General Managerial Skills, Tolerance for Failure, and Stock Price Crash Risk*

Daewoung Choi
Louisiana State University Shreveport
joey.choi@lsus.edu

Thanh Ngo
East Carolina University
ngot@ecu.edu

Ha-Chin Yi
Texas State University
hy11@txstate.edu

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Daewoung Choi (Correponding author): 339B BE Building, 1 Univ. Place, Shreveport, LA 71115, Tel. (318)-797-5241, jchoi@lsus.edu
Ha-Chin Yi: 504 McCoy Hall, 601 University Dr. San Marcos, TX 78666, Tel. (512)-245-3251, hy11@txstate.edu
Thanh Ngo: 3127 Bate Building, Greenville, NC 27858, Tel (252)-328-4038, ngot@ecu.edu

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Abstract

We explore whether CEO lifetime work experiences are associated with stock price crash risk. Using the general managerial ability index of Custódio, Ferreira, and Matos (2013), we find that firms featuring CEOs with general managerial ability (“generalist” CEOs) experience less stock price crash risk than their counterpart firms featuring specialist CEOs, and our results are stronger for firms with tight local labor market competition, financial ditress, and greater industry media coverage, in which generalist CEO skills are in more demand and easily observed. Our results are enforced by the notion that a broad set of outside employment options create a mechanism of tolerance for failure, which reduces termination concern in one place and thereby weaken the incentive for generalist CEOs to delay bad news to secure a job. Our results are robust to alternative empirical specifications and estimation methods for mitigating endogeneity concerns.

JEL Classification: G21, G32

Keywords: Stock price crash risk; CEOs; Information hoarding; Tolerance for Failure

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1. Introduction

Do CEOs matter in Corporate America? According to the literature, yes. CEO traits and characteristics explain the cross-sectional difference in firm capital structure (Hackbarth, 2008), acquisition decision (Graham et al., 2013), corporate investment (Malmendier and Tate, 2005), earnings management (Ali and Zhang, 2015), corporate innovations (Manso, 2011; Custódio et al., 2017) and firm performance (Kaplan et al, 2012). Importantly, previous studies on the determinants of the third moment of stock returns or negative skewness show that CEOs have a significant influence on stock price crash risk (hereafter, crash risk). More specifically, a CEO hoards bad information, causing it to stockpile until it reaches a tipping point, engendering a large, negative drop in stock price. Thus, the accumulation of bad news is a catalyst for the stock crash (Jin and Myers, 2006). What types of managerial traits or characteristics are related to stock price crash risk?

In this study, we focus on CEOs' lifetime experiences—whether CEOs have accumulated diverse backgrounds from multiple industries or limited to specific industry or firm—and its impact on stock price crash risk (hereafter, crash risk). Previous studies find that managers' certain idiosyncratic characteristics, including CEO overconfidence (Kim et al., 2016), cultural background (Fu et al., 2019), CEO age (Andreou et al., 2017), along with superior inside formation shape their decision choice to withhold negative news, are known to have explanatory power for crash risk. Aligning with extant literature, we attempt to explain the cross-sectional difference in sample firms' crash risk with one particular characteristic of CEOs, their lifetime work experience.

We classify our sample CEOs with dichotomous categories, following Custódio et al.'s (2013) methodology. CEOs with general managerial skills (hereafter, generalist CEOs) have accumulated diverse experiences not specific to any organization and transferable across firms or industries, while CEOs with firm-specific managerial skills (hereafter, specialist CEOs) remain in one industry or one firm, and therefore, are valuable only within an organization.

We argue that generalist CEOs are less likely to hoard bad information; rather, they release bad (or good) information as it occurs for two primary reasons. First, generalists' mobility across industries/firms promote a labor market mechanism of tolerance for failure (Manso, 2011; and Custódio et al., 2017), which can reduce their incentive to hoard negative information. Specialists, however, have less bargaining power in the CEO labor market than generalists, especially in the unfavorable macro-economic environment[1]. Recognizing little outside job opportunity and greater career concerns, specialists are more sensitive to termination risk and may choose not to release bad information in a timely manner (Baginski et al., 2018). Second, general managerial skills allow top executives to manage the fast-changing business environment amplifying the effect of CEO ability on firm value (Garicano and Rossi-Hansberg, 2006), which leads to the current market's favorable treatment and high demand for general managerial skills[2]. We argue that generalist CEOs are less incentivized to hoard bad information than specialist CEOs as such forces and market expectations create greater reputational capital for CEOs with general skills. Relatedly,

[1] Custódio et al. (2013) argue that gain from a better fit between the hiring firm's objectives and incoming generalist CEO's skill set outweighs cost from losing a firm-specific skill set of outgoing specialist CEOs. Therefore, generalists are paid higher compensation

[2] A CEO's diverse business experience is in high demand due to today's complex business environment shifted by industry deregulation (Hubbard and Palia,1995; Cuñat and Guadalupe, 2009a), foreign competition (Cuñat and Guadalupe, 2009b), changes in technology and management practices (Custódio et al., 2017), and restructurings and acquisitions (Custódio et al., 2013; Mishara, 2014).

Haunschild and Rhee (2004) find that generalists respond more to reputation-damaging events among other failures due to their greater visibility.

We investigate whether CEOs becoming a generalist or a specialist is directly related to crash risk using the S&P 1500 sample firms from fiscal years 1993 to 2007. To measure general managerial skills, we use the *General Index* (GI) developed by Custódio et al. (2013). The higher the level of GI, the more various industry/firm experiences a CEO has accumulated over time. Controlling for various firm and CEO characteristics, and industry and year fixed effects, we find robust results that the index of general skills is negatively related to crash risk.

Endogeneity can occur in our study due to an omission of economically significant variables and the firm's unobservable time-invariant heterogeneity. To alleviate the omitted variable concerns, we test our baseline model incorporating additional variables of CEO-specific traits and corporate governance and firm fixed effects. We also perform change-on-change regression. The primary results stay qualitatively the same under these robustness checks. Another endogeneity source may be the sample selection bias. For example, our estimates will be biased if generalist CEOs self-select or are self-selected into firms with low business risk. We construct the propensity-score matching (PSM) sample and confirm that the relation between the index of general skills and crash risk is not primarily driven by such endogenous selection of managers or firms. And, the simultaneity (or reverse causality) problem may arise because unobservable common factors jointly affect both general managerial skills and crash risk. To mitigate the concern of simultaneity, we conduct the two-stage least squares (2SLS) regressions. We use the Garmaise (2009) index on the enforceability of non-compete agreements at the state-year level across positions of the executive with experience in publicly traded firms as an instrumental variable. The labor laws on non-compete agreements prevent executives from moving or forming a competing firm when their contracts are terminated, thus within-industry employee transfers are limited, while between-industry transfers are increased (Garmaise, 2009; Marx et al., 2009; Custódio et al., 2017). Thus, we expect the enforcement index to be positively associated with the generalist skills because CEOs have an ex-ante incentive to accumulate more general skills so as to enhance future mobility across different industries when they work in states enforcing stricter non-compete clauses (Custódio et al., 2017). And, we do not expect the instrument to influence crash risk through paths other than the indirect path of enhanced motivation to accumulate transferable skills. Our results from the 2SLS regressions using full and PSM samples confirm our predictions and reveal robust results. We also test our models using an alternative dichotomy proxy of crash risk and the CEO fixed effects to reduce the influence of a CEO's time-invariant traits. Our results largely remain the same.

For generalist CEOs, the broader set of outside employment options and job mobility across diverse industries act as an executive labor market mechanism of tolerance for failure. This positive mechanism can reduce termination concern in one place and thereby weaken an incentive to secure a job by delaying bad news when a corporate project fails. This underlying mechanism will become more effective when a CEO's transferable skills are largely demanded and easily observed in the labor market[3]. We use labor market tightness and media coverage intensity of industries to investigate whether the negative relation between generalist CEOs and crash risk is

[3] Mishara (2014) find that expected returns are higher for firms featuring generalist CEOs, especially in M&A-intensive industries.

more pronounced. Consistent with this idea, our results become stronger in tight labor markets and industries with intense media coverage.

Our study contributes to the literature on crash risk in several ways. First, our work complements previous findings that CEO style, traits, or characteristics are critical components of firm performance, risk profile, firms' investment policies, and financing decision. This paper is closely related to Andreou et al.'s (2017) in that both studies examine a link between CEO traits and crash risk. Andreou et al. (2017) articulate the importance of CEO age in explaining the cross variation of crash risk. However, our study offers further insights because CEO age may be mainly a proxy for CEO lifetime experiences: CEO age is correlated with maturity, general work experiences, and other learning effects for CEOs engaging in multi-stages of work experiences. Our study identifies specific types of work experiences as an important determinant of CEO behavior. In addition, we introduce possible underlying mechanisms that support the finding of the negative relation between generalist managerial skills and bad news hoarding.

The remainder of this paper is organized as follows. In Section 2, we review the related literature and develop hypotheses. Section 3 discusses the sample and empirical design. Main results are presented in Section 4 and Section 5 concludes.

2. Literature Review and Hypotheses Development

2.1 Stock price crash risk

Conventional portfolio theory was developed based upon a mean-variance analysis with an assumption that stock returns are normally distributed (e.g., Markowitz, 1991). If managers disclose randomly arriving information as it occurs, one would expect symmetrically distributed stock returns, not negatively skewed returns. However, Graham et al. (2005) report that some CFOs delay bad information in the hope that a firm's future performance will improve.

In reality, average CEOs are highly obsessed with firm performance because their future personal wealth is directly related to firm performance through pay-for-performance compensation schemes. Managers are incentivized to hold negative information. Kothari, Shu, and Wysocki (2009) show that managers, due to career concerns, accumulate and withhold bad news for an extended period, but immediately release good news. The implication is that negative news cannot be withheld once information hoarding reaches a certain threshold. Naturally, a sudden release of bad news may result in a large scale decline in stock price (Jin and Myers, 2006).

The third moment in stock return distributions such as skewness is crucially important to investors' portfolio allocation (Harvey and Siddique, 2000; Hong and Stein, 2003).[4] Previous studies have investigated the underlying factors to explain the cross difference of crash risk among sample firms. Habib et al. (2017) provide several illustrations of those identified factors, including financial reporting quality, managerial characteristics, capital market transactions, and corporate governance[5]. Similar to studies of managerial characteristics[6], we provide fresh insights into whether CEO experiences are beneficial or detrimental to investor wealth, which is still an unresolved debate in the extant literature.

