0.053	0.044

This table presents the effect of CEO early-life disaster experience on stock price crash risk after controlling for firm and cohort fixed effect. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. The constant term, firm fixed effects, year fixed effects, grow-up state fixed effects and birth year fixed effects are included in all regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

with disaster experience to one without disaster experience. Notwithstanding a small sample size used in this test, the difference between the two cases is statistically significant for all three crash risk measures. For robustness purposes, we repeat our analysis using a sample of exogenous and forced CEO turnover events (Eisfeldt and Kuhnen, 2013; Peters and Wagner, 2014).[10] This leaves a sample of only 34 CEO turnover events, of which 18 events are about changing from CEO without disaster experience to CEO with disaster experience, and 16 events are about changing from CEO with disaster experience to CEO without disaster experience. The results of this analysis are reported in Panel B of Table 9 and are consistent with those reported in Panel A of the table.

4.5. Placebo tests

In this section, we consider the possibility that the documented effect of CEO early-life disaster experience is driven by spurious correlations in our data. To examine this issue, we conduct a series of placebo tests in which we randomly assign a grown-up state for each CEO in our sample. We then measure CEO early-life disaster experience based on the randomly assigned grow-up state and

[10] The data for this analysis was obtained from Wharton Research Data Services (Contributed Data sub-directory) and Camelia Kuhnen homepage (http://public.kenan-flagler.unc.edu/faculty/kuhnenc/research/research.html).

Table 7
Matched sample.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$DISASTER_t$	0.950***	0.290***	0.161**	0.509***	0.103**	0.075**
	(3.481)	(2.892)	(2.382)	(3.243)	(2.122)	(2.285)
$NSKEW_t$	0.001	−0.038	−0.030	−0.023	−0.004	−0.014
	(0.004)	(−0.614)	(−0.788)	(−0.212)	(−0.089)	(−0.531)
$SIZE_t$	−0.202	0.047	0.033	0.177*	0.074**	0.027
	(−1.182)	(1.003)	(1.112)	(1.730)	(2.536)	(1.352)
LEV_t	3.290*	0.687*	0.429*	1.224	0.155	0.153
	(1.698)	(1.885)	(1.914)	(1.240)	(0.511)	(0.760)
MB_t	−0.036	0.007	0.009*	0.004	0.007	0.003
	(−1.046)	(1.122)	(1.757)	(0.268)	(1.221)	(0.791)
ROA_t	5.955	1.066	0.424	0.580	0.086	0.160
	(1.311)	(1.365)	(0.765)	(0.325)	(0.157)	(0.465)
$DTURN_t$	7.354	0.527	−0.311	3.329	0.603	0.164
	(1.598)	(0.673)	(−0.698)	(1.535)	(1.093)	(0.429)
RET_t	−5.330	3.210*	3.480***	2.908	3.501**	2.688***
	(−0.724)	(1.872)	(2.992)	(0.650)	(2.485)	(2.839)
$SIGMA_t$	−48.088	13.294	16.238**	10.541	19.543***	14.568***
	(−1.225)	(1.338)	(2.605)	(0.430)	(2.675)	(3.057)
$OPAQUE_t$	1.281	0.230	0.060	0.326	0.038	0.099
	(1.159)	(1.173)	(0.462)	(0.622)	(0.248)	(0.988)
$CASH_t$	0.403	−0.208	−0.010	−0.843	−0.566	−0.229
	(0.281)	(−0.384)	(−0.031)	(−0.766)	(−1.449)	(−0.861)
ACQ_t	−0.490	−0.018	0.005	0.030	0.093	0.064*
	(−1.491)	(−0.213)	(0.084)	(0.146)	(1.639)	(1.789)
AGE_t	−0.141	0.113	0.109**	0.478**	0.022	0.018
	(−0.287)	(1.393)	(2.079)	(2.196)	(0.402)	(0.501)
AGE^2_t	0.001	−0.001	−0.001**	−0.004**	−0.000	−0.000
	(0.247)	(−1.325)	(−2.024)	(−2.199)	(−0.379)	(−0.444)
$GENDER_t$	0.387	0.151	0.170*	0.130	0.152	0.123
	(0.596)	(1.021)	(1.848)	(0.253)	(0.798)	(1.009)
Constant	8.937	−3.220	−2.871*	−15.062**	−1.439	−0.971
	(0.678)	(−1.288)	(−1.781)	(−2.347)	(−0.897)	(−0.946)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1018	1290	1290	961	982	982
Pseudo/Adjusted R^2	0.179	0.211	0.191	0.121	0.060	0.038

This table presents the effect of CEO early-life disaster experience on stock price crash risk using matched sample. In column (1–3), we only keep firms led by CEOs whose county of grow-up experienced a disaster (treatment group) and firms led by CEOs who grew up in unaffected counties within 100 miles from the disaster county (control group). In column (4)–(6), we use propensity score matched sample. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes and year fixed effect are included in the regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

construct a pseudo-*DISASTER* variable. We estimate our baseline models using a pseudo-*DISASTER* variable instead of a true *DISASTER* variable. We repeat this procedure 500 times, thereby generating 500 coefficient estimates of the pseudo-*DISASTER* variable for each of the three crash risk measures employed in our analysis. Using these estimates, we construct an empirical distribution of the *DISASTER* coefficient under the scenario that the relation between CEO early-life disaster experience and crash risk is of a spurious nature. The results of this analysis are reported in Table 10. For each of the three crash risk measures, we report a set of percentiles from the corresponding empirical distribution of pseudo-*DISASTER* coefficient estimates. To facilitate comparison, we also report the actual *DISASTER* coefficient estimates (from Table 4). The table shows that actual *DISASTER* coefficient estimates lie at the extreme upper tail of the empirical distributions of pseudo-*DISASTER* coefficients, implying that spurious correlations are unlikely to drive our baseline results.

5. Cross-sectional tests and supplemental analyses

5.1. Cross-sectional tests

The extent to which managers hoard bad news is a function of managers' incentives and abilities to withhold negative information from outside investors (Kothari et al., 2009). Accordingly, if our reasoning is valid, the documented effect of CEO disaster experience

Table 8
Instrumental variable estimation.

