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Generalist CEOs and stock price crash risk

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Abstract

We investigate whether generalist chief executive officers (CEOs), that is, CEOs who gain transferable skills across firms and industries, have less incentive to hoard bad news. To address endogeneity concerns stemming from firm-CEO matching, we deploy a difference-in-differences method utilizing exogenous CEO turnovers, propensity score matching and entropy balancing matching methods, and Oster's coefficient stability test. Supporting our conjecture, we find a negative relation between CEOs' general ability index (GAI) and future stock price crash risk. The effect of CEOs' GAI on crash risk is stronger when labor demand is stronger and when firms have more agency conflicts. Our analysis further suggests that generalist CEOs attenuate crash risk by increasing conditional accounting conservatism and reducing real earnings management. Taken together, our findings highlight the role of CEOs' general human capital in increasing their tolerance for failure and mitigating the agency problem.

KEYWORDS

bad news hoarding, career concerns, chief executive officers, crash risk, general managerial skills, tolerance for failure

JEL CLASSIFICATION G12, G32, G34, J24

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1 INTRODUCTION

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A chief executive officer (CEO)'s human capital is an important factor in shaping corporate outcomes. US corporations have had a growing appetite for hiring generalist CEOs with diverse career backgrounds and industry experiences since the 1980s (Crossland et al., 2014). Today, generalist CEOs, that is, CEOs whose managerial skills are transferable across industries or firms, receive pay premiums relative to those who have managerial skills specific to one industry or firm (Custódio et al., 2013). As generalist CEOs' transferable skills help them find an outside job more easily, a failure in one firm might not severely affect their long-term career path. Generalist CEOs could act as a double-edged sword for shareholders. On the bright side, the broader set of outside options for generalist CEOs increases their job security and tolerance for failure, which fosters corporate innovation (Custódio et al., 2019). On the dark side, a higher tolerance for failure may encourage generalist CEOs to take excessive risks, which results in higher costs of equity (Mishra, 2014), a larger likelihood of initial public offering (IPO) firms' failure (Gounopoulos & Pham, 2018) and lower credit ratings (Ma et al., 2021). Our paper intends to contribute to the ongoing debate in the generalist CEO literature by examining the empirical relation between CEOs' general skills and stock price crash risk, a consequence of managerial bad news hoarding.

Corporate managers possess superior information on firm performance relative to outside investors. Managers tend to withhold bad news stemming from temporary bad firm performance, as they worry about the negative impact of bad news on their compensation and future career (Verrecchia, 2001). The literature on crash risk indicates that when bad news stockpiled within a firm reaches a critical level at which the costs of hoarding bad news exceed the benefits of doing so, the firm's managers have to disclose the bad news all together at once in the market, leading to a stock price crash. Jin and Myers' (2006) model shows that when cash flows are lower than investors' expectations, managers hide bad news from investors in an effort to protect their jobs (career concerns). Kothari et al. (2009) and Ali and Zhang (2015) provided empirical evidence that career concerns can motivate managers to withhold bad news. As general managerial skills enhance CEOs' between-industry or across-firm transfers, we expect that generalist CEOs' betwee their incentives to hide bad news, resulting in lower stock price crash risk.

Besides the tolerance for failure mechanism, generalist CEOs' broad experience and diverse knowledge are valuable for modern corporations in terms of addressing complex corporate tasks (Custódio et al., 2013; Ferreira & Sah, 2012). Numerous anecdotes and research-based evidence show that CEOs not only engage in a firm's strategic policymaking process but also its daily business operation. Although chief financial officers (CFOs) have the most direct impact of all top executives on a firm's financial reporting process, they may succumb to the pressure from CEOs to make financial reporting adjustments (e.g., Feng et al., 2011; Friedman, 2014). A CEO, who has worked in different positions, firms and industries, accumulates general skills that put him in a better position to monitor the CFO's information manipulation, especially when the firm has more market uncertainty and organizational complexity. Therefore, we conjecture that generalist CEOs also mitigate crash risk by effectively leveraging their skills to manage market uncertainty and organizational complexity.

An opposite possibility is that generalist CEOs' high tolerance for failure incentivizes them to invest in risky projects, which increases the *ex-ante* firm risk and the likelihood of huge future revenue losses. Mishra (2014) showed that generalist CEOs have risk-taking incentives that are less aligned with their firms, which may lead to higher agency problems. Gounopoulos and Pham (2018) found that IPO firms with generalist CEOs have a higher probability of failure and a shorter time to survive after the offering. Ma et al. (2021) showed that generalist CEOs' risk-taking incentives are perceived negatively by bondholders, leading to a lower credit rating. These studies suggest that if the tolerance for failure mechanism encourages generalist CEOs to take excessive risk, firms with generalist CEOs may have higher downside risk. Therefore, it is an empirical question whether CEOs' general skills have a positive or negative impact on future stock price crash risk.

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Managerial bad news hoarding revealed in stock price crash risk provides us with an ideal empirical setting to investigate the impact of CEOs' general skills on managerial bad news hoarding. Managers can utilize multiple channels to withhold bad news, such as accruals-based earnings management, opaque footnotes in the financial statements, offbalance-sheet activities, tax avoidance and ambiguous statements in press releases and conference calls. Therefore, crash risk, as a market-based risk measure reflecting the aggregate effect of these channels, is a more comprehensive metric than a specific channel metric (Bauer et al., 2021). Furthermore, a CEO may prefer a specific channel over the others or substitute a specific channel for the others in order to adapt to new regulations. The empirical inference based on only one specific channel metric would not reflect the real impact of CEOs' general skills on managerial bad news hoarding.

To examine our research question, we employ a panel sample of Standard and Poor's (S&P) 1500 firms spanning 1992–2016, during which the data on Custódio et al.'s (2013) CEO general managerial skills is available. Custódio et al. (2013) developed a general ability index (GAI) to capture five aspects of a CEO's career path: the number of job positions (1), companies (2) and industries (3) in which she has worked; experience of holding a CEO position at more than one company (4); and work experience at a conglomerate company (5). As defined in Custódio et al. (2013) and Ma et al. (2021), a generalist (specialist) CEO's GAI is above (below) the 75th percentile of the index distribution in a year.

We adopt two measures of stock price crash risk, that is, the negative skewness of stock returns and the asymmetric volatility of negative and positive stock returns, in the previous studies (e.g., Chen et al., 2001; DeFond et al., 2015; Kim et al., 2014; Xu et al., 2014), which enable us to evaluate whether our finding is sensitive to alternative return-based crash risk proxies. The results of our baseline regression show that CEOs' general skills are negatively associated with future crash risk after controlling for a comprehensive set of firm-specific characteristics that might affect crash risk (e.g., Bauer et al., 2021; Kim et al., 2011a). With regard to the marginal effect, an interquartile change in CEOs' general skills from the 25th to the 75th percentile is associated with at least a 23.7% decrease in stock price crash risk.

To address the omitted variable bias and the possibility of nonrandom mutual selection between generalist CEOs and firms, we employ multiple identification methods. First, we perform a difference-in-differences (DID) test. Utilizing a sample of 3 years before and after exogenous CEO turnovers, we find a significant decrease in crash risk surrounding the transitions from specialist CEOs to generalist CEOs compared to the control group. Second, we use a propensity score matching (PSM) method and an entropy balancing (EB) matching method to ensure that firms in the treatment (with generalist CEOs) and control (with specialist CEOs) groups have little difference in observable firm characteristics. Our finding remains robust in the PSM and EB samples. Third, we adopt the coefficient sensitivity test proposed by Oster (2019) to address any omitted variable bias. Our test statistics suggest that even if we could control for both observable and unobservable variables, it would not lead to a very different conclusion than only controlling for the observable variables in our baseline regression. Our three identification methods largely mitigate any potential endogeneity concern.

Next, we exploit the cross-sectional variations of our main finding in order to further isolate the impact of CEOs' general skills on stock price crash risk. First, we find that CEOs' general skills play a larger role in mitigating crash risk when CEOs have more outside options. Custódio et al. (2019) argued that managers are more likely to receive outside job offers from other firms in a tight labor market where the annual unemployment rate is lower. CEOs' general skills are more valuable in a tight labor market where their skills are transferable across firms and industries. Second, we find that the impact of CEOs' general skills on crash risk is stronger for firms with more agency conflicts, measured by CEO age, firm complexity and product market threats. Our findings support the view that CEOs' general skills play a greater role in mitigating agency conflicts that ultimately lead to managerial bad news hoarding behavior.

In a battery of sensitivity tests, we first show that the negative relation between CEOs' general skills and future stock price crash risk is robust after controlling for CEO traits, including compensation equity incentive, age, tenure, gender, education background, military service experience and whether the CEO is externally hired. Next, we find that our main result remains robust after controlling for Li et al.'s (2021) five corporate culture values of innovation, integrity, quality, respect and teamwork, as well as after controlling for Andreou et al.'s (2022) thrust to compete

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culture. Third, our main results hold after controlling for three additional proxies for corporate governance: co-opted board, distance to Securities and Exchange Commission offices and CEO duality. Finally, we show that our main result is robust to using alternative crash risk measures.

Our paper contributes to the literature in three ways. First, our paper advances the ongoing debate on the benefits and costs of hiring generalist CEOs. Although specialist CEOs tend to have a high degree of awareness in their specialized field, they may not fit a CEO position that requires a diverse collection of knowledge and a big-picture thinker (Murphy & Zabojnik, 2004). A recent trend in the executive labor market is that US companies prefer external CEOs with diverse career backgrounds and experiences (Crossland et al., 2014; Ertimur et al., 2018). The mobility of generalist CEOs across firms and industries, together with the increasing demand for their general managerial skills, helps to explain the pay gap between generalist and specialist CEOs (Custódio et al., 2013; Frydman, 2019). Previous studies show that firms with generalist CEOs produce more patents (Custódio et al., 2019) and have better firm performance (Betzer et al., 2020). Our paper highlights that generalist CEOs attenuate bad news hoarding and improve the quality of information disclosure.

Second, our paper contributes to the literature on the impact of managers' inherent and organization-specific traits on stock price crash risk. Recent studies find that CFOs' compensation incentives (Kim et al., 2011a), CEOs' excess perks (Xu et al., 2014), CEO overconfidence (Kim et al., 2016) and CEO power (Al Mamun et al., 2020) are positively associated with future stock price crash risk, whereas CEO age (Andreou et al., 2016), female CFOs (Li & Zeng, 2019) and CEO centrality (Krishnamurti et al., 2021) are negatively related to crash risk. However, there is a paucity of empirical evidence on how managerial professional experience has a direct impact on tail risk in the capital market. In this study, we fill this gap in the literature by providing evidence of a negative relation between CEOs' general management skills and stock price crash risk and implying as a consequence that CEOs' general management skills have a disincentive effect on managerial bad-news-hoarding activities. Our research advocates that CEOs' formative experience, as "soft information," influences managerial incentives to hoard bad news and should not be left out when researchers and investors model the tail risk of stock returns.

Especially, our study is related to Andreou et al. (2023) who criticize the efficacy of accounting opacity as a channel in explaining crash risk. By contrast, earlier studies (e.g., Hutton et al., 2009; Jin & Myers, 2006) suggest that accounting opacity is an important mechanism in predicting stock price crash risk. Thus, Andreou et al. (2023) suggested more future research to rationalize the puzzling surge in stock price crashes. Responding to Andreou et al. (2023), we examine how managerial professional experience (i.e., CEOs' general management skills vs. specialized skills), as one of the critical CEO characteristics, affects stock price crash risk. Our findings highlight that CEOs' general human capital plays a role of managerial incentive against information manipulation in increasing their tolerance for failure and mitigating the agency problem. Our empirical evidence not only supports Andreou et al.'s (2023) null findings on the prediction power of accounting opacity but also shows that CEOs' incentive against bad news hoarding engendered by their professional experience functions as an important disciplinary mechanism in predicting tail risk. Our findings answer Andreou et al.'s (2023) call by implying that the direct measure capturing CEOs' bad news hoarding (dis)incentive is more critical in explaining crash risk than the indirect measure reflecting the operating channel of bad news hoarding (e.g., accounting opacity).

Our research is also related to two recent studies focusing on the relation between executive incentive/compensation and stock price crash risk. First, Hanlon et al. (2023) examined the effect of boardroom backscratching (i.e., when a firm's CEO and directors concurrently receive excessive remuneration) on stock price crash risk and documented a significant positive relation between them. Their findings suggest that boardroom backscratching compromises the constructive criticism and monitoring from corporate board, therefore leading to a greater likelihood of bad news hoarding. To a broad extent, both our paper and Hanlon et al. (2023) reflect how CEO and board characteristics affect the effectiveness of corporate governance manifested in managerial bad-newshoarding behavior. As CEOs' general management skills versus specialized skills are likely to be captured by their own compensations in the labor market, we follow Hanlon et al. (2023) and control for CEOs' overall compensation and excessive compensation, including backscratching, in order to make sure that our findings are not driven by the compensation factor. Our inferences continue to hold. Second, Fang et al. (2023) examined whether the equity incentive heterogeneity of the executive team engenders a positive externality by curtailing stock price crash risk. They show a negative relation between the equity incentive heterogeneity of the executive team and stock price crash risk, suggesting that the equity incentive heterogeneity plays a major internal governance role in preempting corporate bad news hoarding activities. Although their study examines the executive team as a whole to evaluate the effect of incentive structure on alleviating agency problems, we focus on the managerial skill set of a CEO as a corporate leader with different implications on stock price crash risk. Our findings have implications for agency theory that generalist CEOs' human capital may reduce bad news hoarding due to mitigated career concerns. In fact, our study illuminates the different pathways through which executive characteristics impact crash risk and governance from Fang et al. (2023).¹ Collectively, our results are in line with the importance of CEOs' general management skills to deter corporate misbehavior, which, in turn, constrains stock price crash risk, beyond the traditional incentive/compensation consideration.

Third, our analysis complements the broad management research on the impact of CEO attributes on corporate outcome (e.g., Arena et al., 2018; Buchholtz & Ribbens, 1994; Chen et al., 2015; Galariotis et al., 2022; Hambrick & Mason, 1984; Mackey, 2008; Quigley & Hambrick, 2015; Waldman et al., 2001). Distinct from these studies, our research focuses on a relatively underexplored CEO trait, general management skills, to provide evidence on its role in shaping corporate information disclosure policies.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops our hypotheses. Section 3 discusses the sample selection, measurement of key variables and our research design. Section 4 presents the descriptive statistics, baseline regression results and the results of three identification tests, whereas Section 5 discusses supplementary findings and robustness tests. Section 6 concludes.

2 RELATED LITERATURE AND HYPOTHESIS DEVELOPMENT

Earlier literature on the sources of stock price crashes mainly focuses on the mechanisms at the market level. For example, Hong and Stein (2003) provided theoretical evidence that when investors hold different opinions on a firm's fundamental value, negative information cannot be fully incorporated into stock prices because short-sales constraints keep bearish investors out of the market. When accumulated hidden information comes out at once, we observe large negative return outliers at the market level. Supporting Hong and Stein's (2003) prediction, Chen et al. (2001) adopted trading volume as a proxy for differences of opinion and documented a positive relation between differences of opinion and stock price crash risk. Recent finance and economics literature has investigated the determinants of stock price crash risk in the setting of managerial incentives of private benefits. Jin and Myers' (2006) theoretical model shows that even in an informationally efficient stock market with no short-sale constraints, managerial bad news hoarding due to the agency problem leads to future stock price crashes. When accumulated bad news over a long-run period eventually exceeds a critical threshold level at which the costs of hiding bad news are greater than the benefits of doing so, managers choose to release all the hidden bad news at once, triggering a significant decline in stock price or a stock price crash (Hutton et al., 2009).