[4] Similarly, Merton (1990) shows that stock returns are unlikely to be normally distributed.
[5] The determinants of third moment of stock returns or negative skewness from prior studies are many such as accounting practices (Kim et al, 2016), analyst coverages (Xu et al., 2013), production market competition (Ngo et al., 2018), CEO characteristics (Kim et al., 2011a and 2016; Andreou et al., 2017), corporate governance (Andreou et al., 2016a), stock liquidity (Chang et al., 2017), to name a few.
[6] For example, those attributes of managers, including CEO overconfidence (Kim et al., 2016), cultural background (Fu et al., 2019), CEO age (Andreou et al., 2017) and others are known to have explanatory power for stock crash risk.

2.2 CEO traits and styles and their impact on information hoarding

The CEO literature documents several aspects of CEO personal traits as a determining factor for the CEO's risk-taking behavior in firms and corporate success. For example, CEO overconfidence is a well-researched item that explains corporate investment (Malmendier and Tate, 2005), financial policies (Malmendier et al., 2011), and crash risk (Kim et al., 2016). Andreou et al. (2017, p. 1289) argue when examining the importance of CEO age on the crash risk that "Physiological and psychological characteristics of the CEO and heterogeneous abilities change with age, and some of these characteristics might provoke stock price crashes." Equally, an important aspect of CEO abilities is CEO post-education work experience. The question of which ability is more important is one of *nature* versus *nurture*. Most CEOs probably agree that both nature- and nurture-based qualities are important in a complex, modern corporate environment. In a certain setting, a CEO's nature-based *instinct* can be critical while in another setting nurture-based *experience* can be a dominant factor to explain CEO behaviors.

In this study, we want to address whether nurture-based quality (i.e., lifetime work experience) is related to the CEO's risk-taking behavior, which can amplify crash risk. The variable lifetime work experience is a challenge for researchers because of its ambiguity. Andreou et al. (2017, p. 1289), who test the CEO age effect on crash risk, argue that "Youthful creativeness and inexperience with corporate communication are more problematic to control directly because it is difficult to measure them precisely." However, the authors further argue that "Nevertheless, we can observe their consequences, and hence, we can design appropriate tests to examine their merit as alternative explanations of the CEO age effect" (Andreou et al., 2017, p. 1289). Those

CEO psychological traits change over a CEO's lifetime work experience and therefore we can model work experience to explain the crash risk difference among sample firms.

Previous studies find that executives' characteristics or psychological traits partially explain stock price crashes across sample firms. Hong and Stein (2003) show that investor heterogeneity is central to negative skewness in stock returns. More specifically, Kothari, Shu, and Wysocki (2009) show that managers, due to career concern, accumulate and withhold bad news for an extended period, but immediately release good news.

However, we argue that CEOs who tend to act less instinctively (i.e., the CEO age effect) than average managers, because doing so will accompany negative consequences such as removal from their current position, are more driven by their own prior experience (i.e., the CEO experience effect). For example, specialist CEOs may more actively react to analysts' optimistic earnings expectations than generalist CEOs. Therefore, specialist CEOs hoard bad news to meet analyst earnings forecasts, which will increase future crash risk.

Kim et al. (2016) find that CEO overconfidence increase crash risk. Overconfident managers tend to overestimate future cash flows from their own risk-taking activities (Malmendier et al. 2011). Overconfident CEOs are more common among specialists because they have limited industry experience and they may think they know enough about the firm's future growth prospects and the surrounding environment, holding other factors constant. This familiarity-bias effect is consistent with the propensity that specialist CEOs are more likely to voluntarily hold in-the-money stock options even after the vesting period.

Bleck and Liu (2007) offer a related but slightly different explanation for stock price crashes. They argue that a manager has an incentive to keep a bad project as long as possible to derive private benefits for a longer period. This phenomenon may be more prevalent among specialist CEOs because of their lack of a second chance in the labor market in the case of replacement, which is conducive to a greater level of crash risk. Specialist CEOs have more financial incentives to intentionally conceal and to accumulate adverse operating outcomes from investors, increasing the probability of a stock price crash in the future.

On the contrary, generalists have more outside options, giving them less incentive to hide information when their project fails to produce positive net present values. Generalists are less sensitive to the risk of termination, given their more diverse business experience. A labor market mechanism of tolerance for failure reduces the incentive to hoard negative news in addition to internal mechanisms such as executive compensation plans. Generalists are also effective in adapting to an evolving business environment. For example, generalists are more likely to be hired to perform M&As. Product market changes due to industry deregulation, technology change, and foreign competition are related to managerial general skills. The increased awareness of general skills could result in better information transparency, which we test in a later section of this paper.

3. Empirical Design and Sample Description

3.1. Description of CEO information in the sample

We measure CEOs' general managerial skills by using Custódio et al.'s (2013) GI. Specifically, they identify CEOs from the ExcuComp database and match them with CEO profiles from the BoardEx database. The authors consider five aspects of a CEO's professional career: past number of (1) positions, (2) firms, and (3) industries in which a CEO was employed; (4) whether the CEO held a CEO position at a different company; and (5) whether the CEO worked for a conglomerate. To combine these five variables into a one-dimensional index of general managerial skill, principal components analysis is used to extract the five proxies, which is a linear combination of the proxies, with more weight given to those that more accurately reflect a CEO's general skills and allow us to classify a CEO as a generalist or specialist. More specifically, the index gives close to equal weights to the past number of positions, firms, and industries and a lower weight to the past CEO and conglomerate experiences. Thus, a higher level of general human capital is reflected in a higher value of the index. The index is standardized to have a zero mean and a standard deviation of 1. The final sample consists of a panel of 17,017 firm-year observations from 1993 to 2007, including all non-financial, non-utility firms having common shares listed at NYSE, AMEX, or NASDAQ.

3.2. Description of Crash risk Measures

We followed the standard methodology in crash risk literature to construct two main measures of crash risk as outlined specifically in Hutton et al.'s (2009) study. First, we estimate the following expanded market and industry index model regression for each firm and year:

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t-1} + \beta_{2,i} r_{\varphi,t-1} + \beta_{3,i} r_{m,t} + \beta_{4,i} r_{\varphi,t} + \beta_{5,i} r_{m,t+1} + \beta_{6,i} r_{\varphi,t+1} + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the return on stock *i* in week *t*; $r_{m,t}$ is the return on the CRSP value-weighted index in week *t*; $r_{\varphi,t}$ is the return on the return on the value-weighted industry index based on Fama-French 48-sector classification in week *t*. Dimson (1979) suggests the inclusion of the lead and lag return terms to control for nonsynchronous trading. We then calculate firm-specific weekly returns as the natural logarithm of one plus the residual return from Equation (1).

Once we obtain the firm-specific weekly returns, we calculate the first measure of crash risk, the negative conditional skewness of firm-specific weekly returns *NCSKEW*. *NCSKEW* is the negative of the third moment of firm-specific weekly returns for each year scaled by the standard deviation of firm-specific weekly returns raised to the third power as presented in the following formula.

$$NCSKEW_{i,\tau} = -\frac{n(n-1)^{\frac{3}{2}}\sum W_{i,t}^{3}}{(n-1)(n-2)\left(\sum W_{i,t}^{2}\right)^{\frac{3}{2}}} \qquad (2)$$

This regression separate returns due to market-wide movements, as measured by the fitted value of the regression and firm-specific returns, as captured by the residuals of the regression. In this formula (2), $W_{i,t}$ is the firm-specific weekly return for firm *i* in week *t*, where $W_{i,t}$ is equal to the natural logarithm of 1 plus the residual, $\varepsilon_{i,t}$ and n is the number of firm-specific weekly returns in a year τ. The denominator is a normalization factor. By attaching a minus sign in Equation (2), *NCKSKEW* captures the size of the left tail and therefore, the higher the value of *NCSKEW*, the higher the imminent crash risk.

The second measure of crash risk is the down-to-up volatility measure of the crash likelihood (*DUVOL*). For each firm *i* in each year τ, we calculate the standard deviation of firm-specific weekly returns separately for the “down” weeks when the returns are below the annual average returns and for the “up” weeks when the returns are above the annual average returns. *DUVOL* is then calculated as the natural logarithm of the ratio of the standard deviation in the “down” weeks to the standard deviation in the “up” weeks as presented in the following formula:

$$DUVOL_{i,\tau} = log\left[\frac{(n_{up}-1)\sum W_{down,i,t}^{2}}{(n_{down}-1)(\sum W_{up,i,t}^{2})}\right] \quad (3)$$

where n_{up} and n_{down} are the numbers of "up" weeks and "down" weeks for firm i in each year τ. The higher the value of *DUVOL*, the higher the imminent crash risk.

In addition to *NCSKEW* and *DUVOL*, we construct an alternative measure of crash risk for a robustness test. Following Hutton et al. (2009) and Andreou et. al (2016), we calculate the difference between the number of crashes and the number of jumps in the firm-year. In a year, a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviation below (above) its mean over the year. Hutton et al. (2009) chose 3.09 to generate 0.1% in the normal distribution. We then create a dummy firm-year variable *CRASH*, which is coded as 1 when there is at least one firm-specific weekly return 3.09 standard deviation below its mean over the year, and 0 otherwise.

4. Empirical Results

4.1. Summary statistics

Our initial sample consists of a panel of 17,017 firm-year observations in the period of 1993-2007. Table 1 shows summary statistics by firm-level (Panel A), the mean difference between generalists versus specialists (Panel B), industry breakdown (Panel C), and yearly observations of crash frequencies and corresponding *NCSKEW* and *DUVOL* (Panel D). Two main measures of crash risk along with the alternative measure presented in Table 1. *NCSKEW* measures the size of the left tail and intuitively captures a negative outlier in the distribution of returns. The mean value for *NCSKEW* is slightly positive (0.020), indicating that the sample firm's' returns are negatively skewed on average. However, the median value of *NCSKEW* is negative (-0.027), suggesting that some observations experience extremely negative returns. The mean value of *DUVOL* is slightly negative (-0.025). Chen, Hong, and Stein (2001) use the "down-to-up volatility" measure (*DUVOL*), which captures asymmetric volatilities between negative and positive firm-specific weekly returns. A higher value of *DUVOL* corresponds to stock more "crash-prone." Interestingly, the mean value of *CRASH* variable 18.2%, suggesting that the probability of a firm-specific crash during a year is 18.2 percent and crashes are more prevalent than would have been expected under a normal distribution. This non-normality of return distributions is consistent with previous studies showing negative skewness (Harvey and Siddique, 2000; Chen et al., 2002; Theodossiou, 2015; Kim et al., 2011b).