	First stage	Second stage		
	$DISASTER_t$	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)	(4)
$DISASTER_t$		0.080***	0.145**	0.099**
		(2.617)	(2.456)	(2.437)
$HQ\_DISASTER_t$	5.527***			
	(5.718)			
$NSKEW_t$	0.120*	0.021*	0.030	0.018
	(1.953)	(1.883)	(1.338)	(1.350)
$SIZE_t$	0.013	0.009	0.058***	0.035***
	(0.170)	(1.187)	(4.383)	(3.987)
LEV_t	0.147	0.115	0.089	0.046
	(0.216)	(1.536)	(0.640)	(0.513)
MB_t	0.023	0.002	0.009**	0.004*
	(1.140)	(0.978)	(2.466)	(1.699)
ROA_t	0.215	0.071	0.141	0.066
	(0.174)	(0.513)	(0.492)	(0.330)
$DTURN_t$	0.071	0.135	0.532	0.345
	(0.104)	(0.763)	(1.605)	(1.506)
RET_t	2.456	0.339	1.196**	0.718*
	(1.032)	(0.920)	(1.993)	(1.794)
$SIGMA_t$	14.511	1.798	7.886**	4.720**
	(1.093)	(0.920)	(2.420)	(2.162)
$OPAQUE_t$	0.314	0.118**	0.065	0.053
	(0.683)	(2.315)	(0.666)	(0.832)
$CASH_t$	1.361	−0.172	−0.659***	−0.302**
	(1.351)	(−1.542)	(−2.954)	(−2.157)
ACQ_t	−0.191*	0.006	0.015	0.015
	(−1.872)	(0.390)	(0.568)	(0.885)
AGE_t	−0.001	0.017	0.021	0.013
	(−0.004)	(1.108)	(0.764)	(0.764)
AGE^2_t	0.000	−0.000	−0.000	−0.000
	(0.093)	(−1.180)	(−0.805)	(−0.755)
$GENDER_t$	0.639	0.085	0.128	0.117**
	(1.231)	(1.604)	(1.371)	(2.154)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3479	3479	3479	3479
Pseudo/Adjusted R^2	0.420	0.033	0.044	0.044

This table presents the effect of CEO early-life disaster experience on stock price crash risk using the instrumental variable estimation. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. *HQ_DISASTER* is the historical average number of disasters in the firm's headquarter state divided by the state's average population. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes and year fixed effect are included in all regressions. The *t*-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

on crash risk should be amplified in firms where CEOs have greater incentives and power to withhold bad news.

Prior research suggests that equity risk-taking incentives stemming from convexity of equity compensation incentivize executives to engage in intentional information management and bad news hoarding (Kim et al., 2011a; Armstrong et al., 2013; Laux, 2014). Building on this insight, we use the sensitivity of CEO compensation to stock return volatility (vega) to capture CEO incentives to withhold bad news. We calculate *Vega* as the natural logarithm of the dollar change in the value of CEO option holdings resulting from a 0.01 unit increase in stock return volatility following Core and Guay (2002) and modify our baseline model to include the $DISASTER \times VEGA$ interaction term. The results of this estimation are reported in columns (1–3) of Table 11 and show that the coefficient of the $DISASTER \times VEGA$ interaction term is significantly positive for *CRASH* (z-statistic = 2.685) and *NSKEW* (t-statistic = 2.078), while positive but insignificant for *DUVOL*. These results are consistent with the notion that the effect of CEO disaster experience on crash risk is amplified when CEOs have greater equity pay-based incentives to hoard bad news.

We use CEO-chairman of the board duality to capture CEO power to withhold bad news. Corporate boards constitute a key governance mechanism for mitigating agency issues and maintaining integrity and transparency of financial reporting (Denis and McConnell, 2003; Hermalin and Weisbach, 2003; Fauver et al., 2017), and thus play a material role in disciplining CEOs against concealing bad news from the market. CEO-chairman duality undermines the board's ability to effectively monitor and constrain self-interested CEOs (e.g., Fama and Jensen, 1983), thereby providing CEOs with greater ability to engage in bad news hoarding (Andreou et al., 2017). Accordingly, we reason that the documented effect of CEO early-life disaster experience on crash risk should be amplified in firms where CEO also serves as the chairman of the board. To test this conjecture, we modify our baseline model to include the

Table 9
Changes in stock price crash risk around CEO turnover events.

Panel A: All CEO turnover events

	CEO without disaster experience to CEO with disaster experience (*N* = 39)	CEO with disaster experience to CEO without disaster experience (*N* = 40)	(1) minus (2)
	(1)	(2)	(3)
ΔCRASH	0.098	−0.137	0.236
	(1.996)	(−2.365)	(3.088)
ΔNSKEW	0.247	−0.160	0.407
	(2.324)	(−1.457)	(2.660)
ΔDUVOL	0.136	−0.108	0.245
	(1.931)	(−1.328)	(2.263)

Panel B: Exogenous and forced CEO turnover events using data from Eisfeldt and Kuhnen (2013) and Peters and Wagner (2014)

	CEO without disaster experience to CEO with disaster experience (*N* = 18)	CEO with disaster experience to CEO without disaster experience (*N* = 16)	(1) minus (2)
	(1)	(2)	(3)
ΔCRASH	0.148	−0.229	0.377
	(2.082)	(−2.668)	(3.409)
ΔNSKEW	0.354	−0.318	0.672
	(2.067)	(−2.291)	(3.001)
ΔDUVOL	0.205	−0.227	0.432
	(1.699)	(−2.178)	(2.678)

This table presents the changes in crash risk measures around CEO turnover events, where CEO with (without) early-life disaster experience replaced CEO without (with) early-life disaster experience. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. For each CEO turnover event happened in year t, the change of crash variables is calculated by subtracting the average value of the variable over years [t-2,t-1] from the average value of the variable over year [t,$t+2$]. The first column reports the mean change around CEO turnover events where the incoming CEO has early-life disaster experience, while prior CEO does not have early-life disaster experience. The second column reports the mean change around CEO turnover events where the incoming CEO does not have early-life disaster experience, while prior CEO has early-life disaster experience. The third column reports the difference between column (1) and column (2). The *t*-statistics are reported in the parentheses.