Supporting the agency perspective proposed by Jin and Myers (2006), recent empirical studies show that stock price crash risk is positively associated with managerial bad news hoarding activities manifested in financial opacity (Hutton et al., 2009), tax avoidance (Kim et al., 2011b), accrual management (Zhu, 2016), ambiguity of annual reports (Ertugrul et al., 2017) and earnings smoothing (Khurana et al., 2018). Earlier crash risk studies also show that mechanisms, such as managerial compensation incentives (Kim et al., 2011a), executives' excess perks (Xu et al., 2014), CEO overconfidence (Kim et al., 2016) and clawback provisions in top executives' compensation contracts (Bao et al., 2018), increase managers' incentives to hide bad news and lead to higher crash risk. Meanwhile, crash risk is attenuated by mechanisms such as dedicated institutional investor ownership (An & Zhang, 2013), institutional investor stability

 1 In the untabulated analysis, we further show that our findings remain robust after controlling for equity incentive heterogeneity of an executive team.

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(Callen & Fang, 2013), religion at the US county level (Callen & Fang, 2015), mandatory International Financial Reporting Standards adoption (DeFond et al., 2015), CEO age (Andreou et al., 2016), accounting conservatism (Kim & Zhang, 2016), auditor tenure (Callen & Fang, 2017), female gender (Li & Zeng, 2019), IRS enforcement (Bauer et al., 2021) and director external social networks (Fang et al., 2021).

In this study, we extend the literature by investigating the role of generalist CEOs in influencing stock price crash risk due to managerial bad news hoarding. CEOs are responsible for making major corporate decisions and managing the overall operations and resources of a company. A substantial body of management research indicates that the nature and type of CEOs' human capital are important to explain heterogeneity in corporate strategies and firm performance (e.g., Castanias & Helfat, 2001; Coff & Kryscynski, 2011; Harris & Helfat, 1997; Miller et al., 2015). We focus on generalist CEOs, that is, those who obtain a broad set of managerial knowledge and skills from their past employment in different firms and industries.

Consistent with the view that CEOs' general skills benefit modern corporations, generalist CEOs receive significantly higher compensation in the executive labor market than specialist CEOs (e.g., Custódio et al., 2013; Frydman, 2019; Murphy & Zabojnik, 2004). However, previous studies do not draw a conclusion on how CEOs' general skills affect firm performance. Based on a sample of exogenous CEO turnovers, Betzer et al. (2020) found that the difference in a new and departing CEO's general skills is positively related to both the abnormal stock return to the turnover announcement and the post-turnover change in the firm's operating performance. On the contrary, Li and Patel (2019) used a panel sample and found a negative association between CEOs' general skills and firm performance, measured by Tobin's Q, return on assets, return on equity and total shareholder returns.

Here, we expect that generalist CEOs influence bad news hoarding in the following manners. On the one hand, Hermalin and Weisbach's (2012) model illustrates a career-concerned agent with uncertain ability who can be fired if considered to be of low ability type by the principal. As the principal assesses the agent's ability through publicly disclosed financial information, highly uncertain investment outcomes may lead to poor firm performance in the short term and expose the agent to the risk of being misconstrued as having low ability. The agent's career concerns can induce managerial myopic activities to boost short-term firm performance, such as earnings manipulation, in order to favorably influence the principal's perception of her ability. A CEO's career concerns broadly include the effects of disclosing bad news on her contemporaneous compensation and career path, such as early termination of the CEO position and employment opportunities outside the firm (Nagar, 1999; Nagar et al., 2003). Kothari et al. (2009) and Ali and Zhang (2015) provided empirical evidence that managers have strong incentives stemming from career concerns to delay the release of bad news to outside investors. Unlike specialist CEOs, generalist CEOs face less pressure from the executive job market and thus are less likely to aggravate managerial myopic behaviors, such as hoarding bad news. Custódio et al. (2019) showed that CEOs' general skills can be applied in the other firms should their own firms' innovation projects fail, providing a mechanism of tolerance for failure and promoting corporate innovation activities. An effective labor market also provides generalist CEOs with more bargaining power than specialist CEOs to maintain their current compensation when disclosing negative firm information to outside investors.

In addition, generalist CEOs are valuable in addressing complex tasks of modern corporations, especially when the product market changes due to industry deregulation, foreign competition and technology innovation (Cuñat & Guadalupe, 2009a, 2009b; Custódio et al., 2013; Garicano & Rossi-Hansberg, 2006). CEOs with experiences accumulated from different positions, firms and industries can better assess, advise on and support firms' decision-making in complicated scenarios. Thus, CEOs' general managerial skills can help them monitor any bad news hoarding conducted by CFOs. Given that generalist CEOs' better employability in the labor market and superior managerial skills when facing complicated scenarios curb managerial myopic activities, we hypothesize that the presence of generalist CEOs is negatively associated with future stock price crash risk:

H1a. CEOs' general skills are negatively related to stock price crash risk.

On the other hand, generalist CEOs' high tolerance for failure encourages them to invest in risky projects, leading to higher *ex-ante* firm downside risks. For example, Mishra (2014) showed that generalist CEOs have risk-taking incentives that are less aligned with their firms, leading to more severe agency problems. Gounopoulos and Pham (2018) found that IPO firms with generalist CEOs have a higher probability of failure and a shorter time to survive after the offering. Ma et al. (2021) showed that generalist CEOs' risk-taking incentives are perceived negatively by bondholders, resulting in lower credit ratings. The literature on crash risk suggests that managers try to reduce investors' perception of firm riskiness and will hide risk-taking information to support stock prices, linking crash risk to managerial risk-taking (e.g., Kim et al., 2011a). Firms with high levels of risk-taking are more likely to conceal bad news because such negative information may be perceived by investors as the realization of managers' excessive risk-taking behaviors (Callen & Fang, 2015). Given that generalist CEOs' high tolerance for failure may encourage managerial risk-taking activities, we infer the following opposite hypothesis:

H1b. CEOs' general skills are positively related to stock price crash risk.

3 | SAMPLE AND RESEARCH DESIGN

3.1 Sample selection and data sources

Our sample consists of S&P 1500 firm-years drawn from the ExecuComp database during 1992–2016. We obtain the data on CEOs' general skills from Custódio et al. (2013), who extend the data to 2016. We also obtain stock return data from the Center for Research in Security Prices (CRSP), accounting data from Compustat annual files, CEO characteristics data from BoardEx and ExecuComp, financial analyst coverage data from the Institutional Brokers Estimate System, institutional ownership data from the Thompson Reuters Institutional Managers Holdings (13f) database, institutional investor type data from Brian Bushee's website, audit-related data from Audit Analytics, unemployment rate data from the website of the US Bureau of Labor Statistics, firm headquarter location data from the annual financial statements from the Electronic Data Gathering, Analysis, and Retrieval database, CEO turnover information from Factiva, corporate culture data from Li et al. (2021) and thrust to compete data from Andreou et al. (2022).²

Following the crash risk literature (e.g., Hutton et al., 2009; Kim et al., 2011a), we drop observations with missing accounting data in Compustat and missing stock price data in CRSP. We then exclude firm-year observations meeting any of the following criteria: (i) nonpositive book value of total assets; (ii) nonpositive book value of equity; (iii) stock price less than \$1 at the end of a fiscal year and (iv) the number of available weekly stock returns fewer than 26. The final sample includes a total of 25,324 firm-year observations, representing 2383 unique firms. To mitigate the potential impact of outliers on our empirical results, we winsorize all the continuous variables at the top and bottom 1% levels.

3.2 | CEOs' general skill measure

Custódio et al. (2013) proposed an index of CEO general ability that captures the generality of human capital in which CEOs have accumulated from their work experience. The index is constructed based on the first factor of the principal component analysis (PCA) of the following five components: the number of top five executive positions in which a CEO has held, the number of firms at which a CEO has worked, the number of the four-digit industries in which a CEO has worked, a dummy variable indicating whether a CEO has held a CEO position at a different firm and a dummy variable indicating whether a CEO has worked. To mitigate the outlier effect and help us explain

the estimated coefficients of GAI, GAI is standardized to have a mean of zero and a standard deviation of one. A higher GAI value indicates a higher level of CEOs' general skills and human capital. Custódio et al. (2013) found that CEOs with higher general skills receive higher compensation. Custódio et al. (2019) further showed that firms with CEOs who have higher general skills produce more patents.

3.3 Stock price crash risk measure

The primary focus of our analyses is the impact of GAI on stock price crash risk. Following the crash risk literature (e.g., Chen et al., 2001; DeFond et al., 2015; Hutton et al., 2009; Kim et al., 2011a, 2011b), we adopt two measures of crash risk, *NCSKEW* and *DUVOL*, to provide robust evidence. To calculate these two measures, we first estimate the following extended market and industry index model regression for each firm and year (Bauer et al., 2021; Hutton et al., 2009):

$$r_{j,t} = \alpha_j + \beta_{1,j}r_{m,t-1} + \beta_{2,j}r_{m,t} + \beta_{3,j}r_{m,t+1} + \beta_{4,j}r_{i,t-1} + \beta_{5,j}r_{i,t} + \beta_{6,j}r_{i,t+1} + \epsilon_{j,t}$$
(1)

where *j* is firm index, *t* is week index, *i* is industry index, $r_{j,t}$ is the return of stock *j* in week *t*, $r_{m,t}$ is the return of the CRSP value-weighted market index in week *t*, and $r_{i,t}$ is the return on the value-weighted industry index based on Fama–French 48 industry. To correct for nonsynchronous trading (Dimson, 1979), we include the lead and lag terms of the value-weighted market index and industry indices. Our extended market and industry index model separates stock returns into the one correlated with the movement of the stock market index and industry indices, and the one due to the firm-specific shocks ($\epsilon_{j,t}$). We define the firm-specific weekly return, $W_{j,t}$, as $\ln(1 + \epsilon_{j,t})$. The natural logarithm transformation reduces the positive skewness in the stock return distribution and helps ensure the symmetry of $W_{j,t}$ (Chen et al., 2001).

Our first crash risk measure, NCSKEW_{j,T}, is based on return skewness. It is defined as the negative third central moment of $W_{i,t}$ scaled by the cubed standard deviation of $W_{i,t}$:

$$NCSKEW_{j,T} = -\left(n_{j,T}(n_{j,T}-1)^{\frac{3}{2}}\sum_{t=1}^{n_{j,T}}W_{j,t}^{3}\right) / \left((n_{j,T}-1)(n_{j,T}-2)\left(\sum_{t=1}^{n_{j,T}}W_{j,t}^{2}\right)^{\frac{3}{2}}\right)$$
(2)

where *j* is firm index, *T* is year index, *t* is week index, $n_{j,T}$ is the number of available firm-specific weekly returns for firm *j* during fiscal year *T*. When a firm's stock return distribution is left-skewed, the firm is more likely to experience extreme negative stock returns. As negative values for the skewness represent a left-skewed distribution, we multiply the skewness measure by -1 so that an increase in *NCSKEW* corresponds to a higher downside tail risk.

Our second measure of firm-specific crash risk, $DUVOL_{j,T}$, is the natural log of the ratio of the standard deviation of $W_{j,t}$ for the "down-week" sample to the standard deviation of $W_{j,t}$ on the "up-week" sample over fiscal year T:

$$DUVOL_{j,T} = \log\left\{ \left(n_{u,j,T} - 1 \right) \sum_{t=1}^{n_{d,j,T}} W_{j,t}^2 / \left(n_{d,j,T} - 1 \right) \sum_{t=1}^{n_{u,j,T}} W_{j,t}^2 \right\}$$
(3)

where *j* is firm index, *T* is year index, *t* is week index, and $n_{u,j,T}$ and $n_{d,j,T}$ are the number of up- and down-weeks for firm *j*'s stock during fiscal year *T*. For each stock *j* over fiscal year *T*, we define the "up-weeks" (down-weeks) as those when $W_{j,t}$ is above (below) its annual mean. Intuitively, $DUVOL_{j,T}$ is the natural logarithm ratio of the standard deviations of $W_{j,t}$ on down-weeks to the standard deviations of $W_{j,t}$ on up-weeks. Similar to the convention of *NCSKEW_{j,T}*, an increase in $DUVOL_{j,T}$ corresponds to firm *j* having a higher stock price crash risk in fiscal year *T*. As the calculation of DUVOL does not include the third moment, DUVOL is less likely to be excessively affected by a small number of extreme tail returns (Bauer et al., 2021).

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3.4 | Research design

To formally investigate the relation between future stock price crash risk and CEOs' general skills, we adopt the following baseline regression model:

Crash risk_{i,T+1} =
$$\beta_0 + \beta_1 \text{GAI}_{i,T} + \gamma^j \text{Control variables}_{i,T} + \theta_i + \mu_T + \epsilon_{i,T}$$
 (4)

where j is firm index, T is year index, i is industry index, θ_i is Fama–French 48 industry fixed effects, and μ_T is year fixed effects. The dependent variable crash risk is either NCSKEW or DUVOL. Consistent with the previous crash risk studies, we advance the crash risk measures by 1 year in our empirical analyses, so that our dependent variables refer to the 1-year-ahead future stock price crash risk. Our independent variable of interest is GAI. We include the following control variables that are found to be associated with a firm's stock price crash risk: DTURN is the detrended stock trading volume, which is a proxy for the heterogeneity of investor opinions; NCSKEW is the prior stock price crash risk, the third moment of $W_{i,t}$; SIGMA is the standard deviation of $W_{i,t}$, the second moment; RET is the mean of $W_{i,t}$, the first moment; SIZE is the natural logarithm of market capitalization; MTB is the market-to-book ratio; LEV is the ratio of long-term debts to total assets; ROE is the return on equity; and OPAQUE is the financial reporting opacity, the absolute value of the annual performance-adjusted discretionary accruals developed by Kothari et al. (2005).³ We also control for CASHETR, firm-level tax avoidance using cash effective tax rates (Bauer et al., 2021; Kim et al., 2011b); KURT, the kurtosis of Wit, the fourth moment; AUDIT, tenure auditor tenure (Callen & Fang, 2017); BIG4, the presence of a Big Four auditor (Chen et al., 2001); DIVIDEND, the existence of dividend payout (Fang et al., 2021; Kim et al., 2018); ANALYST_Num the natural logarithm of one plus the number of analysts that issue earnings forecasts for a firm; LONG, dedicated and quasi-index institutional (Callen & Fang, 2013) ownership; and SHORT, transient institutional ownership (Callen & Fang, 2013). Detailed definitions of all variables are summarized in Appendix A.