Since our variable of interest, *Generalist Index* (*GI*), is standardized for a zero mean and a standard deviation of one, the slightly positive mean value of *GI* suggests that there are more generalists than specialists in our sample. We check mean differences of a crash variable between generalists and specialist CEOs, and the results are shown in Panel B. Generalists CEOs are associated with lower crash risk regardless of the three different crash risk measures. To investigate our hypothesis at the univariate setting, we plot in Figure 1, the percentage of stock price crashes across firm-years based on CEO GI by dividing up our sample into three equal groups. Figure 1 shows that there is a negative relationship between the likelihood of generalist CEOs and crash risk.

There are industry differences with respect to what type of CEO is common (Panel C). For example, the telecommunication and utilities sectors have more generalist CEOs, while money/financial sector has more specialist CEOs. Some stocks may be more prone to crash due to the industry's fundamental differences, which we will control in multivariate analyses. Table 2, Panel D shows that crashes more common during the Financial Crisis of 2007 – 2008.

4.2. CEO style and crash risk – the OLS approach

We test the hypothesis that firms with generalist CEOs, as opposed to specific skills, are negatively related to future crash risk because generalists tend not to hoard (or to hoard less) negative information. Company-specific information is released in a timely manner under the leadership of generalist CEOs. They are less sensitive to termination risk and have more outside employment options in the case that their current position is not extended. In addition to their labor market flexibility, generalist CEOs can manage operational challenges more effectively because their multi-faceted skillset equips them with diverse experiences accumulated beyond the organization's current domain. Overall, crash risk studies document that the main cause of firm-specific crashes is an accumulation of negative information over a long period. Eventually, the accumulation of negation information will be revealed, and once it reaches a certain threshold, it triggers stock crashes. However, we argue that the accumulation of negative information over a long period is less likely under the leadership of generalist CEOs. The marginal effect of negative information on stock price is, therefore, minimal. Overall, generalist CEOs have less incentive to hide negative information for a long period.

In Table 2, we show the results of the regression analysis of crash risk on the CEOs' GI developed by Custódio et al. (2013) from fiscal years 1993 to 2007. The dependent variables, *NCSKEW*, and *DUVOL* measured in year *t* are our crash risk proxies. The variable of interest in this study is *GI* and *Generalist Index Dummy*. *Generalist Index Dummy* is an indicator variable that is equal to one if the CEO's GI is above the yearly median, and zero otherwise. Other control variables are firm characteristics, including size, market to book ratio, stock volatility, leverage, and ROA. Hong and Stein (2003) show that investor belief heterogeneity predicts the future crash event. To control for this effect, we include the detrended stock trading volume, *DTURNOVER,* in the regression. Accounting transparency is captured with the Modified Jones Model discretionary accrual, *Disc. Accruals*. To alleviate concern for potential cross-sectional and time-series dependence in the sample, we report *t*-values using robust standard errors and clustering by the firm.

We find that across all model specifications, the coefficients on our variables of interest, i.e., *GI* and *Generalist Index Dummy,* are all negative and significant. In other words, the results show that our measure of managerial style (generalists versus specialists) is strongly related to future realized crash risk, which is captured by one-year ahead *NCSKEW*. Negative signs on *Generalist Index* coefficients suggest that CEOs with general, diverse experience from multiple industries are negatively related to future crash risk, after controlling for a set of control variables, including the earnings management via discretionary accrual choice, stock trading volume, and other firm characteristics. In terms of economic significance, a one-standard-deviation increase in *Generalist Index* is associated with a 2.65% decrease relative to the sample mean in a crash risk (*NCSKEW*), which represents a sizeable decrease[7].

Chen et al. (2001) use the "down-to-up volatility" measure (*DUVOL*), which captures asymmetric volatilities between negative and positive firm-specific weekly returns. A higher value

[7] Given that the coefficient and standard deviation of *Generalist Index* are -0.017 and 0.982, a one-standard-deviation change in *Generalist Index* decreases the average of *NCSKEW* by 0.01669, and 2.65% reduction, because the average of *NCSKEW* is 0.02

of *DUVOL* corresponds to stock as more "crash-prone." We re-estimate all the regressions reported in Table 2 (Models 3 and 4), using *DUVOL* as the dependent variable. The results using this alternate measure are qualitatively similar, although statistical significance is marginally reduced. In terms of economic significance, a one-standard-deviation increase in *Generalist Index* increases a crash risk (*DUVOL*) by 0.0265, which is economically significant in comparison to the average (median) crash risk (*DUVOL*) of -0.025 (-0.027) in our sample. We also use the third alternative measure of crashes, defined as an indicator variable that equals one, if there are one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and zero otherwise (Chang et al., 2017). The results are shown in Table A.2, which is qualitatively similar.

Although the OLS approach shows an affirmative result supporting our main hypothesis, several endogeneity issues may undermine reliable economic interpretation and statistical inference. First, the omitted variable concern may exist in our sample. Other unobservable, time-invariant, and heterogeneous CEO characteristics or skills may change along with CEO type, and these changes drive the CEO type-crash risk effect. For example, the CEO's general ability level, communication skill, leadership, power, overconfidence, and creativity may change with the *Generalist Index,* but they are not explicitly captured in our estimation model. Addressing the omitted variable concern is a challenge because those CEO qualities are difficult to observe and therefore, difficult to measure. It is also possible that the CEO type reflects unobservable CEO characteristics that disproportionately affect CEOs with limited industry experience. We attempt to address this issue through the firm-fixed effect and multiple robust approaches to draw more reliable interpretations.

Second, an alternative explanation is possible for the relation between crash risk and CEO type such as reverse causality from crash risk to CEO type. For example, crash risk induces CEO turnover and firms may hire a new CEO with more concentrated experience from a single industry (i.e., specialist CEOs) rather than CEOs with diverse experiences (i.e., generalist CEOs), which may increase future crash risk. However, we find no evidence that firms with newly hired CEOs with a high *Generalist Index* experience more crash risk relative to firms that do not. To ensure that we can provide a more robust interpretation, we employ an instrumental variable approach.

Lastly, a sample selection bias and measurement errors are possible, so we employ propensity score matching approach, change-on-change model, and alternative measure for the main variable of interest. In this way, we can focus on drawing meaningful economic interpretation. We continue our discussion over alternative possibilities in the next sections and attempt to present more rigorous estimations.

4.3 Firm fixed effects

One concern, given the previous regression analysis, is that our estimated model may omit some unobservable crash determinants correlated with both the dependent variable and the other explanatory variables. To control for time-invariant unobserved firm characteristics, we included firm fixed-effects in addition to the same set of explanatory variables as the baseline regressions from Table 2. With the firm-fixed effect, we can reduce alternative explanations for the statistical relation between future crash risk and CEO style because the firm-fixed effect relies solely on within-firm variation. The firm-fixed effect estimator allows for results not driven by unobserved variation at a firm-level also correlated with crash risk. In this way, we can identify a true relation between future crash risk and CEO style because the variation in the *Generalist Index* is matched with the variation of crash risk during CEOs' tenure in the company.

Table 3 shows the results. The relation between *Generalist Index* and future crash risk remained highly significant with an expected negative sign, suggesting that our results are unlikely to be driven by omitted correlated time-invariant variables. The overall fitness of the model improves with firm-fixed effect regressions, compared with results from Table 2. The size of coefficients and the statistical significance both improved with firm fixed effect regressions[8].

Although the results from time-invariant firm-fixed effect regressions are convincing, they do not resolve the potential estimation bias due entirely to another type of endogenous matching between CEO and firm. To further address reverse causality and sample selection bias, we introduce other identification strategies such as propensity score matching (PSM), change-on-change model, and instrumental variable estimations in later sections of this study.

4.4 CEO characteristics, monitoring, and corporate governance

Previous results do not include other potential confounding factors that may contribute to explaining cross-sectional variations of future crash risk. For example, the literature has identified several CEO characteristics, including CEO age (Andreou et al., 2017) as explanatory variables for future crash risk. In this section, we also show the moderating role of internal and external monitoring forces such as independent directors. If the positive relationship between specialist CEO and future crash risk is due to opportunistic managerial behaviors such as bad news hoarding

[8] In terms of economic significance, a one-standard-deviation increase in *Generalist Index* increases a crash risk (*NCSKEW*) by 0.0324, which represents a sizable reduction in comparison to the average (median) crash risk (*NCSKEW*) in our sample of 0.02 (-0.027)

and resource diversion one can expect the strength of the relation to be modulated for firms with effective internal monitoring, external monitoring, or both. Independent directors supposedly play a monitoring role within the firm. Institutional ownership can exert a disciplinary force on CEOs who may otherwise engage in hoarding negative information for the extended periods (Callen and Fang, 2013). Externally, stock analyst coverage may play a similar role as that of corporate governance structure within a firm. Therefore, we run additional regressions to control for these factors. We lose a significant number of observations in this test due to the inclusion of additional variables from the various merged database[9].

Table 4 shows the results of crash risk regressions from our restricted model with CEO characteristics, analyst coverage, independent directors, and corporate governance. In addition, we include the G-Index in the regressions. Table 4 also shows the firm-fixed effect results. The results largely remain the same. Generalist CEOs are still negatively related to future crash risk. Statistical significance is not compromised after the introduction of internal and external corporate governance variables. Corporate governance variables seem to lack explanatory power, except for independent director and CEO tenure. A negative coefficient on the independent director variable suggests a disciplinary force for CEO not to hoard negative information, while a positive coefficient on the CEO tenure variable suggests that CEOs tend to hoard negative information as the probability of CEO's employment extension becomes lower over time.

The *Generalist Index* is correlated with some of the firm and CEO profile variables, and multicollinearity can be a concern. However, Table 2 (baseline regressions) and Table 3 (firm-fixed effect) show that without CEO characteristics, our variable of interest, *Generalist Index*, is

[9] Our results continue to hold when we impose CEO trait and governance related variables separately.

statistically significant. In addition, coefficients of most firm characteristics remain the same as before, suggesting that multicollinearity does not drive the results.

4.5 Sample Selection Bias

One important concern with our findings—a general managerial ability to reduce future crash risk—is a sample selection bias due to endogeneity matching between CEOs and firms. To put it differently, the CEO experience effect reflects unobservable CEO characteristics that disproportionately affect specialist CEOs. For example, some firms are removed due to corporate bankruptcy and disappear from our radar in sample construction. This survivorship bias can be introduced, and discriminatorily assign specialist CEOs to risky firms.

If matching is based only on observable firm and CEO characteristics and time-invariant effects, then the firm and CEO fixed effects regressions address the matching problem. In other words, fixed effects control for time-invariant factors that affect the managers' choice of firm or the firms' choice of manager. However, if managers and firms are matched based on unobserved time-variant firm or manager characteristics, then fixed effects cannot fully address the matching problem. For example, the generalist CEO-crash risk story may be because generalist CEO tends to be disproportionately hired by less risky firms.