Table 10
Placebo tests.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
Mean β for pseudo-*DISASTER*	−0.022	−0.004	−0.001
Min β for pseudo-*DISASTER*	−0.365	−0.100	−0.066
1% percentile β for pseudo-*DISASTER*	−0.259	−0.067	−0.045
5% percentile β for pseudo-*DISASTER*	−0.181	−0.053	−0.033
25% percentile β for pseudo-*DISASTER*	−0.088	−0.024	−0.015
Median β for pseudo-*DISASTER*	−0.017	−0.004	−0.001
75% percentile β for pseudo-*DISASTER*	0.042	0.017	0.012
95% percentile β for pseudo-*DISASTER*	0.137	0.042	0.031
99% percentile β for pseudo-*DISASTER*	0.207	0.065	0.046
Max β for pseudo-*DISASTER*	0.297	0.102	0.062
Coefficient of actual *DISASTER* in Table 4	0.433	0.105	0.063

This table presents the results of placebo tests. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. We randomly assign a grow-up state to each CEO in our sample, generating a pseudo-*DISASTER* variable, and use the pseudo-*DISASTER* variable to estimate our baseline models. We repeat this procedure 500 times, thereby generating 500 coefficient estimates of the pseudo-*DISASTER* variable. These estimates are used to construct an empirical distribution of the *DISASTER* coefficient under the scenario that the relation between CEO early-life disaster experience and crash risk is of a spurious nature. For each of the three crash risk measures, we report a set of percentiles from the corresponding empirical distribution of pseudo *DISASTER* coefficient estimates. For comparison, for each of the three crash risk measures we also report the actual estimate of *DISASTER* coefficient, replicated from Table 4.

DISASTER×*DUAL* interaction term, where *DUAL* is a dummy variable equal to one if the CEO also holds the position of the chairman of the board, and zero otherwise. The results of this analysis are reported in columns (4–6) of Table 11. The coefficient of the *DISASTER*×*DUAL* interaction term is significantly positive for *NSKEW* (t-statistic = 2.335) and *DUVOL* (t-statistic = 2.135) and is positive albeit not significant for *CRASH*. These results provide general support for our conjecture that the documented effect of CEO disaster experience on crash risk is amplified in firms where CEOs have greater power to hoard bad news.

5.2. Bad news hoarding tests

To provide further evidence on the mechanism underpinning our findings, in this section, we examine the nexus between CEO early-life disaster experience and a handful of measures suggested by prior studies to be indicative of bad news hoarding.

Table 11
Cross-sectional tests.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$DISASTER_t$	0.142	0.006	0.018	0.362	−0.171	−0.090
	(0.784)	(0.088)	(0.355)	(0.836)	(−1.244)	(−1.137)
$DISASTER_t \times VEGA_t$	0.642***	0.205**	0.107			
	(2.685)	(2.078)	(1.582)			
$VEGA_t$	0.021	−0.027	−0.031			
	(0.196)	(−0.849)	(−1.450)			
$DISASTER_t \times DUAL_t$				0.131	0.332**	0.180**
				(0.290)	(2.335)	(2.135)
$DUAL_t$				0.090	0.015	0.014
				(0.545)	(0.327)	(0.464)
$NSKEW_t$	0.095	0.017	0.012	0.116*	0.021	0.009
	(1.391)	(0.675)	(0.813)	(1.813)	(0.821)	(0.584)
$SIZE_t$	0.035	0.059***	0.040***	0.089*	0.070***	0.042***
	(0.687)	(3.931)	(4.040)	(1.771)	(4.291)	(4.110)
LEV_t	0.087	0.061	0.050	0.668	0.157	0.083
	(0.164)	(0.377)	(0.472)	(1.237)	(0.924)	(0.779)
MB_t	0.003	0.007*	0.004	0.009	0.011***	0.005**
	(0.238)	(1.651)	(1.462)	(0.927)	(2.627)	(2.208)
ROA_t	0.337	0.401	0.243	1.023	0.385	0.181
	(0.331)	(1.304)	(1.141)	(0.942)	(1.101)	(0.791)
$DTURN_t$	1.395	0.606*	0.268	1.651	0.627*	0.322
	(1.099)	(1.714)	(1.139)	(1.329)	(1.660)	(1.234)
RET_t	3.638	1.732**	0.978**	3.867	1.454**	0.789*
	(1.459)	(2.503)	(2.093)	(1.625)	(2.076)	(1.720)
$SIGMA_t$	18.609	9.885***	5.471**	21.842*	9.511**	5.398**
	(1.375)	(2.672)	(2.193)	(1.695)	(2.496)	(2.168)
$OPAQUE_t$	0.467	0.059	0.069	0.766**	0.060	0.031
	(1.366)	(0.578)	(1.017)	(2.319)	(0.492)	(0.409)
$CASH_t$	−1.006	−0.552**	−0.293*	−0.921	−0.778***	−0.374**
	(−1.212)	(−2.356)	(−1.863)	(−1.239)	(−2.849)	(−2.265)
ACQ_t	0.006	0.013	0.017	−0.034	−0.007	0.006
	(0.064)	(0.449)	(0.923)	(−0.332)	(−0.208)	(0.274)
AGE_t	0.087	0.008	−0.000	0.029	0.010	0.006
	(0.692)	(0.281)	(−0.021)	(0.218)	(0.288)	(0.261)
AGE^2_t	−0.001	−0.000	0.000	−0.000	−0.000	−0.000
	(−0.758)	(−0.336)	(0.012)	(−0.333)	(−0.313)	(−0.207)
$GENDER_t$	0.337	0.048	0.046	0.422*	0.088	0.114**
	(1.022)	(0.462)	(0.753)	(1.697)	(0.937)	(2.014)
Constant	−3.507	0.465	0.413	−2.673	−0.837	−0.536
	(−1.023)	(0.520)	(0.716)	(−0.736)	(−0.822)	(−0.838)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2893	2904	2904	2742	2758	2758
Pseudo/Adjusted R^2	0.053	0.040	0.039	0.056	0.046	0.047

This table presents results of the effects of CEO incentives and power to hoard bad news on the relation between CEO early-life disaster experience and stock price crash risk. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. *VEGA* is a dummy variable equal to one if the CEO's compensation vega is greater than the annual median, and zero otherwise. *DUAL* is a dummy variable equal to one if firm's CEO holds the position of the chairman of the board in the current year. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in all regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