4 | MAIN RESULTS

4.1 | Summary statistics

Panel A of Table 1 presents the summary statistics of our main sample. The mean value and standard deviation of NCSKEW are 0.082 and 0.827. The mean value and standard deviations of DUVOL are -0.007 and 0.370. The summary statistics of our two crash risk measures are comparable to those reported in the studies focusing on the ExecuComp samples (e.g., Andreou et al., 2016, Li & Zeng, 2019; Kim et al., 2011a, 2016). The mean and standard deviation of GAI are -0.170 and 0.880, which are comparable to those reported by Custódio et al. (2013, 2019). The average change in monthly trading volume over a year is 0.4%. An average firm in our sample has a firm-specific weekly return volatility of 4.1%, a firm-specific weekly return of -0.1%, a market capitalization of \$2012 million, a market-to-book ratio of 3.27, a book leverage ratio of 0.203, a return on equity of 0.131 and an absolute value of performance-adjusted discretionary accruals of 0.06. The distributions of our control variables are broadly consistent with those reported in earlier studies. In addition to these variables used in our main analysis, we have constructed the following variables as additional controls. The average firm in our sample pays 34.2% tax on book income, has a kurtosis of firm-specific weekly return of 4.4%, is followed by six financial analysts and has a 60.5% institutional ownership. On average, 81.5% of our sample firms pay dividends, and 86.4% of our sample firms employ a Big Four auditor.

³ In a recent paper, Andreou et al. (2022) found that the relation between opacity and crash risk is not statistically significant, especially during the period following the enforcement of the 2002 Sarbanes–Oxley Act.

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5		p75		0.466	0.224		0.353		0.030	0.447	0.051	0.000	8.612	3.759	0.309	0.211	0.080	0.391	4.909	1.000	1.000	1.000	2.708		0.213	(Continues)
		Median		0.033	-0.018		-0.334		0.002	0:030	0.036	-0.001	7.475	2.333	0.176	0.131	0.041	0.271	3.708	1.000	1.000	1.000	2.140	0.303	0.125	
		p25		-0.364	-0.249		-0.860		-0.024	-0.356	0.025	-0.001	6.477	1.543	0.032	0.057	0.018	0.146	3.036	1.000	0.000	1.000	1.447	0.100	0.050	
		SD		0.827	0.370		0.880		0.103	0.754	0.022	0.001	1.582	3.076	0.188	0.225	0.064	0.298	2.147	0.388	0.497	0.343	0.997	0.000	0.122	
		Mean		0.082	-0.007		-0.170		0.004	0.081	0.041	-0.001	7.607	3.269	0.203	0.131	0.061	0.342	4.377	0.815	0.555	0.864	1.951	0.225	0.143	
Sample description.	stics	Obs.	les	25,324	25,324	of interest	25,324		25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	25,324	0.185	25,324	
TABLE 1 Sample d	Panel A: Summary statistics	Variables	Main dependent variables	NCSKEW _{T+1}	$DUVOL_{T+1}$	Independent variables of interest	GAI_T	Other variables	DTURN _T	NCSKEW _T	$SIGMA_{T}$	RET_T	SIZE _T	MTB_T	LEV _T	ROET	OPAQUET	CASH_ETR _T	KURT _T	AUDIT_Tenure _T	DIVIDEND _T	BIG4 _T	$AUDIT_Num_T$	LONG _T 25,324	$SHORT_T$	

10 | JBFA

TABLE 1	(Continued)	ed)																	
Panel B: Correlation matrix	relation ma	ıtrix																	
	A	ß	U	٥	ш	ш	U	т	-	~	¥	_	Σ	z	0	٩	Q R	s	⊢
NCSKEW _{T+1} A	A 1.000																		
$DUVOL_{T+1}$	B 0.955*	* 1.000																	
GAI_T	C -0.018	C -0.018* -0.008*	1.000																
	D 0.031*		0.027* -0.010	1.000															
$NCSKEW_{T}$	E 0.022*		0.014* -0.014*	0.048*	1.000														
SIGMA _T	F 0.032	0.032* -0.005 -0.164*	-0.164*	0.157*	0.136*	1.000													
RET_T	G -0.021*		0.013* 0.131* -0.162*		-0.113* -0.960*	-0.960*	1.000												
$SIZE_T$	H 0.016*	* 0.046*	0.294*	0.001	-0.037* -0.519*	-0.519*	0.437*	1.000											
MTB_{T}	I 0.049*	* 0.052*	0.028*	0.046*	-0.034* -0.005	-0.005	-0.005	0.276*	1.000										
LEV_T	J -0.003	0.001	0.104*	0.047*	-0.012*	-0.012* -0.088* 0.075*	0.075*	0.088*	0.036*	1.000									
ROE_T	K 0.045*	* 0.062*	0.014*	0.038*	-0.031*	-0.031* -0.272* 0.279*	0.279*	0.281*	0.328*	0.014*	1.000								
OPAQUET	L 0.013*	* 0.002	0.002 -0.046*	0.058*	0.015*		0.286* -0.265* -0.136* 0.104* -0.030* -0.077*	-0.136*	0.104*	-0:030* -	-0.077*	1.000							
CASH_ETR _T M -0.042* -0.056* -0.022* -0.022*	M -0.042	* -0.056*	-0.022*	-0.022*	0.017*		$0.248^* - 0.254^* - 0.190^* - 0.065^* - 0.047^* - 0.349^*$	-0.190* -	-0.065* .	-0.047* -	-0.349*	0.112*	1.000						
KURT _T	N 0.006		-0.004 -0.019*	0.056*	0.022*	0.282* -	$0.282^* - 0.270^* - 0.142^* - 0.014^* - 0.007 - 0.081^*$	-0.142* -	-0.014*	-0.007	-0.081*	0.047*	0.062*	1.000					
AUDIT_ Tenure _T	O -0.011* -0.005	* -0.005	0.035*	0.002	-0.009	-0.009 -0.107* 0.101* 0.122* -0.001 -0.017* 0.017* -0.043* -0.020* -0.017*	0.101*	0.122* -	-0.001	-0.017*	0.017* -	-0.043* -	-0.020* -	-0.017*	1.000				
DIVIDEND _T	P -0.030* -0.010	* -0.010	0.125*	0.009	-0.027*	-0.027* -0.454*	0.382*	0.332* -	0.332* -0.031* 0.075*	0.075*	0.147* -	-0.185* -	0.147* -0.185* -0.086* -0.093*	-0.093*	0.076*	1.000			
$BIG4_{T}$	Q -0.014* -0.005	* -0.005		0.090* -0.002	0.002	-0.085*	0.067*	0.178* -0.001	-0.001	0.013*	0.008 -	-0.034* -0.045*	-0.045*	0.000	0.096*	0.002 1.0	1.000		
ANALYST_ Num _T	R 0.010*	* 0.021*		0.129* -0.017*	0.025*	0.025* -0.190* 0.162*	0.162*	0.454* 0.116* 0.003	0.116*	0.003	0.086* -	-0.072* -	-0.092*	0.086* -0.072* -0.092* -0.068*	0.102*	0.083* 0.118* 1.000	118* 1.00	0	
$LONG_T$	S -0.018	S -0.018* -0.016	0.016* -0.001		-0.026*	-0.026* -0.103* 0.088*	0.088*	0.075* -0.015 -0.010	-0.015	-0.010	0.038* -	-0.042* -	- 0:030* -	-0.033*	0.030*	$0.038^* - 0.042^* - 0.030^* - 0.033^* 0.030^* 0.137^* 0.000 0.237^* 1.000$	00 0.23	7* 1.000	
$SHORT_T$	T 0.063*		0.063* -0.003*	0.051*	0.038*	0.143* -	-0.106* -0.050*		0.051* -0.020*	-0.020*	0.034*	0.061* -0.077*	-0.077*	0.008	-0.104 -	$-0.104 -0.180^* \ 0.070^* \ 0.339^* \ 0.164 \ 1.000$	170* 0.33	9* 0.164	1.000
Note: Panel A reports summary statistics of stock price crash risk variables, CEO-level variables and the other variables used in our empirical tests. Our main sample consists of 25,324 firm-year observations covered by ExecuComp over the period 1992–2016 with available CEO generalist index and other variable information. The number of observations, mean, standard deviation, 25th percentile, median and 75th percentile are reported from left to right, in sequence for each variable. All variables are defined in Appendix A. Panel B presents the pairwise Pearson correlations for all variables reported in Panel A.	reports sun covered by dian and 75 rted in Pane	nmary stat ExecuCom th percent	tistics of si ip over the tile are rep:	tock price e period 1 oorted fro	e crash ris .992-201 m left to r	sk variable 6 with av ight, in se	s, CEO-le ailable CE quence fo	vel variał O genera r each va	oles and t alist index riable. Al	the other < and othe I variables	variables er variable s are defir	used in e e informa ned in Ap	our empir ition. The pendix A.	ical tests number Panel B p	. Our mai of observ. resents th	e crash risk variables, CEO-level variables and the other variables used in our empirical tests. Our main sample consists of 25,324 firm-year 1992–2016 with available CEO generalist index and other variable information. The number of observations, mean, standard deviation, 25th om left to right, in sequence for each variable. All variables are defined in Appendix A. Panel B presents the pairwise Pearson correlations for all	onsists of n, standa Pearson (25,324 fi rd deviati correlatio	irm-year ion, 25th ins for al

* denotes statistical significance at the 10% level or above, respectively.

Panel B of Table 1 presents the Pearson correlation matrix of the variables in our main sample. $NCSKEW_{T+1}$ and $DUVOL_{T+1}$ are highly positively correlated. The pairwise correlations between GAI_T and $NCSKEW_{T+1}$ and between GAI_T and $DUVOL_{T+1}$ are negative and statistically significant, which provide preliminary support for hypothesis H1a.

4.2 | Baseline regression analysis

Table 2 reports the results of our baseline regression in Equation (4). The t-statistics reported in parentheses below the corresponding coefficients are based on standard errors clustered by firm and year (Petersen, 2009). We control for the potential determinants of crash risk which are commonly included in the previous crash risk studies. The coefficients of GAI are negative and statistically significant at the 1% level in columns (1) and (2), suggesting that CEOs' general skills are negatively associated with future stock price crash risk. Moving GAI from its 25th to the 75th percentile translates into NCSKEW and DUVOL falling by 0.019 and 0.008, respectively. Relative to the mean values of the two crash risk measures, an interquartile change in GAI is associated with at least a 23.7% decrease in stock price crash risk. Therefore, the empirical relation between CEOs' general skills and stock price crash risk is both statistically and economically significant. The estimated coefficients on the control variables are generally comparable with earlier studies. Firms with higher trade volume (DTURN), greater prior stock price crash risk (NCSKEW), larger stock return volatility (SIGMA), higher past stock returns (RET), larger firm size (SIZE), better future growth opportunities (MTB), better past accounting performance (ROE), less dedicated and quasi-indexer institutional ownership (LONG) and more transient institutional ownership (SHORT) tend to experience higher future stock price crash risk. To mitigate the concern that CEOs' general skills are related to unobserved firm characteristics that may affect stock price crash risk, we control for the firm and year fixed effects. Untabulated tests show that our main findings remain robust. Overall, the results of our multivariate analyses support hypothesis H1a.

4.3 | Identification tests

Our baseline regression shows that CEOs' general skills are negatively associated with future stock price crash risk after controlling for a set of observed firm characteristics and various fixed effects. However, it is still challenging to draw causal inferences about the impact of CEOs' general skills on crash risk due to potential endogeneity problems. CEOs may not be appointed randomly by firms. The nonrandom selection of CEOs may be due to the confounding factors that affect both the appointments of generalist CEOs and crash risk. If these firm-related factors are not controlled for in our baseline regressions or are unobservable to the researchers, the impact of CEOs' general skills on crash risk is subject to selection bias. We adopt three identification tests to mitigate the endogeneity concern: (i) a DID test, (ii) a PSM test and (iii) Oster's (2019) coefficient stability test.

4.3.1 | Difference-in-differences test

We first employ a DID framework around the CEO appointments to identify the effect of the change in CEOs' general skills on future stock price crash risk. Following Custódio et al. (2013) and Ma et al. (2021), we classify a CEO as a generalist (specialist) if her GAI is above (below) the 75th percentile of the GAI distribution in a year. We then compare stock price crash risk before and after specialist-to-generalist transitions to a control sample of firms undergoing the other CEO transitions. As a firm may adopt a specialist-to-generalist CEO transition in order to reduce the future stock price risk, we drop CEO turnovers which are likely to be endogenous, so that our analysis is less likely to be affected by the change in corporate policies related to crash risk.

TABLE 2 General skills and stock price crash risk of chief executive officers (CEOs).

	NCSKEW _{T+1}	DUVOL _{T+1}
Variables	(1)	(2)
GAI _T	-0.016***	-0.007**
	(-3.175)	(-2.774)
DTURNT	0.195***	0.092***
	(3.172)	(3.174)
NCSKEW _T	0.013*	0.004
	(1.808)	(1.275)
SIGMA _T	5.451***	2.037***
	(5.627)	(4.205)
RET _T	66.181***	29.946***
	(4.710)	(4.055)
SIZE _T	0.024***	0.014***
	(3.376)	(4.450)
MTB _T	0.004*	0.002*
	(1.733)	(1.867)
LEV _T	0.029	0.007
	(0.838)	(0.419)
ROE _T	0.092***	0.050***
	(3.122)	(4.260)
OPAQUET	-0.032	-0.013
	(-0.341)	(-0.310)
CASH_ETR _T	-0.089***	-0.044***
	(-3.742)	(-4.123)
KURT _T	-0.003	-0.001
	(-0.686)	(-0.603)
AUDIT_Tenure _T	-0.015	-0.007
	(-1.225)	(-1.052)
DIVIDEND _T	-0.003	-0.000
	(-0.194)	(-0.059)
BIG4 _T	-0.032	-0.012
	(-1.359)	(-1.084)
ANALYST_Num _T	-0.011	-0.006
	(-1.153)	(-1.527)
LONG _T	-0.072***	-0.036***
	(-3.011)	(-2.979)
SHORT _T	0.273***	0.132***
	(3.661)	(4.250)
Constant	-0.207***	-0.142***
	(-3.196)	(-4.979)
		(Continues)

<u>14 | JBFA</u>

TABLE 2 (Continued)

	NCSKEW _{T+1}	DUVOL _{T+1}
Variables	(1)	(2)
Observations	25,324	25,324
R ² -adjusted	0.024	0.025
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Firm fixed effects	No	No

Note: This table reports the estimates of the panel regressions of future stock price crash risk on the CEO generalist ability index (GAI_{T}) and control variables. The sample covers 25,324 firm-year observations with non-missing values for the regression variables during 1992–2016. The dependent variables are two measures of stock price crash risk: $NCSKEW_{T+1}$ and $DUVOL_{T+1}$. The independent variable of interest is GAI_{T} . The coefficients of Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The *t*-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

We search CEO turnovers on Factiva for articles mentioning the names of departing CEOs or their successors. We read these articles to identify the reasons for CEO turnovers. A CEO turnover is classified as endogenous if (i) a CEO is fired; (ii) a CEO resigns due to corporate policy differences and (iii) a CEO resigns due to corporate board intervention (Li & Zeng, 2019; Parrino, 1997). For the turnovers in which we could not identify any of the above three conditions, we classify a turnover as exogenous if the departing CEO's age is above 60 in the turnover year (Li & Zeng, 2019; Parrino, 1997). We further review articles about turnovers in which the departing CEO's age is below 60. If we could not identify the reasons for CEO departures as death events, poor health issues, the acceptance of another position, retirement in more than 6 months and convincing reasons which are not related to firms' activities, we classify these turnovers as endogenous (Li & Zeng, 2019; Parrino, 1997). After dropping the endogenous CEO turnovers from our sample, we assign the exogenous specialist-to-generalist CEO transitions into our treatment group and the other exogenous CEO transitions into our control group.⁴ The DID identification compares firms' crash risk for two similar groups with and without the specialist-to-generalist CEO turnovers but which would otherwise be subject to similar influence from CEO turnovers. If the change in crash risk around a CEO turnover can be alternatively explained by an unobserved confounding factor, it not only must have coincidentally changed over the CEO turnover but also be unrelated to the turnover itself. Therefore, any difference in the changes in crash risk before and after the specialistto-generalist CEO turnover is more likely due to the impact of CEOs' general skills rather than the difference between the two groups prior to the CEO turnovers.