To control for sample selection bias, we introduce propensity score matching (PSM). Table 5 reports result from the PSM sample. In this approach, first, we estimate the logit regression of the probability that a firm might hire a generalist CEO. All control variables in Table 3 are used in the determinant model. Then we extract the probability from the logit regression and match each firm with a generalist CEO with a firm with specialist CEO and with closest probability (propensity score) for a generalist CEO from the first stage logistic regression[10]. Then, we compare the characteristics of the pairs of firms with the closest propensity score. This is the result in Panel A. In Panel B, we keep only firms with generalist CEOs and matched firms with specialist CEOs identified through the propensity score matching process.

To explore the validity of our matching sample, we compare means of covariates between the pairs of firms with the closest propensity score. Panel A of Table 5 reports no statistically significant differences in characteristics between the two groups. Thus we confirm that our PSM samples are well constructed for further robustness tests while mitigating the concerns of sample selection bias.

In Panel B, we keep only firms with generalist CEOs and matched firms with specialist CEOs identified through the propensity score matching process. Our main variable of interest, *Generalist Index,* is still statistically significant with the expected sign. Therefore, we conclude that our main results are not driven by selection bias.

4.6 CEO fixed Effects

Omitting unobserved time-invariant managerial characteristics in our regression models might lead to biased estimates. It is possible that CEO origin, sex, or other unique attributes of the CEO might capture some potion of marginal effects found in our previous tests. To isolate the unobserved traits of the CEO, we use CEO fixed effects. The estimated coefficients are equivalent. Thus, we confirm that our results are not driven by an unobserved CEO heterogeneity.

[10] We apply a caliper (the maximum tolerated difference between matched subjects) width of 0.03 to implement one-to-one treatment-control pair matching (Sianesi, B., 2001, May. Implementing propensity score matching estimators with Stata. In UK Stata Users Group). When we use a caliper of 0.02 (0.04), our results continue to hold.

4.7 Reverse Causality

Our results might suffer from reverse causality problems. For example, stock price crash measures and *Generalist Index* can be jointly (or simultaneously) determined by some unknown factors. In such a case, the generalist index can be correlated with an error term in the main equation, which causes biased and inconsistent estimates. Thus, to address reverse causality concerns, we used instrumental variables (IV). Two conditions should be met: (1)IV should be correlated with the endogenous explanatory variables; (2) and the instrument cannot be correlated with the error term in the explanatory equation, conditional on the other covariates. It is still the case that the instrumental variable and outcome variable will be correlated, but the only source of such correlation is the indirect path of the instrumental variable correlated with a key repressor, which in turn determines the outcome variable (Cameron and Trivedi, 2005).

We use state-level labor laws on non-compete agreements as a source of exogenous variation in the generality of the human capital of the CEO. Non-compete agreements are contracts that prevent employees from joining or creating a competing company after ending an employment contract. Specifically, we use the Garmaise (2011) index on the enforceability of non-compete agreements during the career of a CEO as an instrument for the *Generalist Index*. The enforceability of such contracts varies across states and over time.

To ensure our choice of instrumental variable to satisfy two IV conditions as mentioned above, we provide more explanations here. First, we expect the Non-Compete Enforcement Index to be positively related to *Generalist Index* because the enforcement of non-compete agreements limit within-industry manager transfers and enhances between-industry transfers (Garmaise, 2009;

Marx et al., 2009; Ertimur et al., 2018). Executives have an ex-ante incentive to accumulate more general skills if they work in states with stricter enforcement of non-compete clauses so that they have more outside options and future mobility (Custódio et al., 2017). Second, we also expect the instrumental variable not to have a direct influence on crash risk. If the correlation with crash risk exists, it might be obtained only through the indirect path of enforcement of non-compete clauses correlated with the generalist index (Cameron and Trivedi, 2005). Ali et al. (2015) show that the correlation between the adoption of the Inevitable Disclosure Doctrine (IDD) and crash risk is achieved only through the restricted executive outside options. With this validation of the proposed IV, Custódio et al. (2017) use state-level laws on non-compete agreements as the instrument for generalist skills to investigate a CEO's risk-taking behavior. Following previous studies, we alleviate the concern of reverse causality by providing the instrumental variable of the average non-compete agreement enforcement index at the state-year level across all career positions the CEO has held in publicly traded firms (Garmaise, 2011).

We report the results of 2SLS with an instrumental variable in Columns 3 to 7 of Table 6. The results of the first-stage model reported in Column 3 suggest that our proposed instrument variable is not weak (F-statistics = 13.34). The second-stage results are reported in Columns 4 to 7. We confirm that the instrumented Generalist Index is still statistically significant with the expected sign in the PSM sample, as well as our original sample, suggesting that reverse causality is not a major concern to derive economic inference.

To confirm the robustness of our results, we also run a change-on-change regression. The results of a change-on-change model and our analysis using CEO fixed effects are reported in Columns 1 and 2 of Table 7. Following change-on-change models used by Hutton et al. (2014)

and Lee et al. (2014), we difference both the dependent and explanatory variables used in Models 1 and 3 of Table 2. Our results show a negative and statistically significant correlation between the change in crash risk measures and change in generalist index, which indicates that an unobserved time constant variable at the firm level does not drive our results.

Another related concern is whether time-invariant CEO fixed effects capture a majority of the variation in corporate events (Graham et al., 2012). We re-test the models in Columns 1 and 3 of Table 4 controlling for CEO fixed effects. The results of Table A.2 suggest that potential omitted variable bias driven by unobserved time-invariant manager attributes is not a major concern in our primary tests.

4.10 Underlying Mechanisms

To explore underlying mechanisms through which CEOs tend to commit more to withhold negative news, we examine our baseline models by providing two moderators. First, we consider media coverage of CEOs as one of two moderators. In today's corporate world, top managers are responsible for various complex projects, and their abilities are often reviewed by press coverage. A manager's visibility on media might reflect his/her reputation in the labor market, which also affects their risk-taking behavior and career path (Rajgopal et al., 2006). For example, more reputable CEOs might find their names in the business press more often than those of lower perceived abilities. Thus, an executive's performance in the financial press would be observable by the market and a potentially reliable guide to the aggregate assessment of their ability. Milbourn (2003) shows that the reputational strength of a CEO is measured as an outside perception of CEO abilities and is constructed by counting the number of articles containing the CEO's name in major business newspapers in the year before the CEO's appointment. Media coverage is essentially CEO credentials and is a good indicator to test their behavioral decision-making. Dyck and Zingales (2002) argue that the media is the channel through which information is aggregated and credibly communicated to the public and across the firm. The media can play a substantial role in reducing the costs of contracting parties for collecting and evaluating information and in shaping contracting parties' reputations. In addition, media attention may be discriminatory in different industries. For example, the high-tech industry is more media-intensive industry when compared with the utilities industry.

We expect generalist CEOs to be more sensitive to the loss of their reputational capital because their general managerial skills draw greater attention from the market along with the favorable market expectation given to them. Dyck and Zingales (2002) find that media attention can affect firms' reputations, and their officers and directors and play a role in corporate governance. Negative attention can hurt the reputations of managers and directors and impose social costs on them. Media attention increases the number of people who learn about others' behavior, thereby increasing the reputation effect. Haunschild and Rhee (2004) find that generalists are more concerned about reputation-damaging events due to their greater visibility. Today's fast-changing business environment expect generalists to perform better in various complex tasks such as restructuring and acquisitions, and also demand such skills due to industry deregulation, foreign competition, and changes in technology and management practices (Hubbard and Palia,1995; Cuñat and Guadalupe, 2009a; Custódio et al., 2017). We argue that generalists are less likely to withhold information than specialists in industries with greater media coverage, in which their skills are more observable and reputational capital is greater.

Models 1 and 2 of Table 7 show how our results change across industries with high and low media coverage. We used the PSM sample to mitigate sample selection bias, which is consistent with the tests in Tables 5 and 6. *High Media Industry* is an indicator variable that equals one if the average media coverage in an industry is above the sample median (LexisNexis). Consistent with our expectation, the interaction term coefficients between generalist index and high media industry dummy are negative and statistically significant, implying that generalist CEOs are less likely to hoard bad news to protect their reputational capital when their managerial skills are more visible in the market.

The second moderating factor we explore is tolerance for failure proxied by labor market condition. A corporate manager facing a failure is subject to the risk of dismissal, but CEOs with diverse work experiences and networks across multiple industries are less sensitive to the risk of termination since a failure in one place might not necessarily indicates the poor ability in other industries. In the event of corporate project failure, generalist CEOs can exercise their rich set of external employment options to move easily to other firms across diverse industries, which is understood as the labor market mechanisms of tolerance for failure (Manso, 2011; Tate and Yang, 2015). Custódio et al. (2017) show that generalists, compared with specialists, take shorter waiting periods to find new executive positions when dismissal decisions are made. Thus, the labor market mechanism of tolerance for failure weakens generalists' incentive to commit in bad information withholding. We expect the tolerance for failure to be stronger in tight labor markets, in which general managerial skills are in more demand.

Models 3 and 4 of Table 7 show the moderator effects. Our proxy of the tolerance for failure is *Tight Labor Market*, which is an indicator variable that equals one if the unemployment rate for one year in the Metropolitan Statistical Area (MSA), is below the median unemployment rate for the MSA over the full sample period. Consistent with our expectation, the coefficient of the interaction term between the generalist index and the tight labor market dummy is negative and statistically significant. Thus, we conclude that a broader set of outside options available to generalists compared to specialists in tight labor markets motivate generalist CEOs to disclose good or bad news with no delay, as their career paths are buffered by a mechanism of tolerance for failure.

4.5. External demand for financial information and information transparency

Although the statistical association between generalist CEOs and the future stock crash is statistically negatively significant in various model specifications with moderating factors, alternative economic channels to understand the findings are warranted to make sure that the association is convincing and consistent. In this section, we present the evidence that generalist CEOs is associated with (1) less dispersion of opinion among stock analysts; (2) more information transparency; and (3) improved quality earnings, which ultimately contributes to lessening future crash risk.