First, we focus on stock price crashes that are associated with breaks of consecutive earnings increases. A break in the streak of earnings increases is likely to reflect accumulation of withheld negative information to a critical limit (Myers et al., 2007; Andreou et al., 2017). Thus, we expect that stock price crashes that are accompanied by breaks of consecutive earnings increases are more likely to be indicative of bad news hoarding. Following Andreou et al. (2017), we construct three variables. *CRASH_BREAK1* is a dummy variable equal to one if the firm experiences stock price crash and reports earnings decrease in year $t + 1$ after reporting a streak of earnings increases in years *t* and *t*-1, and zero otherwise. *CRASH_BREAK2* is a dummy variable equal to one if the firm experiences stock price crash and reports earnings decrease in year $t + 1$ after reporting a streak of earnings increases in years *t*, *t*-1, and *t*-2 and zero otherwise. *CRASH_BREAK3* is a dummy variable equal to one if the firm experiences stock price crash and reports earnings decrease in year $t + 1$ after reporting a streak of earnings increases in years *t*, *t*-1, *t*-2, and *t*-2, and zero otherwise. We then estimate our baseline model (Eq. (3)) three times, using each of the three aforementioned crash measures as the dependent variable, respectively. The results of this estimation are presented in Table 12 and show that the coefficient of *DISASTER* is positive and significant in all three regression models. These results suggest that CEOs with early-life disaster experience, on average, are more prone to hoard bad news in order to maintain the string of earnings increases, increasing the likelihood of subsequent stock price crashes.

Second, we follow Kothari et al. (2009) and Baginski et al. (2018) and examine whether CEO early-life disaster experience is associated with greater delay of bad news releases relative to good news releases in management earnings forecasts. The model specification is as follows:

$$\begin{aligned} CAR_{i,j} &= \beta_0 + \beta_1 BADNEWS_{i,j} + \beta_2 DISASTER_i + \beta_3 DISASTER_i \times BADNEWS_{i,j} \\ &+ \beta_4 MFNEWS_{i,j} + \beta_5 MFNEWS_{i,j} \times BADNEWS_{i,j} + \beta_6 EARNSURP_{i,j} \\ &+ \beta_7 EARNSURP_{i,j} \times BADNEWS_{i,j} + \varepsilon_{i,j} \end{aligned} \tag{4}$$

where *i* denotes the firm, *j* denotes the management earnings forecast and $\varepsilon_j$is the error term. *CAR* is the cumulative abnormal returns over value-weighted market returns for five trading days around the management earnings forecast announcement date. *MFNEWS* is the difference between management earnings forecast and the most recent analyst consensus forecast issued within 30 days prior to the management forecast divided by the analyst consensus forecast. *BADNEWS* is a dummy variable equal to one if *MFNEWS* is negative, and zero otherwise. *EARNSURP* is the difference between actual earnings and the most recent analyst consensus forecast within 30 days prior to the earnings announcement divided by the stock price.

The results of this estimation are reported in Table 13. In column (1), we compare the absolute magnitude of the market reaction to good news forecasts (i.e., $|Constant|$) to the absolute magnitude of the total market reaction to bad news forecasts (i.e., $|Constant + BADNEWS|$). The results of an *F*-test show that $|Constant + BADNEWS|$ - $|Constant|$ is positive and significant, suggesting that the market reaction to bad news disclosures is stronger than that to good news disclosures. These results are consistent with the view that managers tend to delay the disclosure of bad news relative to that of good news (Kothari et al., 2009). More importantly, in column (2), we examine whether the differential market reaction to bad news versus good news is amplified in firms led by CEOs with early-life disaster experience. The result of an *F*-test shows that ($|Constant + BADNEWS + DISASTER + BADNEWS \times DISASTER|$ - $|Constant + DISASTER|$) – ($|Constant + BADNEWS|$ - $|Constant|$) is positive and significant, implying that differential market reaction to bad news disclosures versus good news disclosures is amplified for firms led by CEOs with early-life disaster experience. Overall, these results suggest that CEOs with early-life disaster experience are more prone to delay the disclosure of bad news relative to good news, lending support to bad news hoarding as the mechanism behind our core findings.[11]

5.3. CEO early-life disaster experience and firm's risk taking

We argue that early-life disaster experience makes CEOs more risk tolerant and, consequently, more willing to take risks associated with bad news hoarding, which increases stock crash risk. In this section, we test the validity of this argument by examining the effect of CEO early-life disaster experience on firm's risk taking. Following prior literature (Zhang, 2006; Bernile et al., 2017), we adopt three measures of firm's risk taking: cash flow volatility (*CFVOL*), stock return volatility (*STKVOL*), and idiosyncratic volatility (*IDIOVOL*). We calculate *CFVOL* as the standard deviation of the ratio of operating cash flows over total assets during the past five years, we calculate *STKVOL* as the standard deviation of daily stock returns during the year, and we calculate *IDIOVOL* as the standard deviation of residuals from a Carhart (1997) four-factor model estimated at firm-level using weekly returns during the year. We re-estimate our baseline model with the three variables as the dependent variables, respectively. The results of this estimation are reported in Table 14 and show that the coefficient of *DISASTER* is positive and significant in all three regressions, suggesting that firms led by CEOs with

[11] In an untabulated analysis, we examine the impact of CEO disaster experience on accrual-based earnings management. Ex ante, the impact of CEO disaster experience on accrual-based earnings management is ambiguous. First, accrual manipulation is only one of the many mechanisms available to managers to mask bad firm performance (Kim et al., 2011b; Callen and Fang, 2017). While our arguments suggest that CEO disaster experience impacts crash risk by influencing managers' incentives to hoard bad news, prior literature, based on which we form this prediction, offers no predictions regarding specific mechanisms that CEO would choose to mask poor firm performance. Second, Cohen et al. (2008) document a significant reduction in the accrual-based earnings management starting from early 2000-s (a period that covers most of our sample). Third, prior research (e.g., Keung and Shih, 2014; Owens et al., 2017) emphasizes that estimates of discretionary accruals are inherently noisy—an effect that would bias against finding significant effect of CEO disaster experience on accrual-based management. To examine this issue, we regress abnormal accruals, estimated following Dechow and Dichev (2002) and McNichols (2002), against *DISASTER* and a set of controls from our baseline model. The coefficient of *DISASTER* is not statistically significant in this estimation.