In our DID test sample, we require that a CEO successor keep her position for at least 3 consecutive years, as it may take the new CEO some time to reshape the firm's operations. For comparison, we keep firm-year observations 3 years before and 3 years after an exogenous CEO turnover, excluding the turnover year T (Li & Zeng, 2019; Parrino, 1997).⁵ Firms in our DID sample must have available accounting data in Compustat for at least 2 years before the CEO turnovers. We estimate the following DID regression model:

$$Crash \ risk_{j,T+1} = \beta_0 + \beta_1 Post_{j,T+1} + \beta_2 Turnover_j \times Post_{j,T+1} + \gamma^j Control \ variables_{j,T} + \mu_T + \theta_i + \epsilon_{j,T}$$
(5)

where *j* is firm index, *T* is year index, *Turnover_j* is an indicator variable that equals one if firm *j* experiences an exogenous specialist-to-generalist CEO transition in year *T* and zero if firm *j* experiences an exogenous CEO transition which is

⁴ Our control group includes specialist-to-specialist, generalist-to-generalist and generalist-to-specialist CEO transitions.

⁵ Firms in our DID sample must have available accounting data in Compustat for at least 2 years before the CEO turnovers.

not specialist-to-generalist in year *T*, and *Post*_{*j*,T+1} is an indicator variable that equals one if firm-year *T* + 1 is after the exogenous CEO transition, and zero otherwise. We also control for firm (θ_i) and year (μ_T) fixed effects.⁶

Columns (1) and (2) of Table 3 report the results of our DID tests. The estimated coefficients of $Turnover_j \times Post_{j,T+1}$ are negative and statistically significant at the 5% and 1% levels, suggesting that an increase in CEOs' general skills over the exogenous CEO turnovers reduces future stock price crash risk. The finding of our baseline regression analysis remains robust to the DID identification test.⁷

4.3.2 | Propensity score matching and entropy balancing matching

The empirical relation between CEOs' general skills and crash risk could be driven by the firm characteristics related to the appointment of a generalist CEO. To mitigate this concern, we first adopt a PSM procedure (Rosenbaum & Rubin, 1983) and construct a treatment and a control group that is as similar as possible in terms of the control variables included in our baseline regression other than the treatment variable: *GAI*. Such a statistical matching technique helps us to address the concern on the nonrandom mutual selection between firms and generalist CEOs, which in turn improves the causal inference of our empirical finding.

Following Custódio et al. (2013) and Ma et al. (2021), we define a generalist indicator variable GAI_Dummy which equals one if a CEO's GAI is above the 75th percentile in a year, and zero otherwise. In the first stage of PSM, we estimate a logit model to calculate the propensity score that a firm hires a generalist CEO. In the logit model, the dependent variable is GAI_Dummy, and the independent variables are the control variables of our baseline regression model. Column (1) of Panel A of Table 4 reports the results of the pre-match propensity score regression. The coefficients of *SIZE, LEV, CASH ETR* and *KURT* are positive and statistically significant, whereas the coefficients of MTB and ROE are negative and statistically significant. Consistent with Custódio et al. (2013) and Ma et al. (2021), firms with larger firm size, higher financial leverage, a lower market-to-book ratio and a worse accounting performance tend to appoint a generalist CEO. To ensure that firms in the treatment and control group are comparable, we adopt a nearest-neighbor matching approach and a caliper width of 0.1%.

To verify that firms in the treatment and control group have similar observable characteristics, we first reestimate the logit model for the post-match sample and report the results in column (2) of Panel A of Table 4. All the estimated coefficients are statistically insignificant, suggesting that firms between the treatment and control group do not exhibit distinguishable covariates. In terms of the absolute value, the estimated coefficients in column (2) are generally smaller than the corresponding estimated coefficients in column (1), indicating that the decrease in the statistical significance of the estimated coefficients is not simply driven by the drop in the post-matching sample size. The pseudo R^2 also drops from 0.070 in column (1) to 0.001 in column (2). Next, we directly compare the covariates included in the logit regression between the treatment and control group. Columns (1)–(4) of Panel B of Table 4 show that the differences in the covariates are all statistically insignificant. Although firms with generalist and specialist CEOs are significantly different in many observable covariates, all the differences become statistically insignificant after the matching, suggesting that our PSM process is efficient. These two diagnostic tests assure us that the difference in crash risk between the treatment and control group is likely driven by CEOs' general skills, not the observable covariates.

Columns (1) and (2) of Panel C of Table 4 report the results of our baseline regression Equation (4) based on the PSM sample. We find that the coefficients of GAI are negative and statistically significant, which is consistent with our baseline regression results.

⁶ As we control for the firm fixed effects, it is not necessary to include a separate term, *Turnover_j*, in Equation (5).

⁷ Our DID design assumes that CEO turnover cases here offer a purely exogenous shock that would resolve the issues of endogeneity associated with the nonrandom selection of CEOs. However, our design may suffer from confounding elements that potentially relate to the new CEOs and firms' future crash risk. For example, it is less likely that a new CEO (with less than 3 years in the office) plays a role as a board chairperson. Therefore, it appears plausible that agency problems (e.g., CEO duality) might be mild in the early years of the new CEO. We suggest readers exercise caution in interpreting our DID results.

<u>16 | JBFA</u>

FANG ET AL.

TABLE 3 Difference-in-differences regressions.