Stock analyst coverage: Although all publicly traded firms must meet the strict minimum level of information disclosure standard by the Securities and Exchange Commission (SEC), firms are generally given a tremendous degree of flexibility and discretion beyond and above SEC requirements. For example, a firm uses discretionary disclosure at its free will through a conference call and press releases. In addition, the amount of information is one factor, and the quality of disclosure is another. Here, we present the link between generalist CEOs and analyst coverage, dispersion of analyst forecast, and the ambiguity of disclosure. Lang and Lundholm (1996) find that firms with more informative disclosure policies have a larger analyst following, more accurate analyst earnings forecasts, less dispersion among individual analyst forecasts, and less volatility in forecast revisions. We regress the number of analyst coverage and forecast dispersion on *Generalist Index* and report the results in Table 8. In the column Analyst Coverage, the generalist index is negatively related to demand of stock analyst coverage and forecast dispersion. Generalist CEOs are correlated with a smaller coverage perhaps because those CEOs provide a clearer picture of the firm's operating status more promptly than specialist CEOs, and therefore, require a smaller coverage of external analysts. It can also be related to the fact that generalist CEOs are conducive to increasing information releases in a timely manner, and analyst forecasting tends to converge toward consensus.

Information transparency: In addition to conference calls and press releases, analysts have other channels to express their concerns about covered firms through research reports, recommendations, and forecasts. Reporting firms often use an optimistic tone, which can be defined as the extent to which managers frame their firms' results and/or outlook in a favorable manner. Disclosure tone is influenced by choice of outcomes to emphasize as well as the manner in which management describes those outcomes. Recently, the literature focused on disclosure tone such as ambiguity (or readability) of financial reporting. For example, Ertugrul et al. (2017) find that firms with larger 10-K file size are associated with stricter loan contract terms and greater future crash risk. Ertugrul et al. (2017) create the Fog Index to measure the average number of words per sentence and the percentage of complex words in the document. Similarly, Laughran and McDonald (2014) show that the file size of 10-K filings is significantly related to a poor corporate information environment. Overall, complex financial statements negatively affect information clarity. In Table 8, we regress the file size of 10K filing and the Fog Index on the generalist index with control variables. The coefficient of *Generalist Index* is negative, suggesting that generalist CEOs are negatively related to the ambiguity of financial statement (i.e., a negative coefficient on the *Generalist Index* variable in the *Fog Index* regression) and positively related to the readability of financial statements (i.e., a negative coefficient on the *Generalist Index* variable in the in *File Size* regression).

Quality of earnings: Yu (2008) finds that stock analyst coverage induces fewer earnings management, although some managers feel pressured to manage earnings actively to meet analyst forecast. Hutton et al. (2009) and Chen et al. (2017) suggest that those firms with more opaque financial reporting are more prone to crash risk (also see Chen et al. (2017) for earning smoothing and Kim et al. (2011b) for tax avoidance). Francis et al. (2016) show that firms with more real earnings management post-Sarbanes-Oxley (SOX) are prone to crash risk (see also Khurana et al., 2018). We regress discretionary earnings and financial restatement on *Generalist Index*. Similar to the above results, generalist CEOs are negatively correlated with opaque earnings statements and restatement activities.

5. Conclusion

We test whether a particular type of CEO work experience is related to the cross-firm variation of crash risk. A stock price crash is more prone to occur when a CEO hoards private but potentially negative information for the extended period. Information hoarding eventually became a catalyst for stock price crash when it reaches to a threshold, and the market faces negative information with a surge of panic that eventually triggers the sell stocks at a sudden and on a large scale.

We focus on CEOs and examine their personal attributes, specifically their work experience to explain the CEO-crash relation. CEOs vary in their talents, skill sets, and work experiences. On the one hand, these attributes are *nature*-based in the sense that CEO personality or her/his family environment shapes their leadership style. On the other, those personal attributes are *nurture*-based in the sense that a CEO's post-education work experience constitutes a CEO leadership style. In this study, we focus on the latter and track CEO lifetime work experiences by adopting Custódio et al.'s (2013) methodology.

We find that generalist CEOs, as opposed to specialist CEOs, are negatively related to future crash risk. CEOs examine the risk-return tradeoff with respect to information hoarding. We argue that CEOs with diverse experiences from multiple industries or firms have more mobility (i.e., generalist CEOs) or tolerance for failure in case that their risk-taking becomes futile. This option to move to another firm (i.e., "second chance") allows them to share private information more openly and in a timely manner with the public rather than hoarding it for a long period.

An economic channel for the CEO type-crash effect shows that generalist CEOs are more willing to protect their reputation by *disengaging* in information hoarding. Generalist CEOs have less incentive to hoard negative information because their broader set of outside employment options creates a mechanism of tolerance for failure within their current firm. Consistent with these views, our results are stronger in tight but efficient labor markets and industries with greater media coverage, in which generalist CEOs' skills are in more demand and easily observed. We also show that generalist CEOs engage in less earnings management, are associated with less dispersion of stock analysts' earnings forecasts, and practice more transparent financial reporting to the SEC.

CEO literature is troubled by several endogeneity issues such as time-variant omitted variable concern, reverse causality, and sample selection. We attempt to address these endogenous matching problems with an instrumental variable approach, firm-fixed effect, change-on-change model, and propensity score matching. The statistical results largely remain the same, and the economic interpretation is consistent with that of the OLS approach.

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Appendix A. Variable definitions

Variable	Definition and Sources of data
GAI	Computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, Matos (2013))
GAI DUMMY	Indicator variable that equals one if the CEO's Generalist Index is above the yearly median, and zero otherwise.
CRASH	Indicator variable that equals one if there are one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and zero otherwise (Chang, Chen, Zolotoy (2017))
NCSKEW	Negative of the third moment of firm-specific weekly returns for each year scaled by the standard deviation of firm-specific weekly returns raised to the third power (Hutton et al. (2009))
DUVOL	Natural logarithm of the ratio of the standard deviation of down week to that of up-week firm-specific weekly returns over the fiscal-year period. (Hutton et al. (2009))
DTURNOVER	Average monthly share turnover over the current fiscal-year period minus that of the previous period, where monthly share turnover is the ratio of monthly trading volume to the total number of shares outstanding during the month.
SIZE	Natural logarithm of the market value of equity: From Compustat
LEV	Book leverage: From Compustat
RET	Average firm-specific weekly returns over the fiscal year: From CRSP
SIGMA	Standard deviation of the weekly firm-specific stock return over the fiscal year: From CRSP
ROA	Income before extraordinary items divided by lagged total assets: from Compustat
MB	(Market value of common stock + total debt + preferred stock – deferred taxes and investment tax credit) / Book Assets: from CSRP
ACCR	Discretionary accruals (signed discretionary accruals), where discretionary accruals are computed using the modified Jones (1991) model
VEGA	Natural logarithm of CEO VEGA which is dollar change of CEO's weath with respect to 0.01 change of standard deviation of the stock return
DELTA	Natural logarithm of CEO DELTA which is Dollar change of CEO's weath with respect to 1% change of stock price.

TENURE	The number of years as CEO of the firm: From Execucomp
AGE	CEO age: From ExecuComp
OWNERSHIP	Fraction of ownership held by the CEO, including stock option: From Compustat.
DUALITY	Indicator variable that equals one if the CEO is the chairperson, and zero otherwise: From ISS
CPS	Fraction of total compensation received by the CEO divided by the total compensation of the top 5 compensated individuals of the firm
FLUIDITY	Similarity between the change in a firm's product space and the aggregate changes in the competitors' products, and is a forward-looking measure of a firm's competitive threats (Hoberg, Phillips, and Prabhala (2014))
TRANSIENT	Fraction of ownership held by transient insitutions that focus on the short-term trading profits and that provide less effective monitoring (Bushee (2001)).
G-INDEX	Governance Index: Gompers Ishii Metric (2003). Higher G-INDEX indicates manager friendly governance (more takeover protection), and lower G-INDEX is shareholder friendly governance.
LITIGATION	Indicator variable which equals one if a firm is one of the industries subject to a high incidence of litigation such as biotechnology (SIC codes 2833-2838 and 8731-8734), computers (SIC codes 3570-3577 and 7370-7374), electronics (SIC codes 3600-3674), and retail (SIC codes 5200-5961), and zero otherwise (Kim, Li, Lu, Yu (2015)).
TIGHT LABOR	Indicator variable that equals one if the unemployment rate for a year in the Metropolitan Statistical Area (MSA) is below the median unemployment rate for the MSA over the full sample period: from the Bureau of Labor Statistics
PCT_MSA_IND	Fraction of firms in the MSA that operate in the firm's two sic industry
ALTMAN_Z	Measurement of the firm's financial distress (Altman, 1968)
HOSTILE TAKEOVER	Measuremnt of the threat of takeover, which is constructed from takeover laws, aggregate capital liquidity, and firm age (Cain, McKeon, and Solomon (2017))
HIGH MEDIA	Indicator variable that equals one if the average media coverage in an industry is above the sample median: From LexisNexis
NONCOMPETE	Average non-compete agreement enforcement index at the state-year level across all positions the CEO has had in publicly traded firms (Garmaise (2009)).

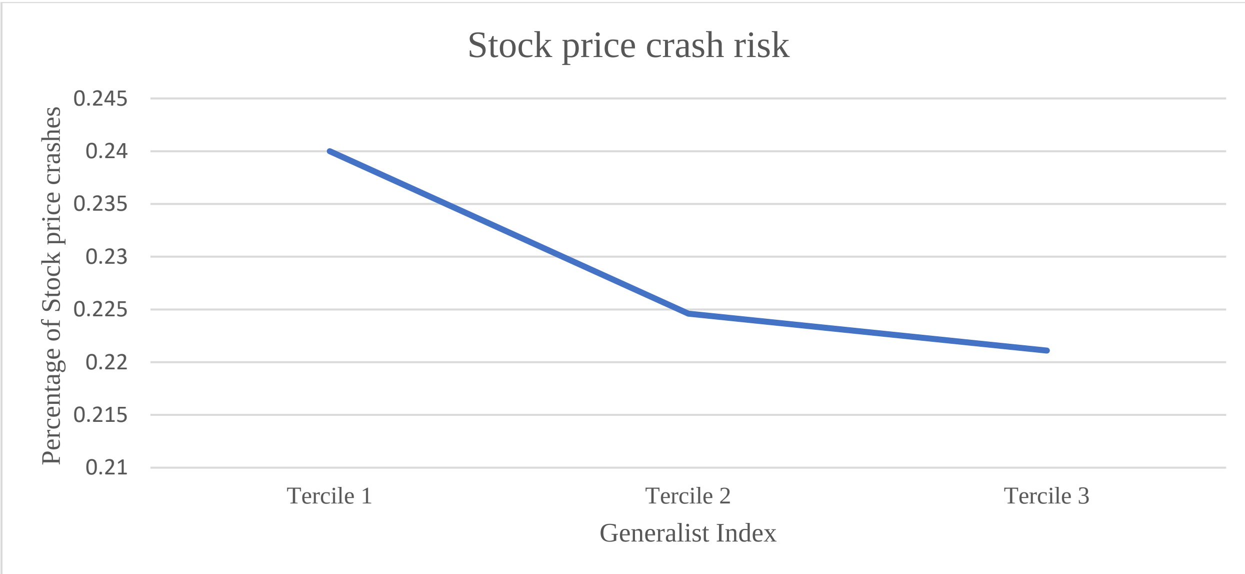

Figure 1. Percentage of stock price crashes across Generalist Index Terciles
This figure shows the percentage of stock price crashes across Generalist Index terciles. For each tercile of Generalist Index, the percentage of stock price crashes is calculated by the number of firm-year crashes divided by the total number of firm-year observations in that tercile.