Table 12
CEO early-life disaster experience and break in the streak of earnings increases.

	CRASH_BREAK1	*CRASH_BREAK2*	*CRASH_BREAK3*
	(1)	*(2)*	*(3)*
$DISASTER_t$	0.437**	0.260**	0.680**
	(1.971)	(2.221)	(2.063)
$NSKEW_t$	0.101	0.064	0.064
	(0.802)	(0.947)	(0.343)
$SIZE_t$	−0.045	−0.028	0.217
	(−0.399)	(−0.498)	(1.336)
LEV_t	2.247**	0.335	0.089
	(2.311)	(0.693)	(0.064)
MB_t	−0.020	0.004	0.027
	(−0.882)	(0.331)	(0.987)
ROA_t	15.056***	8.105***	19.423***
	(6.325)	(6.282)	(4.880)
$DTURN_t$	−1.878	−0.939	−1.931
	(−0.708)	(−0.666)	(−0.370)
RET_t	3.514	−0.757	15.728
	(0.589)	(−0.266)	(1.578)
$SIGMA_t$	20.841	−1.328	80.965*
	(0.713)	(−0.094)	(1.745)
$OPAQUE_t$	0.753	0.107	0.016
	(1.316)	(0.365)	(0.019)
$CASH_t$	−3.737**	−1.844**	−7.885***
	(−2.380)	(−2.137)	(−3.136)
ACQ_t	0.207	0.251**	0.672**
	(1.063)	(2.352)	(2.159)
AGE_t	0.213	0.056	−0.109
	(1.158)	(0.591)	(−0.394)
AGE^2_t	−0.002	−0.001	0.001
	(−1.218)	(−0.612)	(0.498)
$GENDER_t$	1.419***	0.661**	1.016
	(2.928)	(2.086)	(1.088)
Constant	−10.594**	−3.846	−5.636
	(−2.061)	(−1.415)	(−0.676)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3579	3219	2717
Pseudo R^2	0.115	0.146	0.191

This table presents results of the effect of CEO early-life disaster experience on the indicators of break in the streak of earnings increases. *DISASTER* is a dummy variable equal to one if a firm has CEO with early life disaster experience, and zero otherwise. *CRASH_BREAK1* is a dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time $t+1$ but increased in time t and time t-1, and zero otherwise. *CRASH_BREAK2* is a dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time $t+1$ but increased in time t, time t-1, and time t-2, and zero otherwise. *CRASH_BREAK3* is a dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time $t+1$ but increased in time t, time t-1, time t-2, and time t-3, and zero otherwise. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in all regressions. The regressions are performed by logit. The z-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

early-life disaster experience tend to have higher cash-flow volatility and stock return volatility. These findings lend support to our argument that CEOs with early-life disaster experience, on average, are more risk tolerant.

5.4. Severity of disasters

To add further texture to our analysis, in this section, we examine whether the documented effect of CEO early-life disaster experience varies with the intensity of experience—that is, with the severity of disaster. In keeping with prior literature (Kahn, 2005; Berrebi and Ostwald, 2011), we measure disaster severity (*SEVERITY*) using the number of fatalities in a disaster divided by the population of the county where the disaster took place.[12] We categorize disaster experience into three groups: *MARGINAL* (disasters in 1st to 4th severity deciles), *MODERATE* (disasters in 5th to 9th severity deciles), and *EXTREME* (disasters in the top severity decile). We then estimate our baseline model after replacing *DISASTER* with these three dummy variables.

The results of this estimation are reported in Table 15. The coefficients of *MARGINAL* and *MODERATE* are both significantly

[12] For CEOs with multiple disaster experiences we take the sum of the number of fatalities across corresponding disaster events and then scale it by the average population of the county where the disasters took place.

Table 13
CEO early-life disaster experience and delay of bad news disclosure.

	(1)	(2)
	CAR	*CAR*
BADNEWS	−0.015***	−0.013***
	(−3.815)	(−3.341)
DISASTER		0.002
		(0.471)
DISASTER×*BADNEWS*		−0.018**
		(−2.086)
MFNEWS	0.136***	0.135***
	(4.882)	(4.853)
MFNEWS×*BADNEWS*	0.295***	0.293***
	(3.802)	(3.809)
EARNSURP	0.473***	0.468***
	(3.968)	(3.981)
EARNSURP×*BADNEWS*	0.562	0.514
	(1.013)	(0.902)
Constant	0.004***	0.004***
	(2.876)	(2.770)
Obs.	4350	4350
Adjusted R^2	0.124	0.125
Base model[a]	0.006**	
Without disaster[a]		0.004
With disaster[b]		0.018**
Difference[c]		0.014*

This table presents results of the effect of CEO early life disaster experience on the delay of bad news disclosures. *CAR* is cumulative abnormal returns over value-weighted market returns for five trading days around the management earnings forecast announcement date. *MFNEWS* is the difference between management forecasted earnings and the most recent analyst forecast consensus issued within 30 days prior to the management forecast, divided by the analyst forecast consensus. *BADNEWS* is a dummy variable equal to one if *MFNEWS* is negative, and zero otherwise. *EARNSURP* is the difference between actual earnings in an earnings announcement and the most recent analyst forecast consensus within 30 days prior to the earnings announcement, divided by the stock price. The regressions are performed by ordinary least squares (OLS). The *t*-statistics in parentheses are adjusted for heteroscedasticity and clustered by firm. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

a The differential market reaction for "Base model" and "Without disaster" is $|Constant + BADNEWS| - |Constant|$ and the *F*-test tests: $Constant + BADNEWS < -1 \times Constant$.

b The differential market reaction for "With disaster" is $|\ Constant + BADNEWS + DISASTER + BADNEWS \times DISASTER| - |Constant + DISASTER|$ and the *F*-test tests: $Constant + BADNEWS + DISASTER + BADNEWS \times DISASTER < -1\times (Constant + DISASTER)$.

c The difference in market reactions between "With disaster" and "Without disaster" is $(|Constant + BADNEWS + DISASTER + BADNEWS \times DISASTER| - |Constant + DISASTER|) - (|Constant + BADNEWS| - |Constant|)$ and the *F*-test tests: $(|Constant + BADNEWS + DISASTER + BADNEWS * DISATER| - |Constant + DISASTER|) > (|Constant + BADNEWS| - |Constant|)$.

where "With disaster" refers to earnings forecasts by CEOs with early-life disaster experience and "Without disaster" refers to earnings forecasts by CEOs with early-life disaster experience.

positive for all three measures of crash risk, suggesting that for the marginally and moderately severe disaster events CEO early-life disaster experience engenders crash risk. The coefficient of *EXTREME* is negative and marginally significant in the *NSKEW* and *DUVOL* regressions and is negative albeit insignificant in the *CRASH* regression, providing some evidence that firms led by CEOs who experienced extremely severe disasters have lower crash risk.[13] Collectively, these results suggest that the relative importance of the mechanisms through which disaster experience impacts CEO's risk attitudes varies depending on the severity of the disaster (e.g., Bernile et al., 2017), affecting the sign of CEO disaster experience-crash risk relation.