Pestr -0.042° -0.013 Indicion × Postr -0.143° (-1.131) També -0.143° -0.037°° Indicion × Postr -0.143° (-2.194) DTURN 0.05 0.022 0.07011 (0.352) NCSKEW -0.123°° -0.055°° (-6.874) (-6.874) (-6.874) SIGMA7 5.834° 2.9562° (1.881) (1.447) (1.647) SIZEr 0.000° -0000 (1.881) (1.647) (1.647) SIZEr 0.000° -0000 (0.022) (-0.174) (1.637) LEV 0.238° 0.089° (1.641) (1.631) (1.631) DPQUEr -0.044 -0.025 (0.711) (-0.282) (-0.631) OPQUEr -0.044 -0.025 (1.071) (-0.282) (-0.831) QUDIT_Tenure, -0.041 (-0.214) QUDIT_Tenure, -0.017 -0.041 (0.129) (0.011° (0.021) QUDIT_Tenure, -0.017 (-0.436) QUDIT_Tenure, -0.017 (0.012) (0.127) (0.021) (0.021) (0.121	Variables	NCSKEW _{T+1} (1)	DUVOL _{T+1} (2)
Instition × Postγ -0.143** -0.073*** (-2.494) (-2.914) DTURNγ 0.105 0.022 (0.701) (0.352) NCSKEWγ -0.123*** -0.055*** (-8.574) (-8.679) SIGMAγ 5.834** 2.180* (2.065) (1.770) RETγ 76.825* 29.562* (1.881) (1.647) SIZEγ 0.207*** 0.000 (0.022) (-0.174) (1.633) MTBγ 0.000 -0000 (0.022) (-0.174) (1.931) EV 0.238** 0.089* (2.344) (1.931) (1.433) OPAQUEγ -0.044 -0.028 (-0.711) (-0.282) (-0.843) KURTγ 0.011* (0.029) CASH_ETRγ -0.040 -0.017 (-0.439) (-0.249) (0.642) DIVIDENDγ 0.001* (0.024) (0.505) (0.559) (0.559)	Post _T	-0.042*	-0.013
(-2.494)(-2.914)DTURNY0.1050.022(0.701)(0.352)NCSKEWT-0.123***-0.055***(-8.574)(-8.679)(-8.679)SIGMAT76.825*29.562**(1.881)(1.447)SIZET0.020***0.101***(6.843)(7.393)(-0.178)MTBY0.002-0.017*(0.022)(-0.174)(1.931)RCT-0.0440.004*(0.021)(-0.708)(0.143)OPAQUET-0.040-0.017(-0.708)(-0.282)(-0.883)KURTT0.011*-0.028*MUDIT_Tenuret-0.017-0.041(0.179)0.009*(0.191)(0.179)0.015*(1.641)DIVIDENDT0.0090.011*(0.179)0.0042(0.191)(0.179)0.015*(0.559)ANATET, Numy0.0290.015*(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.029)(0.559)(0.064)(0.632)(0.559)(0.064)(0.632)(0.559)(0.064)(0.632)(0.632)(0.064)(0.632)(0.632)(0.064)(0.632)(0.632)(0.064)(0.284)(0.362)(0.064)(0.284) <t< td=""><td></td><td>(-1.673)</td><td>(-1.131)</td></t<>		(-1.673)	(-1.131)
DTURN _T 0.0105 0.022 NCSKEW _T -0.123 ^{***} -0.055 ^{***} (-8.574) (-8.679) SIGMA _T 5.834 ^{**} 2.180° (2.085) (1.770) RET _T 0.207 ^{***} 0.101 ^{***} (6.843) (7.933) MTB _T 0.000 -0.000 (0.22) (-0.174) IEV 0.238 ^{**} 0.089° (0.22) (-0.174) (1.931) MTB _T 0.000 -0.000 (0.22) (-0.174) (1.931) CPAQUE _T -0.044 0.004 (-0.701) (-0.282) (-0.843) CPAQUE _T -0.040 -0.017 (-0.892) (-0.843) (-0.282) CPAQUE _T -0.017 -0.004 (DIVIDEND _T -0.017 -0.014 (0.179) (0.042) (0.642) (0.170) (0.042) (0.642) (0.170) (0.042) (0.559) (0.179) (0.042)	Transition $\times Post_T$	-0.143**	-0.073***
10.701(0.352)NCSKEWT-0.123**-0.055***(-8.574)(-8.679)SGMAr5.834**2.180*(2085)(1.770)RET76.825*29.562*(1.881)(1.881)(1.91***(6.843)(7.939)(1.91***********************************		(-2.494)	(-2.914)
NCSKEW _T -0.123"** -0.055"** (-8.574) (-8.679) SIGMA _T 5.834** 2.180* (2.085) (1.770) RET 76.825* 29.552* (1.881) (1.647) SIZE (6.843) (7.393) MTB _T 0.000 -0.000 (0.022) (-0.174) (1.931) RCF -0.044 0.004 (-0.708) (0.143) (1.931) ROE _T -0.146 -0.025 (-0.708) (-0.028) (-0.028) CASH_ETR _T 0.011* (-0.028) KURT _T 0.011* (-0.028) KURT _T 0.011* (-0.028) KURT _T 0.011* (0.05* (1.641) (1.724) (-0.243) DIVIDEND _T 0.009 (0.011* (0.055) (0.559) (0.559) (0.009 (0.055) (0.559) (0.007 (0.058) (0.559) (0.0088 (0.028) </td <td>DTURN_T</td> <td>0.105</td> <td>0.022</td>	DTURN _T	0.105	0.022
(-8.574) (-8.679) SIGMA _T 5.834** 2.180* (2.085) (1.700) RET _T 76.825* 29.562* (1.881) (1.647) SIZE _T 0.207*** 0.101*** (6.843) (7.393) (7.393) MTB _T 0.000 -0.000 (0.022) (-0.174) (1.931) LEV _T 2.344) (1.931) ROE _T -0.044 0.004 (-0.708) (0.143) (-0.282) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) (-0.214) MUT _T 0.011 (0.021) KURT _T 0.011 (0.021) KURT _T 0.011 (0.021) MUT _T 0.011 (0.021) KURT _T 0.011 (0.021) KURT _T 0.011 (0.021) MUT _T 0.011 (0.021) MUT _T 0.012 (0.012) MUT _T 0.021 ((0.701)	(0.352)
SIGMA _γ 5.834** 2.180* RET _γ 76.825* 29.562* 1.881 (1.647) SIZE _γ 0.007*** 0.014*** (6.843) (7.393) (7.393) MTB _γ 0.000 -0.000 (0.022) (-0.174) (1.931) LEV _γ 2.34* 0.004 (2.344) (1.931) (1.931) ROE _γ -0.146 -0.025 (-0.708) (0.133) (1.931) QPAQUE _γ -0.146 -0.025 (-0.711) (-0.282) (-0.892) KURT _γ -0.040 -0.017 (-0.892) (-0.843) (-0.214) MUDIT_Tenure _γ -0.017 -0.004 (-0.719) 0.005 (-0.214) MUDIT_Tenure _γ -0.017 -0.004 (-0.179) 0.001 (-0.214) MUDIT_Tenure _γ -0.017 -0.004 (0.179) (0.022) (0.158) (0.55) (0.559) (0.559)	NCSKEW _T	-0.123***	-0.055***
1(2.85) 1(770) RET _T 76.825° 29.562° 1(881) (1647) SIZE _T 0.0207°* 0.010°** (6.843) (7.393) (7.393) MTB _T 0.000 -0.000 (0.022) (-0.174) (-0.174) LEV _T 0.238°* 0.089° (2.344) (1.931) (-0.143) ROE _T -0.044 0.004 (-0.708) 0.131 (-0.282) QPAQUE _T -0.146 -0.025 (-0.711) (-0.282) (-0.843) QPAQUE _T -0.040 -0.017 (-0.892) (-0.843) (-0.843) QUDT_Tenure _T -0.017 (-0.843) (-0.436) (-0.214) (-0.214) QUDT_Tenure _T -0.017 (-0.843) (-0.436) (-0.214) (-0.814) QUDT_Tenure _T -0.017 (-0.814) (0.179) (0.021) (-0.814) (0.179) (0.022) (0.178)		(-8.574)	(-8.679)
RET _T 76.825° 29.562° (1881) (1.647) SIZE _T 0.007°° 0.011°° (6.843) (7.393) (7.393) MTB _T 0.000 -0.000 (0.022) (-0.174) (-0.174) LEV _T 0.238° 0.089° (2.344) (1.931) (-0.143) ROE _T -0.044 0.004 (-0.708) (0.13) (-0.282) OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) (-0.892) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.892) (-0.892) KURT _T 0.011° 0.005 MUDI_Tenure _T -0.017 (-0.892) (0.436) (1.724) (-0.892) MUDI_Tenure _T 0.001° (0.012) (0.11° 0.005 (0.559) (0.11° (0.021) (0.622) (0.11° (0.021) (0.621) (0.1079) (0.022) (0.559)	SIGMA _T	5.834**	2.180*
1 1		(2.085)	(1.770)
SIZE _T 0.027*** 0.011*** (6.843) (7.393) MTB _T 0.000 -0.000 (0.022) (-0.174) LEV _T 0.238** 0.089* (2.344) (1.931) (1.931) ROE _T -0.044 0.004 (-0.708) (0.143) (1.931) OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) (-0.892) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) (-0.843) KURT _T 0.011* 0.005* (1.661) (1.724) (1.641) (1.724) DVIDEND _T 0.009 0.001 (0.017) (0.042) BIG4 _T 0.029 0.015 (0.559) (0.559) (0.559) (0.559) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569) (0.569)	RET _T	76.825*	29.562*
16.843 (7.39) MB _T 0.000 -0.000 10.022 (-0.174) LEV _T 0.238* 0.089* 12.344) (1.931) (1.931) ROE _T -0.044 0.013 CPAQUE _T -0.146 -0.025 (-0.708) 0.143 (1.931) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.892) (-0.893) KURT _T 0.011* -0.004 (1.641) (1.724) (1.641) KURT _T 0.017 -0.004 (-0.436) (-0.214) (1.724) MUDIT_Tenure _T -0.017 -0.004 (1.641) (1.724) (1.642) IVIDEND _T 0.009 0.011* (0.017) (0.021) (0.622) IGG4 _T 0.029 0.015 (0.505) (0.559) (0.559) IGA4 _T 0.017 0.009 (0.007 (0.632) (0.768) IGA9 _T 0.018 0.022 IGA9 _T 0.018 0.022 IGA9 _T 0.018 0.021 IGA9 _T 0.017 0.009 IGA9 _T 0.017 0.017		(1.881)	(1.647)
MB _T 0.000 -0.000 LEV _T 0.238** 0.089* (2.344) (1.931) ROE _T -0.044 0.004 (-0.708) 0.143 0 OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) 0 CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) 0 KURT _T 0.011* (-0.843) MUDI_Tenure _T -0.017 (-0.434) DIVIDEND _T 0.009 0.001 (0.036) (-0.146) (-0.214) BIG4 _T 0.029 0.015 (0.050) (0.559) (0.59) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.58) LONG _T 0.088 0.032 (1.092) (0.861) (0.861)	SIZE _T	0.207***	0.101***
10022 (-0.174) LEV _T 0.238* 0.089* (2.344) (1.931) 0.004 COP -0.044 0.004 (-0.708) (0.143) 0.014 OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) 0.017 (CASH_ETR _T) -0.040 -0.017 (CASP2) (-0.892) (-0.813) KURT _T 0.011* 0.005* (1.641) (1.724) 0.001 DUDIT_Tenure _T -0.017 -0.004 (1.0436) (-0.214) 0.005* (1.641) (1.724) 0.001 DUDIT_Tenure _T -0.017 -0.004 (1.0436) (-0.214) 0.011 (0.059) 0.001 0.002 0107 (0.059) 0.051 (0.505) (0.505) 0.505) (0.632) (0.632) (0.632) LONG _T 0.088 0.032 (1.092) (0.861) 0.051		(6.843)	(7.393)
LEV _T 0.238** 0.089 (2.344) (1.931) ROE _T -0.044 0.004 (-0.708) (0.143) OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) -0.043 KURT _T 0.011* 0.005* (1.661) (1.724) -0.017 AUDDIT_Tenure _T -0.017 -0.044 (-0.436) (-0.214) -0.017 DIVIDEND _T -0.017 -0.004 (1.661) (1.724) -0.004 (-0.436) (-0.214) -0.017 DIVIDEND _T -0.017 -0.004 (0.179) (0.012) -0.017 (0.029) 0.015 -0.017 (DUT_Tenure _T) -0.017 -0.017 (0.032) (0.058) -0.019 (DVIDEND _T) 0.029 -0.015 (0.032) (0.632) (0.768) (DNG _T)	MTB _T	0.000	-0.000
12.344) (1.931) ROE _T -0.044 0.004 (-0.708) (0.143) OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) -0.017 KURT _T 0.011* 0.005* AUDIT_Tenure _T -0.017 -0.004 10VIDEND _T 0.009 0.011* BIG4 _T 0.029 0.015* 10NALYST_Num _T 0.017 0.009 10NG _T 0.016* 0.015* 10NG _T 0.017 0.009 10NG _T 0.018 0.032 10NG _T 0.038 0.032 10NG _T 0.088 0.032 10NG _T 0.288* 0.031		(0.022)	(-0.174)
ROE _T -0.044 0.004 (-0.708) (0.143) OPAQUE _T -0.146 -0.025 (-0.711) (-0.282) (ASH_ETR _T) -0.040 -0.017 (CASH_ETR) -0.040 -0.017 (CASH_ETR) -0.040 -0.017 (CASH_ETR) 0.011 0.005* (CASH_ETR) 0.011* 0.005* (CASH_ETR) 0.011* 0.005* (CASH_ETR) 0.011* 0.005* (CASH_ETR) 0.011* 0.001* (CASH_ETR) 0.001* 0.001* (COTT) 0.001* 0.001* (COST) 0.001* 0.001* (COST) 0.001* 0.001* (COST) 0.001* 0.002* (COST) 0.002* 0.002* (CONGT) <	LEV _T	0.238**	0.089*
(-0.708) (0.143) OPAQUE _T -0.046 -0.025 (-0.711) (-0.282) (-0.282) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) (-0.843) KURT _T 0.011° 0.005° (1.661) (1.724) (-0.174) AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) (-0.214) DIVIDEND _T 0.009 0.001 (0.179) 0.004 (-0.214) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_Num _T 0.017 0.009 (LONG _T 0.088 0.032 (LONG _T 0.088 0.032 (1.092) 0.0861) 0.081		(2.344)	(1.931)
OPAQUE _T -0.146 (-0.711) -0.025 (-0.822) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) (-0.843) KURT _T 0.011° 0.005° (1.661) (1.724) (1.724) AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) (-0.214) DIVIDEND _T 0.009 0.001 (0.179) (0.042) (0.042) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.768) LONG _T 0.088 0.032 KURT _T -0.28* -0.091	ROET	-0.044	0.004
(-0.711) (-0.282) CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) (-0.843) KURT _T 0.011* 0.005* (1.661) (1.724) (1.614) AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) (-0.214) DIVIDEND _T 0.009 0.001 (0.179) (0.042) (0.042) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.768) LONG _T 0.088 0.032 (1.092) (0.861) (0.861)		(-0.708)	(0.143)
CASH_ETR _T -0.040 -0.017 (-0.892) (-0.843) KURT _T 0.011* 0.005* (1.661) (1.724) AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) (-0.214) DIVIDEND _T 0.009 0.001 (0.179) 0.004 (0.042) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.321) LONG _T 0.088 0.032 (1.092) (0.861) (0.861)	OPAQUET	-0.146	-0.025
(-0.892) (-0.843) KURT _T 0.011* 0.005* (1.661) (1.724) AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) (-0.214) DIVIDEND _T 0.009 0.001 (1.079) (0.042) (0.042) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.768) LONG _T 0.088 0.032 SHORT _T -0.28* -0.099		(-0.711)	(–0.282)
KURT _T 0.011* 0.005* .1.661 (1.724) AUDIT_Tenure _T -0.017 -0.004 .0.01* (-0.436) (-0.214) DIVIDEND _T 0.009 0.001 .0.179 0.002 0.015 BIG4 _T 0.029 0.015 .0.0505 (0.505) 0.559 ANALYST_Num _T 0.017 0.009 .0.032 (0.768) 0.032 LONG _T 0.088 0.032 .10.92 0.088* 0.032 .10.92 0.088* 0.032	CASH_ETR _T	-0.040	
(1.661) (1.724) AUDIT_TenureT -0.004 (-0.436) (-0.214) DIVIDENDT 0.009 0.0179) (0.042) BIG4T 0.029 0.0505) (0.559) ANALYST_NumT 0.017 LONGT 0.032 100FT 0.088 0.007 0.032 1007 0.032 1009 0.032 1009 0.032 1009 0.032 1009 0.032 1009 0.032 1009 0.032 1009 0.032 1009 0.032		(-0.892)	(-0.843)
AUDIT_Tenure _T -0.017 -0.004 (-0.436) (-0.214) DIVIDEND _T 0.009 0.001 (0.179) (0.042) (0.042) BIG4 _T 0.029 0.015 ANALYST_Num _T 0.017 (0.559) LONG _T 0.038 0.032 LONG _T 0.088 0.032 SHORT _T -0.288* -0.099	KURT _T	0.011*	
(-0.436) (-0.214) DIVIDENDT 0.009 0.001 (0.179) (0.042) BIG4T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_NumT 0.017 0.009 (0.632) (0.768) (0.768) LONGT 0.088 0.032 (1.092) (0.861) (0.861)			(1.724)
DIVIDENDT 0.009 0.001 (0.179) (0.042) BIG4T 0.029 0.015 (0.505) (0.505) (0.559) ANALYST_NumT 0.017 0.009 (0.632) (0.768) LONGT 0.032 (1.092) (0.861) SHORTT -0.288*	AUDIT_Tenure _T	-0.017	
(0.179) (0.042) BIG4 _T 0.029 0.015 (0.505) (0.559) (0.59) ANALYST_Num _T 0.017 0.009 (0.632) (0.768) (0.768) LONG _T 0.088 0.032 (1.092) (0.861) (0.861)			(-0.214)
BIG4 _T 0.029 0.015 (0.505) (0.559) (0.559) ANALYST_NumT 0.017 0.009 (0.632) (0.768) (0.768) LONGT 0.088 0.032 (1.092) (0.861) (0.861)	DIVIDENDT	0.009	0.001
(0.505) (0.559) ANALYST_NumT 0.017 0.009 (0.632) (0.768) LONGT 0.088 0.032 (1.092) (0.861) SHORTT -0.288* -0.099			
ANALYST_Num_T 0.017 0.009 (0.632) (0.768) LONG_T 0.088 0.032 (1.092) (0.861) SHORT_T -0.288* -0.099	BIG4 _T	0.029	
(0.632) (0.768) LONG _T 0.088 0.032 (1.092) (0.861) SHORT _T -0.288* -0.099			
LONG _T 0.088 0.032 (1.092) (0.861) SHORT _T -0.288* -0.099	ANALYST_Num _T		
(1.092) (0.861) SHORT _T -0.288* -0.099			
SHORT _T –0.288* –0.099	LONG _T		
(-1.781) (-1.327)	SHORT _T		-0.099
		(-1.781)	(-1.327)

(Continues)

TABLE 3 (Continued)

Variables	NCSKEW _{T+1} (1)	DUVOL _{T+1} (2)
Constant	-1.367***	-0.716***
	(-4.737)	(–5.736)
Observations	6597	6597
R ² -adjusted	0.041	0.044
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes

Note: This table reports the difference-in-differences regression results of the impact of generalist CEOs on future stock price crash risk. The sample covers firm-year observations 3 years before and 3 years after a CEO exogenous turnover, excluding the year of the turnover. The sample period is 1992–2016. Following Huang and Kisgen (2013), we require that firms have at least 2 years of non-missing data for all variables before the executives' transition. The dependent variables are two measures of stock price crash risk: $NCSKEW_{T+1}$ and $DUVOL_{T+1}$. Transition is an indicator variable that equals one if a firm is a specialist-to-generalist CEO transition firm, and zero otherwise. $Post_T$ is an indicator variable that equals one if year t is after the CEO transition, and zero otherwise. The coefficients of the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

As a robustness check of our matching identification test, we adopt an EB matching method, which reweights observations by imposing constraints in adjusting the mean and variance of firm characteristic variables to achieve a tight covariate balance. Compared to PSM, EB matching retains all sample observations rather than discarding "unmatched" ones. Moreover, it does not necessitate a specific research design to achieve covariate balance, thus alleviating concerns regarding the dependency of results on model specification (DeFond et al., 2016). Hainmueller (2012) asserted that the enhanced balance by EB matching can result in reduced approximation bias and reduced reliance on model specifications in finite sample settings. Columns (5)–(8) of Panel B of Table 4 show that after our EB matching, the mean and variance of the firm characteristics are the same between the treatment and control groups. Columns (3) and (4) of Panel C of Table 4 report the results of our baseline regressions based on the EB-matched sample. The coefficients of GAI remain negative and statistically significant.

4.3.3 | Oster's coefficient stability test

Although the PSM identification mitigates the imbalance in the covariates between firms with generalist and specialist CEOs, the endogeneity concern may persist if the matching variables do not absorb all the heterogeneity related to crash risk between the treatment and control group. The previous literature has shown that crash risk is associated with many firm characteristics and managerial traits. It may not be feasible for us to control for all of them in our empirical tests.

Oster (2019) proposed a coefficient sensitivity test to investigate the importance of the omitted variable bias. Rows (1) and (2) of Table 5 report the estimated coefficients of GAI in Table 2 and the corresponding R^2 . Rows (3) and (4) report the assumptions of *Rmax* and δ used in estimating the bounds of GAI's coefficients. *Rmax* is between the R^2 in our baseline regressions with observable control variables and 1. δ is the ratio of the observable variables' impact on GAI's coefficient to the unobservable variables' impact on GAI's coefficient. According to Oster (2019), we define that the *Rmax* upper bound equals 1.3 times the R^2 and δ equals 1. Next, we estimate the bounds of GAI's coefficient, [$\beta_{baseline}$, $\beta \times *$ (min{1.3× $*R^2_{baseline}$, 1}, 1] and check if the interval excludes zero or not. Rows (5) and (6) show that the bounds of GAI's coefficient exhibit very limited movement and do not include zero, suggesting that controlling for both observable and unobservable variables would not lead to a very different conclusion than only

17

TABLE 4 Propensity score matching and entropy balancing matching.