Table 1. Sample Distribution

This table presents the sample distribution. Panel A presents mean values of stock price crash risk by fiscal year from1993 to 2007. Panel B presents the distribution of generalist index across the Fama-French 12 industry Groups (Fama and French 1997).

Panel A Sample by Year

Year	*N*	*Num. of Crashes*	*Pct. of Crashes*	*ROA during Crashes*	*Stdev of ROA*	*NCSKEW*	*DUVOL*
1993	1,357	322	0.223	0.037	0.082	0.046	-0.028
1994	1,355	300	0.226	0.026	0.169	-0.021	-0.042
1995	1,444	286	0.227	0.032	0.089	-0.098	-0.147
1996	1,568	314	0.226	0.048	0.092	-0.108	-0.159
1997	1,634	323	0.226	0.027	0.133	-0.070	-0.099
1998	1,647	379	0.226	0.042	0.111	-0.009	-0.027
1999	1,565	354	0.227	0.032	0.188	-0.047	-0.132
2000	1,455	357	0.227	-0.002	0.422	0.042	-0.044
2001	1,476	459	0.227	-0.001	0.275	0.150	0.066
2002	1,477	517	0.227	-0.023	0.276	0.202	0.069
2003	1,439	427	0.227	0.024	0.204	-0.01	-0.028
2004	1,405	435	0.228	0.028	0.160	0.051	-0.010
2005	1,341	439	0.228	0.038	0.133	0.012	-0.017
2006	1,405	457	0.227	0.047	0.106	0.001	-0.011
2007	1,569	422	0.227	0.040	0.112	-0.030	0.051

Panel B. Generalist Index by Fama-French 12 Industry

	Mean	*Median*	*Stdev.*
Business equipment	0.036	-0.098	1.038
Chemicals and allied products	0.238	0.154	0.882
Consumer durables	0.008	-0.182	0.946
Energy	-0.018	-0.182	0.892
Health	0.022	-0.063	0.963
Manufacturing	0.092	-0.079	0.911
Money/financial	-0.227	-0.434	0.990
Consumer nondurables	-0.044	-0.274	0.954
Shops	-0.168	-0.358	0.953
Telecommunication	0.447	0.317	1.257
Utilities	0.363	0.302	1.037
Other	-0.040	-0.247	1.045

Table 2. Descriptive Statistics

This table presents summary statistics for various firm-year-level variables. Panel A presents summary statistics of observations for each variable. Panel B presents the mean of the percentage of stock price crashes for the sample of generalist CEOs (those with Generalist Index in the top tercile) and specialist CEOs (those with Generalist Index in the bottom tercile), and the mean difference in the percentage of stock price crashes across the first and third tercile of Generalist Index. Definitions of all other variables are in the Appendix. The *t*-test is used to test the difference in the mean of the two groups. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A Summary Statistics

	N	*Mean*	*Stdev*	*Q5*	*Q25*	*Median*	*Q75*	*Q95*
NCSKEW	17,017	0.020	0.791	-1.108	-0.417	-0.027	0.379	1.372
DUVOL	17,017	-0.025	0.458	-0.760	-0.319	-0.027	0.257	0.740
CRASH	17,017	0.182	0.386	0	0	0	0	1
GAI	17,017	0.004	0.982	-1.336	-0.712	-0.171	0.544	1.829
DTURNOVER	17,017	0.008	0.008	0.001	0.003	0.005	0.010	0.023
SIZE (Log)	17,017	7.341	1.577	4.970	6.259	7.191	8.328	10.20
MB	17,017	3.394	4.449	0.734	1.613	2.476	3.958	9.547
RET	17,017	-0.154	0.185	-0.491	-0.182	-0.092	-0.049	-0.021
LEV	17,017	0.218	0.178	0	0.058	0.205	0.330	0.534
SIGMA	17,017	0.049	0.025	0.0211	0.031	0.043	0.060	0.100
ROA	17,017	0.036	0.171	-0.140	0.018	0.054	0.092	0.170
ACCR	17,017	0.184	0.393	0.004	0.026	0.067	0.165	0.740
VEGA (Log)	14,184	3.842	1.633	0	2.949	3.947	4.930	6.281
DELTA (Log)	14,184	5.536	1.515	3.180	4.572	5.483	6.474	8.025
TENURE	14,184	8.076	7.612	1	3	6	11	24
AGE	14,184	55.32	7.410	43	50	55	60	67
OWNERSHIP	14,184	0.034	0.064	0.001	0.005	0.012	0.030	0.148
DUALITY	14,184	0.631	0.483	0	0	1	1	1
CPS	14,184	0.391	0.128	0.192	0.315	0.386	0.457	0.612
FLUIDITY	13,556	6.037	3.132	2.048	3.709	5.458	7.769	12.13
TRANSIENT	12,201	0.177	0.125	0.0306	0.0846	0.147	0.237	0.425
G-INDEX	11,103	9.280	2.631	5	7	9	11	14
LITIGATION	16,175	0.288	0.453	0	0	0	1	1
NONCOMPETE	15,875	3.917	2.207	0	3	4	5	7
TIGHT LABOR	6,526	0.243	0.429	0	0	0	0	1
PCT_MSA_IND	6,526	0.039	1.392	0.127	0.4	1.063	2.098	4.848
ALTMAN_Z	6,526	5.053	7.314	0.892	2.305	3.559	5.555	14.164
HOSTILE TAKEOVER	6,526	0.177	0.102	0.053	0.096	0.150	0.246	0.365
HIGH MEDIA	6,526	0.407	0.491	0	0	0	1	1

Panel B Univariate Tests	*Specialist CEOs (GAI < Median)*	*Generalist CEOs (GAI > Median)*	*Diff (t-stat)*
NSKEW	0.038	0.011	-0.028 (-2.56**)
DUVOL	-0.006	-0.032	-0.026 (-4.05***)
CRASH	0.199	0.178	-0.022 (-3.89***)

Table 3. General Managerial Ability and Stock Price Crashes

This table presents results from a regression analysis of stock price crash on the general managerial ability measures of Custódio, Ferreira, Matos (2013). *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, Matos (2013)). *GAI DUMMY* is an indicator variable that equals one if the CEO's Generalist Index is above the yearly median, and zero otherwise. In models (1) to (4), year and two sic industry fixed effects are included. In models (5) to (8), year and firm fixed effects are included. Standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$	$NCSKEW_t$	$NCSKEW_t$	$DUVOL_t$	$DUVOL_t$
GAI_{t-1}	-0.022***		-0.011***		-0.035***		-0.021***	
	(-3.16)		(-2.69)		(-2.79)		(-2.83)	
$GAI\ DUMMY_{t-1}$		-0.027**		-0.013*		-0.071***		-0.039***
		(-2.14)		(-1.78)		(-3.08)		(-2.93)
$NCSKEW_{t-1}$	0.014	0.014			-0.099***	-0.099***		
	(1.61)	(1.61)			(-10.33)	(-10.35)		
$DUVOL_{t-1}$			-0.010	-0.009			-0.121***	-0.121***
			(-1.13)	(-1.13)			(-13.52)	(-13.53)
$DTURNOVER_{t-1}$	0.031***	0.031***	0.015**	0.015**	0.001	0.002	-0.001	-0.001
	(3.07)	(3.10)	(2.41)	(2.44)	(0.03)	(0.10)	(-0.15)	(-0.09)
$SIZE_{t-1}$	0.029***	0.027***	0.019***	0.018***	0.217***	0.217***	0.129***	0.129***
	(5.68)	(5.43)	(6.16)	(6.00)	(14.11)	(14.14)	(14.29)	(14.28)
MB_{t-1}	0.005***	0.005***	0.003***	0.003***	0.004**	0.004**	0.003***	0.003***
	(3.32)	(3.39)	(3.07)	(3.13)	(2.01)	(2.04)	(2.76)	(2.80)
RET_{t-1}	0.632***	0.636***	0.477***	0.479***	0.480***	0.480***	0.473***	0.474***
	(5.43)	(5.46)	(6.95)	(6.97)	(3.20)	(3.20)	(5.48)	(5.48)
LEV_{t-1}	-0.001	-0.007	-0.015	-0.018	0.041	0.039	-0.009	-0.010
	(-0.03)	(-0.18)	(-0.65)	(-0.78)	(0.51)	(0.48)	(-0.19)	(-0.22)
$SIGMA_{t-1}$	3.609***	3.630***	2.326***	2.337***	2.563*	2.556*	2.668***	2.667***
	(3.79)	(3.80)	(4.14)	(4.15)	(1.96)	(1.95)	(3.61)	(3.60)
ROA_t	-0.003	0.000	0.010	0.012	-0.094*	-0.093*	-0.041	-0.040
	(-0.08)	(0.01)	(0.45)	(0.51)	(-1.85)	(-1.83)	(-1.29)	(-1.27)
$ACCR_{t-1}$	0.014	0.013	0.008	0.007	0.014	0.014	0.009	0.009
	(0.72)	(0.71)	(0.70)	(0.69)	(0.62)	(0.62)	(0.73)	(0.73)
Constant	-0.482***	-0.452***	-0.331***	-0.316***	-1.682***	-1.647***	-0.930***	-0.911***
	(-4.11)	(-3.99)	(-4.79)	(-4.64)	(-12.80)	(-12.49)	(-12.07)	(-11.71)
Industry FE	*Yes*	*Yes*	*Yes*	*Yes*	*No*	*No*	*No*	*No*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*No*	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	16,174	16,174	16,171	16,171	16,174	16,174	16,171	16,171
R-squared	0.0232	0.0229	0.0428	0.0425	0.0420	0.0422	0.0612	0.0612