5.5. Positive jump risk

In the last set of tests, we examine the effect of CEO early-life disaster experience on positive jump risk—the likelihood of sudden but infrequent large stock price increases. If our results are driven by bad news hoarding, CEO early-life disaster experience should predict one-sided exposure to crashes (Hutton et al., 2009)—i.e., the documented effect should be confined to the left tail of the distribution of stock returns. In contrast, if our findings capture the impact of CEO disaster experience on business risk (Bernile et al.,

[13] Our results remain intact when using categorization of disaster events based on the raw number of fatalities.

Table 14
CEO early-life disaster experience and firm's risk taking.

	$CFOVOL_{t+1}$	$STKVOL_{t+1}$	$IDIOVOL_{t+1}$
	(1)	(2)	(3)
$DISASTER_t$	1.451**	0.095*	0.002**
	(2.153)	(1.832)	(2.282)
$SIZE_t$	4.817***	−0.097***	−0.002***
	(12.078)	(−5.534)	(−6.037)
$DIVIDEND_t$	−1.317***	−0.487***	−0.008***
	(−2.998)	(−6.561)	(−6.945)
LEV_t	−4.693**	−0.130	0.001
	(−2.117)	(−0.707)	(0.164)
MB_t	0.020	0.014**	0.000**
	(0.560)	(2.424)	(2.097)
ROA_t	6.942*	−4.028***	−0.077***
	(1.671)	(−8.753)	(−9.518)
$TANGIBILITY_t$	−0.336	−0.083	−0.002
	(−0.235)	(−0.615)	(−0.855)
$GROWTH_t$	0.477	0.328***	0.006***
	(0.885)	(4.538)	(4.539)
AGE_t	−0.192	−0.071	−0.001*
	(−0.564)	(−1.560)	(−1.787)
$AGE2_t$	0.001	0.001	0.000
	(0.393)	(1.444)	(1.641)
$GENDER_t$	−0.133	0.203*	0.003
	(−0.074)	(1.828)	(1.593)
Constant	−28.970***	5.741***	0.111***
	(−3.171)	(4.534)	(5.325)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3657	3744	3744
Adjusted R^2	0.547	0.626	0.618

This table presents the effect of CEO early-life disaster experience on firm's risk taking. *DISASTER* is a dummy variable equal to one if a firm is led by CEO with early-life disaster experience, and zero otherwise. *CFOVOL* is the standard deviation of the ratio of operating cash flows over total assets over the past five years. *STKVOL* is calculated as the standard deviation of daily stock return during the year. *IDIOVOL* is the standard deviation of residuals from a firm-specific Carhart (1997) four-factor model estimated using weekly return during the year. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in the regressions. The regressions are performed by ordinary least squares (OLS). The *t*-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

2017), CEO disaster experience should be positively related to both crash risk and positive jump risk, reflecting a higher spread of firm performance outcomes.[14]

Following Hutton et al. (2009), we define a positive jump symmetrically to a crash (i.e., 3.09 standard deviations above the mean) and estimate the logit regression for jump probability. The (untabulated) results of this estimation show no statistical evidence of a relation between CEO early-life disaster experience and positive jump risk. For robustness purposes, we repeat this analysis using (1) extremely, moderately, and marginally severe disasters as explanatory variables of interest, (2) alternative thresholds for defining positive jump risk, and (3) the number of positive jumps as a dependent variable. None of these alternative specifications alter our results.

6. Conclusions

In a longitudinal sample of U.S. firms, we find that firms led by CEOs with early-life disaster experience, on average, have higher stock price crash risk. The documented effect of CEO early-life disaster experience on crash risk is amplified for the CEOs with high equity risk-taking incentives and the CEOs serving as the chairman of the board. We also find that stocks of the firms led by CEOs with early-life disaster experience are more likely to experience crashes accompanied by earnings announcements that break the strings of uninterrupted earnings increases and exhibit stronger asymmetric response to bad versus good news disclosures in management earnings forecasts. In addition, we find that firms led by CEOs with early-life disaster experience tend to have higher cash-flow and stock return volatility, and that the effect of CEO early-life disaster experience on crash risk varies in a curvilinear manner with the severity of disaster. Our findings are consistent with the view that, by influencing CEO risk attitudes, early-life disaster experience impacts a CEO's propensity to hoard bad news and, consequently, formation of stock price crashes.

Our study extends a growing stream of research examining the influence of top managers' background characteristics on corporate

[14] As discussed, we control for corporate policies that Bernile et al. (2017) find are associated with CEO early-life disaster experience.

Table 15
Severity of disasters.