Denal A. Due weetsh www.wewsite.e.		at wantals die awantie wanwantie wa
Panel A: Pre-match propensity se	core regressions and po	st-match diagnostic regressions

	Pre-match	Post-match
	GAI_Dummy _T	GAI_Dummy _T
Variables	(1)	(2)
DTURN _T	0.155	-0.067
	(0.841)	(-0.290)
NCSKEW _T	-0.030	-0.007
	(-1.417)	(-0.286)
SIGMA _T	-3.184	-0.961
	(-0.575)	(-0.160)
RET _T	-45.985	-25.711
	(-0.605)	(-0.306)
SIZE⊤	0.373***	0.000
	(10.422)	(0.012)
MTB _T	-0.039***	-0.003
	(-3.407)	(-0.237)
LEV _T	0.599***	0.109
	(3.453)	(0.563)
ROE _T	-0.314***	0.011
	(-2.940)	(0.098)
OPAQUE _T	0.152	0.002
	(0.471)	(0.006)
CASH_ETR _T	0.232***	-0.053
	(2.842)	(-0.605)
KURT _T	0.017**	-0.006
	(2.032)	(-0.577)
AUDIT_Tenure _T	-0.035	0.008
	(-0.542)	(0.110)
DIVIDEND _T	0.130	-0.002
	(1.391)	(-0.016)
BIG4 _T	0.003	-0.011
	(0.027)	(-0.095)
ANALYST_Num _T	-0.010	-0.025
	(-0.240)	(-0.546)
LONG _T	-0.097	0.043
	(-0.639)	(0.263)
SHORT _T	0.288	-0.018
	(0.982)	(-0.057)
Constant	-3.746***	0.131
	(-4.431)	(0.142)
		(Continue

(Continues)

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TABLE 4 (Continued)

Panel A: Pre-match propensity score r	regressions and post-match diagnostic regressions	
	Pre-match	Post-match
	GAI_Dummy _T	GAI_Dummy _T
Variables	(1)	(2)
Observations	25,324	12,524
Pseudo R ²	0.070	0.001
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes

Panel B: Differences in firm characteristics

		PSM			EB matching				
	Generalist CEO (N = 6262)	Specialist CEO (N = 6262)	Difference	T-statistics		ent group 6503)		ol group 8,821)	
					Mean	Variance	Mean	Variance	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
DTURN _T	0.005	0.005	-0.000	-0.028	0.005	0.006	0.005	0.006	
NCSKEW _T	0.061	0.066	0.005	0.361	0.060	0.539	0.060	0.539	
SIGMAT	0.037	0.037	-0.000	-0.083	0.037	0.000	0.037	0.004	
RET _T	-0.001	-0.001	0.000	0.21	-0.009	0.000	-0.009	0.000	
SIZET	8.128	8.137	0.009	0.313	8.208	2.518	8.208	2.519	
MTB _T	3.345	3.370	0.026	0.474	3.345	9.997	3.345	9.997	
LEV _T	0.223	0.220	-0.004	-1.136	0.225	0.314	0.225	0.314	
ROET	0.137	0.136	-0.001	-0.173	0.137	0.053	0.137	0.053	
OPAQUET	0.058	0.058	-0.000	-0.047	0.057	0.004	0.057	0.004	
CASH_ETR _T	0.337	0.341	0.004	0.683	0.338	0.091	0.338	0.091	
KURT _T	4.308	4.332	0.024	0.637	4.299	4.464	4.299	4.464	
AUDIT_Tenure _T	0.826	0.825	-0.000	-0.071	0.827	0.143	0.827	0.143	
	0.638	0.637	-0.000	-0.037	0.647	0.229	0.647	0.229	
BIG4 _T	0.883	0.885	0.002	0.418	0.883	0.103	0.883	0.103	
ANALYST_Num _T	2.090	2.112	0.021	1.172	2.106	1.056	2.106	1.056	
LONGT	0.193	0.193	-0.000	-0.073	0.192	0.051	0.192	0.051	
	0.140	0.142	0.002	0.857	0.139	0.014	0.139	0.014	

Panel C: Propensity score matching and entropy balancing matching estimators

	PS	м	EB matching			
	NCSKEW _{T+1}	DUVOL _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}		
Variables	(1)	(2)	(3)	(4)		
GAI _T	-0.014**	-0.007*	-0.013**	-0.006**		
	(-2.107)	(-1.955)	(-2.033)	(-1.971)		
Constant	-0.011	-0.053	-0.132	-0.105		
	(-0.118)	(-1.217)	(-0.625)	(-1.073)		

BFA | 19

(Continues)

TABLE 4 (Continued)

Panel C: Propensity score matching and entropy balancing matching estimators						
	PSI	М	EB mate	hing		
	NCSKEW _{T+1}	DUVOL _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}		
Variables	(1)	(2)	(3)	(4)		
Control variables	Yes	Yes	Yes	Yes		
Observations	12,524	12,524	25,324	25,324		
R ² -adjusted	0.020	0.020	0.022	0.022		
Year fixed effects	Yes	Yes	Yes	Yes		
Industry fixed effects	Yes	Yes	Yes	Yes		

Note: Panel A reports the parameter estimates from the logit model used to estimate the propensity scores. The sample covers firm-year observations with non-missing values for all variables during 1992-2016. The dependent variables are GAI Dummy, (Custódio et al., 2013). The independent variables are all the firm characteristics included in our panel regression analyses. We use a one-to-one match and require that the difference between the propensity score of the firm run by a generalist CEO and its matching peer does not exceed 0.1% in absolute value. Column (1) reports the pre-match propensity score regression, and column (2) reports the post-match diagnostic regression. The coefficients of the Fama-French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). Panel B reports the univariate comparisons of firm characteristics between treatment and control groups. Columns (1)-(4) are about the propensity score matching (PSM) and columns (5)-(8) are about the entropy balancing (EB) matching. In columns (1) and (2), we report the mean value of firm characteristics. In column (3), we report the differences between the treatment and control groups. In column (4), we report the t-statistics of the univariate comparisons. In columns (5) and (6), we report the mean and variance of the firm characteristics in the treatment group. In columns (7) and (8), we report the mean and variance of the firm characteristics in the control group. Panel C reports the average treatment effects in the propensity score matching (PSM) sample (columns (1) and (2)) and in the entropy balancing (EB) matching sample (columns (3) and (4)). The dependent variables are NCSKEW_{T+1} and DUVOL_{T+1}. The independent variable of interest is GAI t. The control variables are the same as those reported in Table 2. The coefficients of the control variables, the Fama-French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

Abbreviation: CEO, chief executive officers.

***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

controlling for the observable variables in our baseline regressions. Rows (7) and (8) report Oster's δ , which leads to GAI's coefficient being zero with the assumption of $R_{max} = 1.3 * R_{baseline}^2$. Oster's δ indicates the degree of selection on unobservable variables relative to observable variables that would be required to fully explain our result by omitted variable bias. Based on Oster's (2019) recommendation, we compare the values of δ to 1 and confirm that all δ estimates are greater than 1. High δ values indicate that the unobservable variables have less effect on the GAI's coefficient than the observable variables. The absolute values of δ estimates range between 2.9 and 32.0 across the four specifications in our baseline regressions. It is very unlikely that unobservable variables are 2.9–32.0 times as important as all the observable variables included in our baseline regressions.

Overall, our three identification tests suggest that after controlling for the selection bias and omitted variable bias, the negative relation between CEOs' general skills and stock price crash risk remains robust.

5 | SUPPLEMENTARY TESTS

5.1 Cross-sectional analyses

In this section, we seek to identify and understand the underlying economic factors that lead to cross-sectional differences in the economic consequences of generalist CEOs to investors.

TABLE 5 Coefficient stability after correcting for omitted variable bias.

		NCSKEW _{T+1}	DUVOL _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}
		(1)	(2)	(3)	(4)
(1)	GAI _T	-0.016***	-0.007***	-0.030***	-0.012***
(2)	R ²	0.024	0.025	0.036	0.040
(3)	δ	1	1	1	1
(4)	$Rmax = 1.3 \times R^2$	0.031	0.033	0.047	0.052
(5)	Bounds on the treatment effect	(-0.018, -0.015)	(-0.010, -0.007)	(-0.032, -0.030)	(-0.013, -0.012)
(6)	Treatment effect excludes 0	Yes	Yes	Yes	Yes
(7)	Oster's δ	-32.013	-2.934	-13.180	-12.049
(8)	$ \delta > 1$	Yes	Yes	Yes	Yes

Note: This table reports the results of Oster's (2019) approach to evaluating the robustness to omitted variable bias. Rows (1) and (2) present the coefficients of GAI_T and R^2 reported in Table 2. Rows (3) and (4) present the assumption of δ and *Rmax*. δ is assumed to be one so that the observed and unobserved factors have an equally important effect on the coefficient of GAI_T . *Rmax* is the upper bound of R^2 which would result if all unobservable factors were included in the regression. Following the suggestion of Oster (2019), we define *Rmax* as 1.3 times R^2 from our baseline regressions that controls for all observable factors. Rows (5) and (6) report the bounds on the coefficient of GAI_T which are estimated using Stata code psacalc. Rows (7) and (8) report the value of δ when $Rmax = 1.3 \times R^2$ and the coefficient of GAI_T is zero.

 $^{\ast\ast\ast}, ^{\ast\ast}$ and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

5.1.1 | Outside options

First, the transferable skills of generalist CEOs make it easier for them to move across industries, so generalist CEOs are more competitive in the external job market (Custódio et al., 2013, 2019; Ma et al., 2021). Here, the underlying premise is that the presence of outside options would make generalist CEOs more likely to exert their transferable professional skills than specialist CEOs. When the external job market is ice cold, there are few outside options for both generalist and specialist CEOs. On the contrary, when the external job market is hot, generalist CEOs would benefit more than specialist CEOs from the strong demand for managers as CEOs' general management skills are not specific to any organization and are transferable across firms and industries.

Oyer's (2004) wage indexation theory implies that due to geographic segmentation in the US market, the external job opportunities of CEOs are more likely from firms in the same region than those located in the other regions (Knyazeva et al., 2013; Yonker, 2017). Following Custódio et al. (2019), we adopt local labor market conditions as a proxy for the variation in the value of CEOs' outside options. *TIGHT* is an indicator variable that equals one if the annual unemployment rate in the Metropolitan Statistical Area where a firm's headquarter locates is less than the annual sample median, and zero otherwise. CEOs are more likely to receive an external job offer in a tight labor market as the demand for workers is stronger in these markets. Given that general skills are transferable across firms and industries, generalist CEOs should benefit more than specialist CEOs in tight labor markets (Custódio et al., 2019). Therefore, we should observe a greater reduction in crash risk for firms located in the tight labor market.

In Panel A of Table 6, we separate our sample into two subsamples, tight-market and non-tight-market, using the indicator variable *TIGHT*. We reestimate our baseline regression in these two subsamples. The estimated coefficients of *GAI* are negative and statistically significant in the tight-market subsamples but statistically insignificant in the non-tight-market subsamples. Our results suggest that generalist CEOs' outside opportunities in tight labor markets help to explain the negative relation between CEOs' general skills and crash risk.

21

FA B 22

TABLE 6 Cross-sectional analyses.

	NCS	NCSKEW _{T+1}		DUVOL ₇₊₁		
Variables	(1)	(2)	(3)	(4)		
Panel A: External labo	r market competition					
	Tight-market	Non-tight-market	Tight-market	Non-tight-market		
GAI _T	-0.027***	-0.009	-0.012**	-0.005		
	(-3.243)	(-1.652)	(-3.062)	(-1.591)		
Constant	-0.252***	-0.221***	-0.152***	-0.164***		
	(-2.849)	(-3.324)	(-3.778)	(-5.148)		
Control variables	Yes	Yes	Yes	Yes		
Observations	11,867	12,136	11,867	12,136		
R ² -adjusted	0.019	0.021	0.019	0.024		
Year fixed effects	Yes	Yes	Yes	Yes		
Industry fixed effects	Yes	Yes	Yes	Yes		
Panel B: CEO age						
	Old	Young	Old	Young		
GAI _T	-0.024***	-0.010	-0.010***	-0.004		
	(-3.615)	(-1.282)	(-3.064)	(-1.114)		
Constant	-0.114	-0.335***	-0.101**	-0.203***		
	(-1.084)	(-4.881)	(-2.286)	(-6.057)		
Control variables	Yes	Yes	Yes	Yes		
Observations	12,680	12,644	12,680	12,644		
R ² -adjusted	0.018	0.025	0.019	0.024		
Year fixed effects	Yes	Yes	Yes	Yes		
Industry fixed effects	Yes	Yes	Yes	Yes		
Panel C: Firm complexity						
	High	Low	High	Low		
GAI _T	-0.024***	-0.010	-0.010***	-0.004		
	(-3.615)	(-1.282)	(-3.064)	(-1.114)		
Constant	-0.114	-0.335***	-0.101**	-0.203***		
	(-1.084)	(-4.881)	(-2.286)	(–6.057)		
Control variables	Yes	Yes	Yes	Yes		
Observations	12,680	12,644	12,680	12,644		
R ² -adjusted	0.018	0.025	0.019	0.024		
Year fixed effects	Yes	Yes	Yes	Yes		
Industry fixed effects	Yes	Yes	Yes	Yes		
Panel D: Product mark	ket competition					
	High	Low	High	Low		
GAI _T	-0.021***	-0.011	-0.009***	-0.006		
	(-3.519)	(-1.169)	(-3.087)	(-1.427)		
				1 -		

(Continues)

TABLE 6 (Continued)

Panel D: Product market competition						
	High	Low	High	Low		
Constant	-0.136	-0.310***	-0.123***	-0.170***		
	(-1.653)	(-3.699)	(-3.162)	(-4.199)		
Control variables	Yes	Yes	Yes	Yes		
Observations	12,369	12,365	12,369	12,365		
R ² -adjusted	0.022	0.020	0.022	0.020		
Year fixed effects	Yes	Yes	Yes	Yes		
Industry fixed effects	Yes	Yes	Yes	Yes		

Note: This table reports the cross-sectional analyses on the effect of generalist CEOs on future stock price crash risk. The sample covers firm-year observations with non-missing values for all variables during 1992-2016. In Panel A, we divide our main sample into two subsamples based on the indicator variable $TIGHT_T$. $TIGHT_T$ equals one in the tight-market subsample and zero in the non-tight-market. In Panel B, we divide our main sample into two subsamples based on the indicator variable $CEO Age_T$. $CEO AGE_T$ equals one in the old subsample and zero in the young subsample. In Panel C, we divide our main sample into two subsamples based on the indicator variable $COMPLEXITY_T$. $COMPLEXITY_T$ equals one in the high subsample and zero in the low subsamples based on the indicator variable $COMPLEXITY_T$. $COMPLEXITY_T$ equals one in the high subsample and zero in the low subsamples based on the indicator variable $TOMPLEXITY_T$ equals one in the high subsample and zero in the low subsamples based on the indicator variable $TOMPLEXITY_T$ equals one in the high subsample and zero in the low subsamples based on the indicator variable $TOMPLEXITY_T$ equals one in the high subsample and zero in the low subsample. The dependent variables are two measures of stock price crash risk: $NCSKEW_{T+1}$ and $DUVOL_{T+1}$. The independent variable of interest is CEO generalist ability index (GAI_T). The control variables are the same as those reported in Table 2. The coefficients of the control variables, the Fama–French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). ****, *** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

5.1.2 | Agency conflicts

Another presumption underlying the negative relation between CEOs' general skills and future firm-specific crash risk is agency conflicts between managers and shareholders that ultimately lead to managerial bad news hoarding behavior. Kim et al. (2011a) and Callen and Fang (2013) suggested that firms with weaker monitoring mechanisms tend to suppress bad news and suffer crash risk. Thus, we expect that in firms with more severe agency conflicts, CEOs' general skills would play a greater role in preempting managerial bad news hoarding activity and reducing stock price crash risk. Empirically, we look at three aspects of agency conflicts: (i) CEO age; (ii) firm complexity; and (iii) product market competition.

First, Andreou et al. (2016) showed that firms with younger CEOs are more likely to experience stock price crashes. Their findings suggest that CEOs have financial incentives directly related to their personal wealth for hoarding bad news in their earlier career, which results in future stock price crashes. We adopt CEO age as the first proxy for agency conflicts and conjecture that the negative relation between CEO general skills and crash risk is stronger among firms with younger CEOs. In Panel B of Table 6, we separate our sample into two subsamples based on the annual sample median value of CEO age. We find that the estimated coefficients of *GAI* in our baseline regression are negative and statistically significant in the subsamples with young CEOs but statistically insignificant in the subsamples with old CEOs.