Table 4. Equity Incentives, Overconfidence, and CEO Fixed Effects

This table presents results from a regression analysis of stock price crash on the general managerial ability measures of Custódio, Ferreira, and Matos (2013). *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, Matos (2013)). In models (1) to (3) and models (6) to (8), year and firm fixed effects are included and standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. In models (4) and (9), two sic industry, year and CEO fixed effects are included and standard errors are robust and clustered by CEO and t-statistics are in parentheses beneath the coefficients. In models (5) and (10), year, firm and CEO fixed effects are included and standard errors are robust and clustered by firm and CEO and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: $NCSKEW_t$					*Dependent Variable: $DUVOL_t$*				
GAI_{t-1}	-0.022***	-0.022***	-0.022***	-0.036**	-0.037**	-0.011***	-0.012***	-0.012***	-0.021**	-0.024**
	(-3.11)	(-3.05)	(-3.01)	(-2.06)	(-2.02)	(-2.64)	(-3.06)	(-2.81)	(-2.12)	(-2.30)
$NCSKEW_{t-1}$	0.021**	0.019**	0.020**	-0.164***	-0.167***					
	(2.14)	(2.01)	(2.01)	(-15.38)	(-15.48)					
$DUVOL_{t-1}$						-0.001	-0.002	-0.000	-0.183***	-0.185***
						(-0.06)	(-0.23)	(-0.01)	(-19.26)	(-19.07)
$DTURNOVER_{t-1}$	0.029***	0.032***	0.028**	0.008	0.006	0.014**	0.017***	0.014**	-0.003	-0.004
	(2.74)	(2.98)	(2.49)	(0.39)	(0.31)	(2.21)	(2.61)	(2.13)	(-0.27)	(-0.31)
$SIZE_{t-1}$	0.021***	0.026***	0.010	0.229***	0.257***	0.016***	0.017***	0.012***	0.131***	0.145***
	(3.24)	(4.88)	(1.39)	(9.57)	(10.67)	(4.27)	(5.55)	(2.64)	(9.51)	(10.29)
MB_{t-1}	0.007***	0.007***	0.007***	0.004*	0.004	0.003***	0.003***	0.003***	0.002*	0.002
	(4.00)	(4.10)	(4.02)	(1.71)	(1.50)	(3.05)	(3.40)	(3.19)	(1.85)	(1.58)
RET_{t-1}	0.659***	0.699***	0.680***	0.360*	0.338*	0.523***	0.515***	0.527***	0.417***	0.414***
	(5.25)	(5.49)	(5.23)	(1.89)	(1.77)	(7.35)	(7.26)	(7.23)	(3.85)	(3.80)
LEV_{t-1}	-0.000***	-0.000***	-0.000***	0.000	0.000	-0.000***	-0.000***	-0.000***	-0.000	-0.000
	(-3.60)	(-3.55)	(-3.42)	(0.57)	(0.71)	(-4.76)	(-4.84)	(-4.63)	(-0.18)	(-0.09)
$SIGMA_{t-1}$	3.989***	4.315***	4.124***	2.198	1.929	2.640***	2.548***	2.649***	2.488***	2.418***
	(3.89)	(4.18)	(3.91)	(1.39)	(1.21)	(4.58)	(4.44)	(4.48)	(2.77)	(2.70)
ROA_t	0.010	0.030	0.019	-0.127**	-0.123**	0.022	0.030	0.025	-0.043	-0.039
	(0.28)	(0.79)	(0.49)	(-2.26)	(-2.20)	(0.96)	(1.24)	(1.02)	(-1.28)	(-1.13)
$ACCR_{t-1}$	0.024	0.038*	0.035	0.005	0.003	0.005	0.011	0.009	0.003	0.001
	(1.07)	(1.67)	(1.51)	(0.20)	(0.10)	(0.45)	(0.93)	(0.74)	(0.22)	(0.07)
$VEGA_{t-1}$	-0.000		-0.005	-0.003	-0.000	-0.003		-0.006	-0.005	-0.004
	(-0.04)		(-0.72)	(-0.26)	(-0.02)	(-0.87)		(-1.44)	(-0.71)	(-0.54)
$DELTA_{t-1}$	0.006		0.026***	0.027	0.017	0.003		0.012**	0.025**	0.019*
	(1.08)		(2.63)	(1.41)	(0.90)	(0.75)		(2.11)	(2.31)	(1.80)

$TENURE_{t-1}$		0.149**	0.157**	0.144	0.126		0.064*	0.079**	0.068	0.059
		(2.22)	(2.24)	(1.63)	(1.39)		(1.66)	(1.98)	(1.35)	(1.13)
$TENURE^2_{t-1}$		-0.044**	-0.049**	-0.058*	-0.049		-0.021*	-0.027**	-0.022	-0.018
		(-2.13)	(-2.31)	(-1.88)	(-1.58)		(-1.75)	(-2.17)	(-1.29)	(-1.04)
AGE_{t-1}		0.766	1.256	-7.358*	-6.971*		1.161	1.507	-4.716*	-4.548*
		(0.38)	(0.59)	(-1.78)	(-1.65)		(1.02)	(1.22)	(-1.96)	(-1.88)
AGE^2_{t-1}		-0.093	-0.152	0.951*	0.904*		-0.142	-0.184	0.585*	0.565*
		(-0.37)	(-0.58)	(1.84)	(1.70)		(-1.00)	(-1.20)	(1.94)	(1.86)
$OWNERSHIP_{t-1}$		-0.084	-0.361**	-0.055	0.037		-0.021	-0.147	-0.087	-0.035
		(-0.87)	(-2.41)	(-0.19)	(0.12)		(-0.35)	(-1.58)	(-0.52)	(-0.20)
$DUALITY_{t-1}$		-0.027*	-0.034**	-0.028	-0.024		-0.010	-0.013	-0.008	-0.005
		(-1.85)	(-2.21)	(-0.97)	(-0.79)		(-1.21)	(-1.52)	(-0.46)	(-0.29)
CPS_{t-1}		0.041	0.054	-0.016	-0.015		0.038	0.049	-0.007	-0.002
		(0.78)	(0.99)	(-0.21)	(-0.21)		(1.25)	(1.55)	(-0.16)	(-0.04)
Constant	-0.241***	-1.947	-2.937	12.079	11.502	-0.058*	-2.483	-3.190	8.064*	7.952*
	(-4.11)	(-0.49)	(-0.69)	(1.46)	(1.36)	(-1.66)	(-1.09)	(-1.29)	(1.67)	(1.65)
Industry FE	*No*	*No*	*No*	*Yes*	*No*	*No*	*No*	*No*	*Yes*	*No*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*Yes*	*Yes*	*No*	*Yes*
CEO FE	*No*	*No*	*No*	*Yes*	*Yes*	*No*	*No*	*No*	*Yes*	*Yes*
Clustering	*Firm*	*Firm*	*Firm*	*CEO*	*Firm/CEO*	*Firm*	*Firm*	*Firm*	*CEO*	*Firm/CEO*
Observations	14,874	15,381	14,433	13,750	13,728	14,873	15,380	14,432	13,749	13,727
R-squared	0.0119	0.0123	0.0134	0.2564	0.2611	0.0321	0.0317	0.0329	0.2765	0.2800

Table 5. Mechanisms: Outside Options and Reputational Capital

This table presents results from a regression analysis of stock price crash on the general managerial ability measures of Custódio, Ferreira, Matos (2013). *TIGHT LABOR* is an indicator variable that equals one if the unemployment rate for a year in the Metropolitan Statistical Area (MSA) is below the median unemployment rate for the MSA over the full sample period. *PCT_MSA_IND* the fraction of firms in the MSA that operate in the firm's two sic industry. DISTRESS FIRM is an indicator variable that equals one if the firm's ROA is below the industry median (two-digit SIC) for two consecutive years. *HOSTLE TAKEOVER* measurs the threat of takeover, which is constructed from takeover laws, aggregate capital liquidity, and firm age (Cain, McKeon, and Solomon (2017)). *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past number of positions, number of firms, number of industries, CEO experience dummy, and conglomerate experience dummy (Custódio, Ferreira, Matos, 2013). In all models, year and firm fixed effects are included. Standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Local Labor Market Demand	(1) $NCSKEW_t$	(2) $DUVOL_t$	(3) $NCSKEW_t$	(4) $DUVOL_t$
GAI_{t-1}	-0.028	-0.012	0.000	-0.002
	(-1.51)	(-1.05)	(0.01)	(-0.14)
$TIGHT\ LABOR_{t-1}$	-0.116***	-0.041***		
	(-5.06)	(-3.03)		
GAI_{t-1} X $TIGHT\ LABOR_{t-1}$	-0.045**	-0.025**		
	(-2.04)	(-1.96)		
$PCT\_MSA\_IND_{t-1}$			0.000	-0.007
			(0.03)	(-0.94)
GAI_{t-1} X $PCT\_MSA\_IND_{t-1}$			-0.023***	-0.013***
			(-3.37)	(-2.97)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	12,241	12,238	12,241	12,238
R-squared	0.0337	0.0356	0.0353	0.0447

Panel A: Demand for Skills in Complex Business Environment	(1)	(2)	(3)	(4)
	$NCSKEW_t$	*$DUVOL_t$*	*$NCSKEW_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.032*	-0.015	0.012	0.021
	(-1.94)	(-1.49)	(0.31)	(0.87)
$DISTRESS\ FIRM_{t-1}$	-0.089***	-0.039**		
	(-3.35)	(-2.53)		
GAI_{t-1} X $DISTRESS\ FIRM_{t-1}$	-0.018**	-0.018*		
	(-2.14)	(-1.86)		
$HOSTILE\ TAKEOVER_{t-1}$			-1.422***	-0.743***
			(-4.03)	(-3.49)
GAI_{t-1} X $HOSTILE\ TAKEOVER_{t-1}$			-0.264*	-0.192**
			(-1.67)	(-1.99)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	11,128	11,125	11,467	11,464
R-squared	0.0311	0.0370	0.0325	0.0381