	$CRASH_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
	(1)	(2)	(3)
$MARGINAL_t$	0.693***	0.208***	0.132***
	(3.055)	(3.012)	(3.007)
$MODERATE_t$	0.474***	0.140***	0.074**
	(3.938)	(2.911)	(2.312)
$EXTREME_t$	−0.138	−0.181*	−0.095*
	(−0.438)	(−1.805)	(−1.647)
$NSKEW_t$	0.102*	0.025	0.014
	(1.670)	(1.171)	(1.071)
$SIZE_t$	0.066	0.061***	0.038***
	(1.433)	(4.678)	(4.262)
LEV_t	0.737	0.111	0.048
	(1.601)	(0.820)	(0.540)
MB_t	0.008	0.008**	0.003
	(0.804)	(2.277)	(1.398)
ROA_t	0.877	0.246	0.158
	(0.965)	(0.860)	(0.802)
$DTURN_t$	0.825	0.493	0.266
	(0.765)	(1.582)	(1.246)
RET_t	2.469	1.397**	0.848**
	(1.172)	(2.414)	(2.133)
$SIGMA_t$	13.443	9.091***	5.664***
	(1.176)	(2.895)	(2.633)
$OPAQUE_t$	0.512*	0.069	0.063
	(1.847)	(0.755)	(1.046)
$CASH_t$	−1.195*	−0.645***	−0.297**
	(−1.769)	(−3.169)	(−2.245)
ACQ_t	0.017	0.001	0.007
	(0.190)	(0.057)	(0.422)
AGE_t	0.070	0.014	0.012
	(0.652)	(0.576)	(0.727)
AGE^2_t	−0.001	−0.000	−0.000
	(−0.713)	(−0.580)	(−0.679)
$GENDER_t$	0.494**	0.130	0.113**
	(2.003)	(1.457)	(2.140)
Constant	−3.403	−1.064	−0.896*
	(−1.137)	(−1.469)	(−1.941)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3728	3744	3744
Pseudo/Adjusted R^2	0.049	0.046	0.045

This table presents results of the effect of the severity of the disaster on the relation between CEO early-life disaster experience and stock price crash risk. *EXTREME/ MODERATE/ MARGINAL* is a dummy variable equal to one if a firm is led by CEO with extreme/moderate/marginal early-life disaster experience, and zero otherwise. *CRASH* is a dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. *NSKEW* is the negative skewness of firm-specific weekly returns over the fiscal year period. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. Other variables are defined in Appendix C. The constant term, industry fixed effects based on 2-digit Standard Industrial Classification (SIC) codes, and year fixed effect are included in all regressions. The regressions are performed by logit or ordinary least squares (OLS) depending on the model. The $z-/t$-statistics in parentheses are adjusted for heteroscedasticity and clustering by firm.

policies and practices. Our study also contributes to the literature examining the antecedents of stock price crash risk by documenting the role of CEOs' formative experiences in formation of stock price crashes. Further, our findings provide important insights for investment practitioners, suggesting that investors should consider CEOs' early-life disaster experiences when modeling downside equity risk.

Similar to prior studies, ours has limitations which offer directions for future research. We focus on firms in the Fortune 500 list—large firms—because CEOs in these firms receive more media exposure, which makes their bio information more comprehensive and reliable, allowing a large-scale archival research design. Future studies in this area may adopt a survey-based research design that would include CEOs of smaller companies. Also, in our cross-sectional analysis, we employ CEO-chairman duality—a measure of CEO structural power (Finkelstein, 1992). Future research could fruitfully extend this analysis by considering the role of CEO ownership power (e.g., CEO founder status and CEO stock ownership) in shaping the relation between CEO formative experiences and crash risk.

Appendix A. Data sources for disaster events

The disaster events included in our analysis are the natural disasters such as earthquakes, volcanic eruptions, tsunamis, hurricanes, tornadoes, severe storms, floods, landslides, extreme temperature and wildfires, and other miscellaneous accidents (e.g., coal mine explosion, traffic accidents etc.) that caused severe economic and life losses. The United States Spatial Hazard Events and Losses Database (SHELDUS™) contains the county-level natural hazard information from 1960 to present. Since most of the CEOs in our sample were born before 1960, we construct a disaster event dataset equivalent to SHELDUS™ that spans the 1900 to 1959 period. We combine all the sources listed below to construct our dataset.

Data sources	Description
SHELDUS™	SHELDUS™ is a county-level hazard data set for the U.S. and covers natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, heavy rainfall, etc., covering period from January 1960 to December 2017. It was originally developed by the Hazards and Vulnerability Research Institute at the University of South Carolina. Since 2018, the Arizona State University Center for Emergency Management and Homeland Security supports and maintains SHELDUS™.
http://ccdb.lib.virginia.edu	The University of Virginia County and City Data Books service cover the years 1944 through 2000. It contains county level data such as population, health, education, income, housing, employment, crime, manufacturing, agriculture and trade.
The United States Census Bureau: http://www.census.gov/statab/www/ccdb.html	We use this database to search whether disaster events happen for each CEO in our sample. The search spans the 1900 to 2010 period.
The United States National Geophysical Data Center	We mainly search for natural disaster events in this database.
The United States Geological Survey (USGS)	This database provides a list of events of natural hazards that threatened lives and livelihoods going back to 1900.
National Weather Service (NWS) of the National Oceanic and Atmospheric Administration.	We mainly search for hurricanes, tornadoes, and severe storm events in this database.
http://www.gendisasters.com/fires/index.htm	We search for wildfire events and the number of fatalities caused by disaster events in this database.
The United States National Climatic Data Center (NCDC)	We use this database to search for natural disasters which caused deaths or injuries of many. When the events of similar scale happened multiple times during the same year, we choose the most severe one.
The International Emergency Disasters Database (EMDAT)	We use this database to search for geographic locations of disaster events. We first conduct a search at state-level and then narrow it down to county-level.
Wikipedia.org	We search separately for CEOs' biographical details and whether disaster events happened during CEOs' formative years in this website whenever available to cross-validate the data obtained from other sources used in our study.

Appendix B. Collection process of CEO bios

Our initial sample consists of all U.S. born CEOs of firms in the Fortune 500 list from 1992 to 2016. For each CEO in our sample, we first get the basic bio information such as full name, gender, current company etc., from Execucomp. We double check the information with BoardEx and get further information such as accomplishments and education background from BoardEx. We then hand collect the CEO bios, specifically the birth and grow up places of CEOs, from the following organized sources: official publications containing biographical information (books such as Steve Jobs by Isaacson, online resources such as Encyclopedia, NNDB), obituary, university websites (such as distinguished alumni interviews, university foundation board of directors introductions, etc.), local and national newspaper (from ProQuest historical newspapers archive), magazines, and company official websites. For CEOs whose bios are not available from the above organized sources, we search for the CEOs using Google and Wikipedia to obtain their bios from sources such as award-winning introductions (such as Franklin Institute awards), official publications of academic and industrial societies, etc.[15] The bio information is cross-validated with at least one other source whenever possible. In the final sample, we have 598 unique CEOs. From the aforementioned data sources, we are able to find the exact birth place for all the 598 CEOs and the grow up place for 429 CEOs. For those CEOs that we are unable to find the exact grow up place, we use their birth place instead. Further, among the 429 CEOs that we are able to obtain both their birth place and grow up place, 103 CEOs moved to another place in their childhood and 326 CEOs grew up in their birth place. The following table summarizes the main data sources of the CEO bios.