Second, previous studies maintain that managers suppress negative news from investors as long as possible due to empire building (e.g., Basu, 1997). Empirically, firm complexity potentially captures the important role of managerial tendency in engaging in empire building. It is likely that complex firms are more likely to be subject to managerial bad news hoarding and thus future stock price crash risk. Following Markarian and Parbonetti (2007), we adopt an external complexity measure *COMPLEXITY*, which is an indicator variable that equals one if the percentage of a firm's sales with respect to the total sales within the industry (*Sales-to-Ind*) is larger than the median value of *Sales-to-Ind*, and zero otherwise. When a firm's sales within its industry increase, the firm tends to cater for a larger consumer base with continuously changing demand and preference. Market leaders are also more likely to face competitors attempting to replicate their products and take over their leadership position (Markarian & Parbonetti, 2007). In Panel C of Table 6, we separate our sample into two subsamples, high and low complexity, based on the indicator variable *COMPLEXITY*. We reestimate our baseline regression in these two subsamples. The estimated coefficients of *GAI* are negative and statistically significant in the high complexity subsamples but statistically insignificant in the low complexity subsamples.

Last, Li and Zhan (2019) examined the effect of product market competition on stock price crash risk. They argue that competitive pressures aggravate managerial inclination to hide negative information, and they find that firms facing higher market competition are more likely to suffer from stock price crashes. Following Li and Zhan (2019), we measure the intensity of product market competition using Hoberg et al.'s (2014) fluidity measure, *FLUIDITY*, which assesses the degree of competitive threat and product market change surrounding a firm. The fluidity measure is based on product descriptions in a firm's 10-K filings and captures the degree to which the firm's products are sensitive to the evolution of its rivals' products. The greater similarity in the product descriptions between a firm and its rivals implies that the firm encounters higher competitive threats, which are likely to expose the firm to potentially large losses. In Panel D of Table 6, we separate our sample into two subsamples, high and low product market competition, based on the annual sample median value of *FLUIDITY*. We find that the estimated coefficients of *GAI* in our baseline regression are negative and statistically significant in the subsamples with high product market competition but statistically insignificant in the subsamples with low product market competition. The finding supports the view that the influence of CEOs' general skills on future crash risk is concentrated in firms facing higher product market competition.⁸

Overall, these results support the view that CEOs' general skills play a greater role in reducing stock price crash risk for firms with more severe agency conflicts.

5.2 Channel tests

24

The premise underlying the relation between CEOs' general ability and future stock price crash risk is that CEOs' general ability influences bad news hoarding. Literature on crash risk is based on the maintained hypothesis that idiosyncratic crashes are caused by bad news hoarding. By and large, the existing literature tests the implications of this maintained hypothesis but refrains from testing the maintained hypothesis per se. However, it is challenging to directly determine, in all but the most egregious cases, that managers engage in bad news hoarding based on public information such as firm press releases or from the press itself.

In order to help validate the underlying premise that CEOs' general ability affects stock price crash risk through facilitating managerial bad news hoarding activities, we examine whether CEOs' general ability is associated with the channels of bad news hoarding documented in prior research (e.g., Francis et al., 2016; Kim & Zhang, 2016). Francis et al. (2016) documented that real earnings management (REM), which reflects a deviation in real operations from industry norms, is positively associated with a firm's future stock price crash risk. This finding suggests that real operations can be used to withhold from investors bad news about performance and prospects. Kim and Zhang (2016) found that financial reporting conservatism is associated with a lower likelihood of a firm's future stock price crashes. This is consistent with the notion that financial reporting conservatism plays an important role in constraining managers' incentives and ability to overstate performance and hide bad news from investors.

Specifically, we investigate the empirical link between GAI and the following avenues of bad news hoarding: (i) financial reporting conservatism (CSCORE), proxied by Khan and Watts (2009)'s firm-year measure; (ii) REM, measured by the aggregate value of abnormal operating cash flow, abnormal production costs and abnormal discretionary expenses

⁸ To compare the differences in the estimated coefficients of GAI across the subsamples, we extend our baseline regression by adding each of these four indicator variables and their interaction with GAI. The estimated coefficients (untabulated) on the interaction terms are statistically significant.

developed by Roychowdhury (2006); (iii) PCA-based real earning management (*PCA_REM*), which is proposed by Christensen et al. (2023) and (iv) PCA-based accruals and real earning management (*PCA_AREM*) in Christensen et al. (2022).⁹

In this analysis, we regress the variables listed above on GAI, a series of firm characteristics variables including *SIZE*, *MTB*, *LEV*, *ROE*, *SALES_Vol*, *SALES_Growth*, *CF_Vol* and *AGE*, year and industry fixed effects. Table 7 provides the regression results. We find that firms with a higher value of GAI are associated with a higher level of accounting conservatism and a lower level of REM (t-statistics = 1.865, -2.899, -3.874 and -3.115, respectively). The evidence is consistent with our conjecture that CEOs' general ability plays an important role in limiting bad news hoarding activities, lending additional support to the explanation for our main findings.¹⁰

5.3 | Controlling for CEO traits

We follow the previous crash risk studies and include a set of firm characteristics as the control variables in our baseline regression. Recent studies suggest that some managerial traits are related to crash risk. Kim et al. (2011a) showed that CEOs' equity incentives have a weakly positive impact on crash risk. Andreou et al. (2016) found that firms with younger CEOs are more likely to experience future stock price crashes. In a similar spirit, Armstrong and Vashishtha (2012) found that manager tenure is negatively related to firm systematic and idiosyncratic risk. Li and Zeng (2019) showed that firms with female CFOs tend to have less crash risk. In addition, CEO characteristics, such as education background, army service experience and whether a CEO is hired outside the incumbent firm, may affect both CEOs' general skills and crash risk. In columns (1) and (2) of Table 8, we add the abovementioned CEO traits as control variables in our baseline regression. We find that the estimated coefficients of GAI remain negative and statistically significant.

One recent study, that is, Hanlon et al. (2023) explored the impact of boardroom backscratching, defined as the simultaneous excessive remuneration of a firm's CEO and directors, on stock price crash risk. The study documents a significant positive relation between backscratching and stock price crash risk, implying that boardroom backscratching undermines the effectiveness of constructive criticism and oversight from corporate boards and thus exacerbates the likelihood of managerial concealment of negative information. Given that the general management skills of CEOs compared to their specialized skills are likely to be reflected in their compensation within the labor market, we follow the approach of Hanlon et al. (2023) and control for both CEO's overall compensation and boardroom backscratching to ensure that our findings are not driven by compensation-related factors. In columns (3) and (4) of Table 8, we control for the natural logarithm of CEO total compensation (*CEO_TC*) and backscratching (*BST*). Despite the significant sample attrition, the results show that the estimated coefficients of *GAI* remain negative and statistically significant at the 5% and 1% levels.¹¹

⁹ The three real earnings management measures are abnormal cuts to discretionary expenses, abnormal production, and abnormally low cash flow from operations. The accruals earning management measure is estimated by the method of Francis et al. (2005) who supplement Dechow and Dichev (2002)'s model by including change in sales and property, plant, equipment (PPE) in the first-stage regression. The dependent variable in the first-stage regression is comprehensive accruals which is change in equity less change in cash, scaled by lagged assets. We thank Christensen et al. (2022) for generously providing us with the data for this measure. Please refer to Christensen et al. (2022) for the details.

¹⁰ Nevertheless, we suggest that readers exercise caution in interpreting our findings here. The specific bad news hoarding channels we examine here are nonexhaustive. Moreover, it is likely that managers are engaged in bad news hoarding behaviors through other manners than we examine here, even choosing not to report or disclose bad news. Thus, the impact of CEOs' general ability on bad news hoarding is not limited to the channels we examine above. Instead, stock price crash risk is a far more comprehensive metric that should reflect all manners of bad news hoarding relative to specific channel metrics.

¹¹ The correlation between CEO_TC and BST is less than 2%, suggesting no presence of the multicollinearity issue. Moreover, we added these two controls in the regression, separately. The untabulated results on GAI remain almost identical.

<u>²⁶ | JBFA</u>

TABLE 7 Channel tests.

		REMT	PCA_REM _T	PCA_AREM _T
Variables	(1)	(2)	(3)	(4)
GAI _T	0.001*	-0.017***	-0.030***	-0.062***
	(1.865)	(-2.899)	(-3.874)	(-3.115)
SIZE _T	-0.041***	0.011**	0.074***	0.047***
	(-93.074)	(2.149)	(11.255)	(3.116)
MTB _T	-0.001***	-0.032***	-0.031***	-0.066***
	(-9.593)	(-13.626)	(-10.104)	(-11.760)
LEV _T	0.039***	0.316***	0.479***	0.823***
	(21.806)	(10.709)	(12.863)	(9.475)
ROE _T	-0.011***	-0.145***	0.223***	-0.210***
	(-9.315)	(-6.169)	(6.428)	(-4.080)
SALES_Vol _T	-0.011	0.567***	-0.469***	0.411***
	(-1.608)	(9.392)	(-5.816)	(5.065)
$SALES_Growth_T$	0.001	-0.027***	0.009	0.000
	(0.674)	(-5.066)	(1.043)	(1.178)
CF_Vol _T	-0.000***	-0.906***	-1.132***	-0.443
	(-12.908)	(-4.359)	(-4.061)	(-1.067)
AGE _T	0.000***	0.003***	-0.002***	0.004***
	(4.293)	(5.402)	(-3.885)	(3.139)
Constant	0.375***	-0.171***	-0.145**	-0.452***
	(129.982)	(-4.190)	(-2.772)	(-3.967)
Observations	21,290	22,876	22,437	13,202
R ² -adjusted	0.930	0.173	0.367	0.124
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Note: This table reports the results of tests examining the channels through which generalist CEOs affect stock price crash risk. In column (1), the dependent variable is conditional accounting conservatism ($CSCORE_T$) introduced by Khan and Watts (2009). In column (2), the dependent variable is real earnings management (REM_T), defined as the sum of the values of three real earnings management measures developed by Roychowdhury (2006). In column (3), the dependent variable is a proxy for real earnings management based on the principal component analysis (PCA_REM_T) developed by Christensen et al. (2023). In column (4), the dependent variable is a measure of accruals earnings management and real earnings management based on the principal component analysis (PCA_REM_T) developed by Christensen et al. (2023). In column (4), the dependent variable is a measure of accruals earnings management and real earnings management based on the principal component analysis (PCA_REM_T) developed by Christensen et al. (2023). In column (4), the dependent variable is a measure of accruals earnings management and real earnings management based on the principal component analysis (PCA_REM_T) reported by Christensen et al. (2022). The independent variable of interest is CEO generalist index (GAI_T). The control variables are $SIZE_T$, MTB_T , LEV_T , ROE_T , $SALES_VoI_T$, $SALES_Growth_T$, CF_VoI_T and AGE_T . The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

 $^{\ast\ast\ast}, ^{\ast\ast}$ and * denote statistical significance at the 1%, 5% and 10% level, respectively.

5.4 | Controlling for corporate culture

Corporate culture could be an omitted variable in our baseline regression which simultaneously reduces crash risk and increases the likelihood of appointing generalist CEOs. For example, firms with a collaborative-orientated corporate culture may hire CEOs with high general skills because generalist CEOs may facilitate and enhance teamwork among

TABLE 8 Additional controls: chief executive officers (CEO) traits.

	NCSKEW _{T+1}	DUVOL _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}
Variables	(1)	(2)	(3)	(4)
GAI _T	-0.019**	-0.007*	-0.009**	-0.024***
	(-2.070)	(-1.710)	(-2.252)	(-3.232)
CEO_Equity_Inc _T	0.044	0.020	-0.006	0.003
	(1.513)	(1.544)	(-0.131)	(0.031)
CEO_Age _T	0.001	0.000	0.000	0.002
	(0.689)	(0.591)	(0.413)	(0.560)
CEO_Tenure _T	-0.001	-0.000	-0.001	-0.002
	(-0.787)	(-0.651)	(-0.649)	(-0.836)
CEO_Gender _T	0.031	0.011	0.033	0.087
	(0.759)	(0.547)	(1.374)	(1.625)
$CEO_External_Hire_T$	0.027	0.007	-0.001	0.010
	(1.375)	(0.775)	(-0.078)	(0.236)
CEO_Ivy_League _T	-0.013	-0.007	-0.011	-0.015
	(-0.678)	(-0.809)	(-0.596)	(-0.326)
CEO_Army _T	-0.000	0.000	0.039	0.110*
	(-0.016)	(0.037)	(1.429)	(1.836)
CEO_TC _T			-0.013	-0.023
			(-1.485)	(-1.267)
BST _T			0.009	0.020
			(1.009)	(0.789)
Constant	-0.197*	-0.125**	-0.084	-0.088
	(-1.911)	(-2.693)	(-0.858)	(-0.455)
Control variables	Yes	Yes	Yes	Yes
Observations	18,196	18,196	5764	5764
R ² -adjusted	0.018	0.017	0.014	0.012
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Note: This table reports the estimates of the panel regressions of future stock price crash risk on CEO generalist ability index (*GAI*₇), CEO traits and control variables. The sample covers firm-year observations with non-missing values for all variables during 1992-2016. We control for *CEO_Equity_Inc*_T, *CEO_Age*_T, *CEO_Tenure*_T, *CEO_Gender*_T, *CEO_External_Hire*_T, *CEO_Ivy_League*_T and *CEO_Army*_T in columns (1) and (2). In columns (3) and (4), we add two additional control variables: *CEO_TC*_T and *BST*_T. The other control variables are the same as those reported in Table 2. The coefficients of the other control variables, the Fama-French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The *t*-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

colleagues. Meanwhile, due to the collaborative-oriented culture, bad news hoarding activities are more likely to be a joint decision among top executives. It is less likely that one top executive chooses to blow the whistle when she uncovers any accounting misconduct, which leads to higher stock price crash risk. In this section, we directly control for corporate culture in our empirical analysis. Li et al. (2021) proposed a new semisupervised machine learning approach and construct five corporate culture values of innovation, integrity, quality, respect and teamwork based on earnings

TABLE 9 Additional controls: corporate culture.

	NCSK	KEW _{T+1}	DUVC	0L _{T+1}
Variables	(1)	(2)	(3)	(4)
GAI _T	-0.017**	-0.020***	-0.007*	-0.009***
	(-2.248)	(-3.550)	(-1.928)	(-3.160)
TRUST_TO_COMPETE _T		0.014		0.020
		(0.270)		(0.780)
INTEGRITY _T	-0.039*		-0.023**	
	(-1.953)		(-2.385)	
TEAMWORK _T	0.028*		0.017**	
	(1.824)		(2.348)	
INNOVATION _T	-0.023		-0.012**	
	(-1.696)		(-2.183)	
RESPECT _T	0.000		0.002	
	(0.038)		(0.319)	
QUALITY _T	0.021		0.007	
	(1.568)		(1.192)	
Constant	-0.062	-1.101	-0.085**	-0.999***
	(-0.819)	(-1.560)	(-2.396)	(-3.320)
Control variables	Yes	Yes	Yes	Yes
Observations	15,215	22,986	15,215	22,986
R ² -adjusted	0.012	0.020	0.014	0.020
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

Note: This table reports the estimates of the panel regressions of future stock price crash risk on the CEO generalist ability index (GAI_T), corporate culture and control variables. The sample covers firm-year observations with non-missing values for all variables during 1992–2016. The dependent variable is $NCSKEW_{T+1}$ in columns (1) and (2) and $DUVOL_{T+1}$ in columns (3) and (4). In columns (1) and (3), we control for Li et al.'s (2021) five corporate culture values: $INTEGRITY_T$, $TEAMWORK_T$, $INNOVATION_T$, $RESPECT_T$ and $QUALITY_T$. In column (2) and (4), we control for firm's thrust to compete, as an attribute of corporate culture, developed by Andreou et al. (2022). The other control variables are the same as those reported in Table 2. The coefficients of the other control variables, the Fama–French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

call transcripts. Li et al. (2021) showed that their corporate culture scores are related to business outcomes, such as operational efficiency, risk-taking, earnings management, executive compensation design and firm value.