Table 6. Endogeneity Tests

The table presents the robustness of the results in Table 2 to the endogeneity issues. Panel A shows the results of the change-on-change regression where we regress the annual changes in stock crash risk variables on changes in generalist index. Following Hutton, Jiang, Kumar (2014), Chava, Livdan, and Purnanandam (2008), and Lee, Lee, and Nagarajan (2014), we difference generalist index and other control variables used in Table 2. Panel B shows the results of univariate analysis of *GAI* of newly hired CEOs of firms that experience a stock price crash (CRASH = 1) relative to firms that do not (CRASH = 0). Panel C shows results of instrumental variable estimation using two-state least squares (2SLS) panel regressions. *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, Matos (2013)). *GAI DUMMY* is an indicator variable that equals one if the CEO's Generalist Index is above the yearly median, and zero otherwise. The instrument for *GAI* is *NONCOMPETE* which is the level of enforcement of noncompete agreements of the state and year of the first position over the CEO's career (Garmaise, 2009; Custódio, Ferreira, Matos, 2018). Panel D and E report results from propensity score matching (PSM) sample. This matching technique is employed to address the endogeneity of firm selection while reducing the concern that the firm hires a generalist CEO due to the nonrandom event of hiring decisions given to firms. We first estimate a logit model where the dependent variable is *GAI DUMMY*. The independent variables in Table 2 are used in the logit model. We then calculate a propensity score for the likelihood of each firm having a generalist CEO from the regression and rank each firm by their propensity score to find one nearest-neighbor control group of the non-generalist CEO firms. We obtain 6,312 matched pairs. Panel D reports mean differences in covariates between treated (GAI > median) and control (GAI < median) group. Panel E reports regression results from regression analysis of stock price crash on the CEO's Generalist Index using the PSM sample. Model (2) shows the second stage results using the predicted value of GAI in Panel B. In all models, year and firm fixed effects are included. Standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix A. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Change-on-Change Regresions

	(1)	(2)
	Δ *NCSKEW*$_{t\ to\ t+1}$	Δ *DUVOL*$_{t\ to\ t+1}$
Δ *GAI*$_{t-1\ to\ t}$	-0.032*	-0.021**
	(-1.83)	(-1.98)
Δ *Controls*$_{t-1\ to\ t}$	*Yes*	*Yes*
Year FE	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*
Observations	14,027	14,025
R-squared	0.2877	0.3167

Panel B: GAI of Newly Hired CEOs	*High Crash Firms (CRASH = 1)*	*Low Crash Firms (CRASH = 0)*	*Diff (t-stat)*
GAI$_{t-1}$	0.104	0.090	0.014 (0.23)

Panel C: 2SLS	First Stage	Second Stage	
	(1)	(2)	(3)
	GAI_t	$NCSKEW_t$	$DUVOL_t$
NONCOMPETE	0.062***		
	(3.76)		
GAI (Instrumented)$_{t-1}$		-0.195***	-0.149***
		(-3.37)	(-4.10)
F-statistics	13.34		
Controls	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*
Observations	14,591	13,977	13,973
R-squared	0.1458	0.0442	0.0616

Panel D: PSM - Balancing Test	*Treated*	*Control*	*Difference*	*T-Stat*
SIZE	8.4275	8.4261	0.0014	0.04
MB	3.8570	3.7549	0.1021	0.98
RET	-0.0878	-0.0879	0.0001	0.04
SIGMA	0.0386	0.0385	0.0001	0.11
LEV	0.2109	0.2093	0.0016	0.10
ROA	0.0609	0.0610	-0.0001	-0.18
ACCR	0.1824	0.1868	-0.0044	-0.45

Panel E: PSM Sample	(1)	(2)	(3)	(4)
	$NCSKEW_t$	$DUVOL_t$	$NCSKEW_t$	$DUVOL_t$
GAI_{t-1}	-0.044**	-0.020**		
	(-2.30)	(-2.38)		
GAI (Instrumented)$_{t-1}$			-0.172**	-0.158***
			(-1.99)	(-2.79)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,311	6,312	5,949	5,948
R-squared	0.0492	0.0639	0.0527	0.0652

Table 7. Subsample Analysis

This table presents results from a regression analysis of stock price crash on the general managerial ability measures of Custódio, Ferreira, Matos (2013). In Panel A, we partition the sameple based on the median value of the product market competition measures (*FLUIDITY*) of Hoberg, Phillips, and Prabhala (2014). In Panel B, we partition the sameple based on the median value of the percentage of transient (TRANSIENT) institutional ownership measured by Bushee (2001)). In Panel C, we partition the sameple based on the median value of the governance index (G-INDEX) measured by Gompers, Ishii and Metrick (2003). In Panel D, we partition the sameple based on the median value of the firm's financial leverage. In Panel E, we partition the sameple based on *Hi-Tech Firms* indicator variable which equals one if a firm is one of the industries such as Fama-Fren Industry Code 12 (Medical Equipment), 13 (Pharmaceutical Products), 14 (Chemicals), 22 (Electrical Equipment), 32 (Communication), 35 (Computer Hardware), 36 (Computer Software), 37 (Electronic Equipment), 38 (Measuring and Control Equipment), and zero otherwise (Kim, Li, Lu, Yu (2015)). *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, Matos (2013)). In all models, year and firm fixed effects are included. Standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Product Market Threats (FLUIDITY)				
	Low	High	Low	High
	(1)	(2)	(4)	(5)
	$NCSKEW_t$	*$NCSKEW_t$*	*$DUVOL_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.058***	-0.049**	-0.038***	-0.020
	(-2.58)	(-1.96)	(-2.86)	(-1.41)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,285	5,293	6,284	5,293
R-squared	0.0515	0.0609	0.0690	0.0789

Panel B: Transient Institutional Ownership (TRANSIENT)				
	Low	High	Low	High
	(1)	(2)	(4)	(5)
	$NCSKEW_t$	*$NCSKEW_t$*	*$DUVOL_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.019	-0.065**	-0.014	-0.026*
	(-0.78)	(-2.50)	(-1.02)	(-1.82)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,931	5,529	4,930	5,529
R-squared	0.0500	0.0743	0.0757	0.0794

Panel C: G-INDEX				
	Low	High	Low	High
	(1)	(2)	(4)	(5)
	$NCSKEW_t$	*$NCSKEW_t$*	*$DUVOL_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.022	-0.063***	-0.010	-0.029**
	(-0.99)	(-2.69)	(-0.75)	(-2.28)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	5,595	4,806	5,594	4,806
R-squared	0.0489	0.0490	0.0543	0.0632

Panel D: Financial Leverage				
	Low	High	Low	High
	(1)	(2)	(4)	(5)
	$NCSKEW_t$	*$NCSKEW_t$*	*$DUVOL_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.015	-0.053***	-0.009	-0.025**
	(-0.68)	(-2.72)	(-0.67)	(-2.19)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	7,353	6,613	7,353	6,612
R-squared	0.0477	0.0585	0.0651	0.0737

Panel E: High-Tech Firms				
	Low	High	Low	High
	(1)	(2)	(4)	(5)
	$NCSKEW_t$	*$NCSKEW_t$*	*$DUVOL_t$*	*$DUVOL_t$*
GAI_{t-1}	-0.030**	-0.052**	-0.019**	-0.027**
	(-1.98)	(-2.27)	(-2.02)	(-2.18)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	10,873	5,243	10,870	5,243
R-squared	0.0449	0.0452	0.0651	0.0662

Table 8. Alternative Measure: Crash

This table presents results from a regression analysis of stock price crash on the general managerial ability measures of Custódio, Ferreira, Matos (2013). *Crash* is an indicator variable that equals one if there are one or more weekly returns falling 3.09 standard deviations below the mean weekly returns over the fiscal year, and zero otherwise (Chang, Chen, and Zolotoy (2017)). *GAI* is computed by the first factor of applying principal components analysis to five proxies of general managerial ability: past Number of Positions, Number of Firms, Number of Industries, CEO Experience Dummy, and Conglomerate Experience Dummy (Custódio, Ferreira, and Matos (2013)). *GAI DUMMY* is an indicator variable that equals one if the CEO's Generalist Index is above the yearly median, and zero otherwise. In all models, year and firm fixed effects are included. Standard errors are robust and clustered by firm and t-statistics are in parentheses beneath the coefficients. Definitions of all other variables are in the Appendix. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Logit	*Logit*	*LPM*	*LPM*	*LPM*	*LPM*
	(1)	(2)	(3)	(4)	(5)	(6)
			Dependent Variable $CRASH_t$			
GAI_{t-1}	-0.063***		-0.010***		-0.013**	
	(-2.66)		(-2.74)		(-2.04)	
$GAI\ DUMMY_{t-1}$		-0.145***		-0.022***		-0.035***
		(-3.29)		(-3.34)		(-3.21)
$NCSKEW_{t-1}$	0.355***	0.354***	0.060***	0.060***	0.033***	0.033***
	(7.07)	(7.07)	(7.29)	(7.28)	(3.81)	(3.78)
$DUVOL_{t-1}$	-0.160*	-0.159*	-0.030**	-0.030**	-0.015	-0.015
	(-1.87)	(-1.87)	(-2.31)	(-2.31)	(-1.10)	(-1.08)
$DTURNOVER_{t-1}$	0.156***	0.157***	0.026***	0.026***	0.014*	0.014*
	(5.14)	(5.18)	(4.74)	(4.77)	(1.71)	(1.77)
$SIZE_{t-1}$	0.004	0.003	0.000	0.000	0.066***	0.066***
	(0.25)	(0.19)	(0.07)	(0.03)	(9.08)	(9.09)
MB_{t-1}	0.010**	0.010**	0.002**	0.002**	0.000	0.000
	(2.11)	(2.13)	(2.03)	(2.05)	(0.23)	(0.24)
RET_{t-1}	1.758***	1.761***	0.236***	0.237***	0.044	0.043
	(3.86)	(3.87)	(4.16)	(4.17)	(0.62)	(0.62)
LEV_{t-1}	-0.005	-0.008	0.003	0.003	0.095**	0.095**
	(-0.04)	(-0.06)	(0.16)	(0.13)	(2.56)	(2.55)
$SIGMA_{t-1}$	9.347***	9.323***	1.233**	1.229**	-1.032*	-1.043*
	(2.69)	(2.68)	(2.57)	(2.57)	(-1.71)	(-1.73)
ROA_t	-0.442***	-0.444***	-0.080***	-0.081***	-0.111***	-0.111***
	(-3.01)	(-3.00)	(-3.06)	(-3.07)	(-3.01)	(-3.00)
$ACCR_{t-1}$	0.042	0.040	0.009	0.009	0.005	0.005
	(0.85)	(0.82)	(1.01)	(0.99)	(0.56)	(0.57)
Constant	-1.593***	-1.508***	0.100**	0.113***	-0.270***	-0.253***
	(-6.11)	(-5.91)	(2.55)	(2.95)	(-4.19)	(-3.90)
Industry FE	*Yes*	*Yes*	*Yes*	*Yes*	*No*	*No*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*No*	*No*	*No*	*No*	*Yes*	*Yes*
Observations	16,170	16,170	16,170	16,170	16,170	16,170
R-squared / Pseudo	0.0407	0.0410	0.0387	0.0389	0.0239	0.0243