Data source	No. of CEO bios	Percentage of CEO bios
Biography	247	41.3
Newspaper	117	19.6

(*continued on next page*)

[15] Our core results remain intact when we exclude observations for which we use Google and/or Wikipedia to obtain biographical information.

(*continued*)

Data source	No. of CEO bios	Percentage of CEO bios
Company website	62	10.4
Obituary	53	8.9
University website	33	5.5
Magazine	16	2.7
Other sources	70	11.6
Total	598	100.0

Appendix C. Variable definitions

Variable	Definition
CRASH	Dummy variable equal to one for a firm-year that experiences one or more crash weeks, and zero otherwise. A crash week is a week with firm-specific weekly returns falling 3.09 standard deviations below the mean firm-specific weekly returns over the year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution.
NSKEW	The negative skewness of firm-specific weekly returns over the year period.
DUVOL	The natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks.
DISASTER	Dummy variable equal to one if a firm has CEO with early-life disaster experience, and zero otherwise.
SIZE	The natural logarithm of market value of equity.
LEV	Total long-term debts divided by total assets.
MB	Market value of equity divided by book value of equity.
ROA	Income before extraordinary items divided by total assets.
DTURN	The average monthly share turnover in the current fiscal year minus the average monthly share turnover in the last fiscal year, where monthly share turnover equals the monthly trading volume divided by the total number of shares outstanding during that month.
RET	The mean of firm-specific weekly returns over the fiscal year, multiplied by 100.
SIGMA	Standard deviation of firm-specific weekly returns over the fiscal year.
OPAQUE	The prior three years' moving sum of the absolute value of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (Hutton et al., 2009).
CASH	Cash and short-term investments divided by total assets.
ACQ	Dummy variable equal to one if the firm announces a merger or acquisition in the current year, and zero otherwise.
AGE	The age of the firm's CEO.
AGE^2	The square of the age of the firm's CEO.
GENDER	A dummy variable that takes the value of one if the firm's CEO is female, and zero otherwise.
OVERCONF	CEO overconfidence calculated following Malmendier and Tate (2005)
TENURE	The natural logarithm of one plus the number of years the CEO is in his/her current position.
EDUCATION	A categorical variable equal to zero for CEOs without college degree, one for CEOs with undergraduate degree, two for CEOs with master degree, and three for CEOs with doctoral degree (Barker III and Mueller, 2002).
ABILITY	CEO ability based on the measure developed by Demerjian et al. (2012).
OWNERSHIP	The proportion of the firm's shares held by the CEO.
OPTINCT	The incentive ratio for executive option holdings, measured as option sensitivity/(option sensitivity+salary+bonus). Option sensitivity is the dollar change in the value of exective option holdings resulting from a 1% increase in the firm's stock price.
FOUNDER	A dummy variable equal to one if the CEO is one of the founders of the firm, and zero otherwise.
CEOFEPCB	A dummy variable equal to one if the CEO is the founder and either the president, chair, or both.
CEOPRCH	A dummy variable equal to one if the CEO is both the president and the chairman.
DUAL	Dummy variable equal to one if firm's CEO holds the position of the chairman of the board in the current year, and zero otherwise.
CSR	The net score of CSR rating based on the MSCI ESG data, measured as total strengths minus total concerns in five categories: community, diversity, employee relations, environment, and product.
SCAPITAL	Social capital, calculated based on the data from the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University.
RELIGION	The number of religious adherents in the county divided by the total population in the county.
TRAIO	The percentage of equity ownership held by transient institutional investors.
BSIZE	The natural logarithm of number of directors sitting on the board.
BOWNERSHIP	The natural logarithm of equity ownership held by directors.
ETRdiff	Effective tax rate differential, calculated as (pre-tax book income − (current federal tax expense + current foreign tax expense + deferred tax expense)/statutory tax rate)/lagged total assets
HQ_DISASTER	The historical average number of disasters in the firm's headquarter state divided by the state's average population.
VEGA	Dummy variable equal to one if the CEO's compensation vega is greater than the annual median, and zero otherwise. CEO compensation vega is calculated as the natural log of the dollar change in the value of CEO option holdings resulting from a 0.01 unit increase in the firm's stock volatility.
CRASH_BREAK1	Dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time *t + 1* but increased in time *t* and time *t-1*, and zero otherwise.
CRASH_BREAK2	Dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time *t + 1* but increased in time *t*, time *t-1*, and time *t-2*, and zero otherwise.
CRASH_BREAK3	Dummy variable equal to one if a firm experiences stock price crash and firm earnings decreased in time *t + 1* but increased in time *t*, time *t-1*, time *t-2*, and time *t-3*, and zero otherwise.
CAR	The cumulative abnormal returns over value-weighted market returns for five trading days around the management earnings forecast announcement date.
MFNEWS	

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(*continued*)

Variable	Definition
	The difference between management forecasted earnings and the most recent analyst forecast consensus issued within 30 days prior to the management forecast, divided by the analyst forecast consensus.
BADNEWS	A dummy variable equal to one if *MFNEWS* is negative, and zero otherwise.
EARNSURP	The difference between actual earnings in an earnings announcement and the most recent analyst forecast consensus within 30 days prior to the earnings announcement, divided by the stock price.
CFOVOL	The standard deviation of the ratio of operating cash flows over total assets over the past five years.
STKVOL	The standard deviation of daily stock return during the year.
IDIOVOL	The standard deviation of residuals from a firm-specific Carhart (1997) four-factor model estimated using weekly return during the year.
EXTREME	Dummy variable equal to one if a firm has CEO with severe early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the top decile) in the current year, and zero otherwise.
MODERATE	Dummy variable equal to one if a firm has CEO with moderate early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the 5th to 9th deciles) in the current year, and zero otherwise.
MARGINAL	Dummy variable equal to one if a firm has CEO with marginal early life disaster experience (the sum of fatalities across the disasters scaled by county population is in the 5th to 9th deciles) in the current year, and zero otherwise.

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