The corporate culture data from Li et al. (2021) are between 2001 and 2018. We merge Li et al.'s (2021) data with our main sample and control for the five corporate culture values in our baseline regression. Table 9 reports the results. In columns (1) and (3), we include the five corporate culture variables as the control variables in our baseline regression. We find that the coefficients of *GAI* remain negative and statistically significant, suggesting that the negative relation between CEOs' general skills and crash risk remains robust after controlling for corporate culture. In columns (1) and (3), the coefficients of *INTEGRITY* are negative and statistically significant, and the coefficients of *TEAMWORK* are positive and statistically significant. In column (3), the coefficient of *INNOVATION* is negative and statistically significant.

Andreou et al. (2022) adopted a textual analysis method to construct a measure of thrust to compete. A firm's thrust to compete is an important element of corporate culture. Andreou et al. (2022) showed that greater transient institutional ownership results in firms intensifying their future thrust to compete, suggesting that firms respond to these investors' preferences and competitive pressures for achieving short-term value creation. In particular, Andreou et al. (2022) documented a positive relation between thrust to compete and future stock price crash risk. In columns (2) and (4) of Table 9, we include *TRUST_TO_COMPETE* as a control variable for corporate culture in our baseline regression. We find that the coefficients of *GAI* remain negative and statistically significant, suggesting that the negative relation between CEOs' general skills and crash risk remains robust after controlling for corporate culture.

5.5 Additional controls for corporate governance

In this section, we incorporate more control variables to the regression at the cost of the reduced sample size. Although this addresses the concern of omitted correlated variables, there exists a balance between generalizability based on larger sample sizes and completeness of regression models.

It is important to control for corporate governance to the extent that managerial career concerns are related to both strong and weak corporate governance frameworks. In the main test, we already controlled for some specific governance/monitoring measures, including institutional ownership (long-term vs. short-term investors), the number of analysts following, Big Four auditors and auditor tenure. We now control for additional dimensions of corporate governance, including corporate board structure and CEO power. Specifically, we control for the natural logarithm of the number of board directors (*BOARD_Size*), the natural logarithm of the average director tenure (*DIRECTOR_Tenure*), the percentage of independent board members (*IND_Director_Ratio*), the percentage of female directors on the board (*Female_Director_Ratio*) and the percentage of coopted directors on the board (*COOPT*). We measure CEO power by whether a CEO is the chairman of the board (*DUALITY*), whether a CEO is the company (*FOUNDER*), CEO's equity ownership (*CEO_STK_Ownership*) and Bebchuk et al. (2009)'s entrenchment index (*EINDEX*).¹²

Table 10 presents the regression results after controlling for the dimensions of board structure and CEO power, separately and together. We find that the coefficients on *GAI* remain significant and negative in columns (1)–(3) when *NCSKEW* is used as a dependent variable (t-statistics = -2.25, -2.05 and -1.92, respectively). We find similar results in columns (4)–(6) when *DUVOL* is used as a dependent variable (t-statistics = -2.57, -2.57, -2.34 and -2.21, respectively). Overall, our findings are robust to controlling for a variety of additional corporate governance measures.

5.6 | Alternative crash risk measures

In our final analysis, we examine whether our main finding is robust to the alternative crash risk definitions in the previous studies. We report the robustness test results in Table 11. In column (1), the dependent variable is *COUNT*, the difference between the number of crash weeks and the number of jump weeks over a fiscal year (Callen & Fang, 2015; Jin & Myers, 2006). A stock price crash (jump) week is defined as a week in which $W_{j,t}$ exceeds 3.2 standard deviations below (above) the mean firm-specific weekly returns over a fiscal year, with 3.2 chosen to generate frequencies of 0.1% in a normal distribution (Kim et al., 2011a). In columns (2)–(4), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated by an extended market model with two leads and two lags of market returns and Fama–French 48 industry returns. In columns (5)–(7), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated by an extended market model with two leads and two lags of market returns. In columns (8)–(10), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated by an extended market model with two leads and two lags of market returns. In columns (8)–(10), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated by an extended market model with two leads and two lags of market returns. In columns (8)–(10), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated by an extended market model with two leads and two lags of market returns. In columns (8)–(10), the dependent variables are *NCSKEW*, *DUVOL* and *COUNT*, which are calculated based on $W_{j,t}$ estimated over 2 years. Overall, the results in Table 11 show

¹² We follow Bebchuk et al. (2009)'s approach and use the RiskMetrics governance database to construct this index.

		NCSKEW _{T+1}			DUVOL _{T+1}	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
GAIT	-0.018**	-0.015**	-0.016*	-0.009**	-0.008**	-0.008**
Unit -	(-2.255)	(-2.047)	(-1.918)	(-2.567)	(-2.341)	(-2.210)
$BOARD_Size_T$	-0.061*	(2.047)	-0.067*	-0.026*	(2.041)	-0.029*
DOMND_31201	(-1.850)		(-1.902)	(-1.737)		(-1.883)
DIRECTOR_Tenure _T	-0.028*		-0.032*	-0.010		-0.013
Director_tendre	(-1.698)		(-1.782)	(-1.410)		(-1.618)
IND_Director_Ratio _™	-0.060		-0.061	-0.020		-0.024
	(-1.088)		(-0.988)	(-0.833)		(-0.876)
Female_Director_Ratio _⊤	0.085		0.043	0.017		0.002
remaic_Director_Natio	(0.973)		(0.467)	(0.452)		(0.043)
COOPT _T	0.004		0.011	0.003		0.006
60011	(0.194)		(0.469)	(0.302)		(0.577)
DUALITYT	(0.174)	-0.005	-0.004	(0.002)	-0.003	-0.003
DOMENTY		(-0.375)	(-0.270)		(-0.469)	(-0.451)
FOUNDERT		0.017	-0.005		0.008	0.000
roonden		(0.360)	(-0.114)		(0.428)	(-0.010)
CEO_STK_Ownership _T		-0.159	-0.018		-0.058	-0.012
		(-0.977)	(-0.086)		(-0.812)	(-0.133)
EINDEX _T		0.003	0.005		0.002	0.003
		(0.509)	(0.703)		(0.679)	(0.887)
Constant	0.386***	0.143*	0.427***	0.122**	0.024	0.148***
Constant	(3.231)	(1.727)	(3.325)	(2.311)	(0.673)	(2.606)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,626	17,970	14,567	15,626	17,970	14,567
R^2 -adjusted	0.023	0.021	0.022	0.022	0.022	0.022
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 10 Additional controls: corporate governance.

Note: This table reports the estimates of the panel regressions of future stock price crash risk on the CEO generalist ability index (*GAI*_T), corporate governance and control variables. The sample covers firm-year observations with non-missing values for all variables during 1992–2016. Here, we control for additional dimensions of corporate governance, including corporate board structure and CEO power. Specifically, we control for the natural logarithm of the number of board directors (*BOARD_Size*), the natural logarithm of the average director tenure (*DIRECTOR_Tenure*), the percentage of independent board members (*IND_Director_Ratio*), the percentage of female directors on the board (*Female_Director_Ratio*) and the percentage of coopted directors on the board (*COOPT*). We measure CEO power by whether a CEO is the chairman of the board (*DUALITY*), whether a CEO is the founder of the company (*FOUNDER*), CEO's equity ownership (*CEO_STK_Ownership*) and Bebchuk et al. (2009)'s entrenchment index (*EINDEX*). The other control variables are the same as those reported in Table 2. The coefficients of the other control variables, the Fama–French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009).

 $^{\ast\ast\ast}, ^{\ast\ast}$ and * denote statistical significance at the 1%, 5% and 10% level, respectively.

30

TABLE 11 Alterna	Alternative crash risk variables.	ables.								
		Two lea	Two leads and lags, with FF48	n FF48	Τw	Two leads and lags	S		Two years	
	COUNT _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}	$COUNT_{T+1}$	NCSKEW _{T+1}	DUVOL _{T+1}	COUNT _{T+1}	NCSKEW _{T+1}	DUVOL _{T+1}	COUNT _{T+1}
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)	(10)
GAI _T	-0.007***	-0.015***	-0.007**	-0.007**	-0.018***	-0.008***	-0.009**	-0.014*	-0.006*	-0.017*
	(-2.774)	(-2.947)	(-2.644)	(-2.218	(-3.434)	(-2.833)	(-2.629)	(-1.718)	(-1.810)	(-1.798)
Constant	-0.146***	-0.091	-0.082***	-0.083**	-0.126**	-0.098***	-0.071*	-0.172**	-0.107***	-0.162
	(-3.735)	(-1.556)	(-2.898)	(-2.140)	(-2.398)	(-3.968)	(-1.902)	(-2.154)	(-3.763)	(-1.686)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,324	25,324	25,324	25,324	25,324	25,324	25,324	22,572	22,572	22,572
R ² -adjusted	0.011	0.019	0.019	0.009	0.025	0:030	0.012	0.029	0.032	0.018
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Note: This table reports the estimates of the panel regressions of alternative future crash risk measures on the CEO generalist ability index (GAI _T) and control variables. The sample covers firm-year observations with non-missing values for the regression variables during 1992–2016. In column (1), the dependent variable is <i>Count</i> _{T+1} , which is the difference between the number of crash weeks and the number of jump weeks over a fiscal year. A stock price crash (jump) week is defined as a week in which the firm-specific weekly return exceeds 3.2 standard deviations below (above) the mean firm-specific weekly returns over a fiscal year, with 3.2 chosen to generate frequencies of 0.1% in a normal distribution (Kim et al., 2011a). In columns (2)-(4), the dependent variables are the three crash risk variables based on the firm-specific weekly returns estimated by an extended market model with two leads and two lags of market returns. In columns (8)-(7), the dependent variables based on the firm-specific weekly returns estimated by an extended market model with two leads and two lags of market returns. In columns (8)-(10), the dependent variables based on the firm-specific weekly returns estimated by an extended market model with two leads and two lags of market returns. In columns (8)-(10), the dependent variables are the three crash risk variables based on the firm-specific weekly returns and Fama-French 48 industry returns. In columns (8)-(10), the dependent variables are the three crash risk variables based on the firm-specific weekly returns and Fama-French 48 industry returns. In columns (8)-(10), the dependent variables are the three crash risk variables based on the firm-specific weekly returns and Fama-French 48 industry returns. In columns (8)-(10), the dependent variables are the three crash risk variables based on the firm-specific weekly returns and Fama-French 48 industry returns. In columns (8)-(10), the dependent variables are the three crash risk variables based on the firm-specific weekly returns	the estimates of the with non-missing var- und the number of ju the mean firm-spe ariables are the three ch 48 industry retui with two leads and	panel regression malues for the regr imp weeks over a cific weekly retui e crash risk varia trns. In columns (f two lags of mark	s of alternative ession variable fiscal year. As t rns over a fiscal bles based on tl ble based on tl of (7), the depe	future crash ris s during 1992– ock price crash year, with 3.2 to ne firm-specific ndent variables blumns (8)–(10)	k measures on th 2016. In column (jump) week is de chosen to genera weekly returns ε are the three ci	ie CEO generali (1), the depend efined as a week the frequencies (astrimated by an ash risk variables are th variables are th	st ability index thent variable is in which the fil of 0.1% in a nor extended mark les based on th the three crash r	regressions of alternative future crash risk measures on the CEO generalist ability index (GA_{17}) and control variables. The sample covers or the regression variables during 1992–2016. In column (1), the dependent variable is $Count_{1+1}$, which is the difference between the eeks over a fiscal year. A stock price crash (jump) week is defined as a week in which the firm-specific weekly return exceeds 3.2 standard weekly returns over a fiscal year, with 3.2 chosen to generate frequencies of 0.1% in a normal distribution (Kim et al., 2011a). In columns the variables based on the firm-specific weekly returns estimated by an extended market model with two leads and two lags of market columns (5)–(7), the dependent variables are the three crash risk variables based on the firm-specific weekly returns estimated by an age of market returns. In columns (8)–(10), the dependent variables are the three crash risk variables based on the firm-specific weekly and the returns are returns.	ol variables. The is the difference (Kim et al., 201 (Kim et al., 201 e ol back and two e of the firm-se	sample covers e between the Is 3.2 standard La). In columns lags of market stimated by an pecific weekly
returns estimated in Equation (1) and measured over 2 years. The independent variable of interest is GAIT. The control variables are the same as those reported in Table 2. The coefficients	ופנוסט (T אוומ נוובפאר	Ired over 2 years.	I ne independe	IT Variable UL	ITELEST IS GAIT. II	Te control varial	DIes are the sam	le as triuse repur	ted in Table 2. I	

of the control variables, the Fama-French 48 industry fixed effects and the year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. est is GAT. The control variables are the same as those reported in Table Z. The coefficients The t-values reported in parentheses are based on standard errors clustered by firm and year (Petersen, 2009). returns estimated in Equation (1) מוומ ווופמצערפט over 2 אבמרא. ווופ ווווטבאטוטפווע אמו ומעוכ

 *** , ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

that the coefficients of GAI are all negative and statistically significant, suggesting that our main finding is robust to these alternative measures of crash risk.

6 | CONCLUSIONS

Building on the upper echelons theory (Hambrick & Mason, 1984), previous studies have investigated the extent to which top executives affect the strategic behavior and outcomes of their firms. In this paper, we examine the impact of generalist CEOs on corporate bad news hoarding in a panel sample of S&P 1500 firms between 1992 and 2016. We find that CEOs' general managerial skills accumulated over their lifetime of work experience are negatively associated with future stock price crash risk. To establish causality and mitigate the potential endogeneity concern that generalist CEOs may not be randomly assigned to firms, we use a DID approach utilizing exogenous CEO turnovers, PSM and EB matching approaches, and Oster's (2019) coefficient stability test. Our three identification tests indicate a causal effect of CEOs' general skills on crash risk. The negative relation also remains robust after controlling for CEO traits, corporate culture and other factors known to affect stock price crash risk. In addition, we find that the effect of CEOs' general skills on crash risk is stronger among firms headquartered in a geographical location with a tighter labor market. This is consistent with the notion that generalist CEOs' better employability in the labor market offers a stronger mechanism of career protection by making them more likely to exert their transferable skills. We also find that the relation between CEOs' general skills and crash risk is more prominent among firms with more agency conflicts, supporting the view that generalist CEOs play a greater role in corporate governance, especially for firms more prone to hoarding bad news. Further analyses suggest that improved accounting conservatism and reduced REM activities are the potential channels through which generalist CEOs mitigate bad news hoarding and attenuate crash risk.

Xing et al. (2010) and Yan (2011) suggested that extreme outcomes in the equity market have a material impact on the welfare of investors and that investors are concerned about the occurrence of these extreme outcomes. Our findings suggest that investors would be well served to invest in firms with generalist CEOs and avoid firms with specialist CEOs. Hence, our study offers investors an effective strategy to predict and eschew future stock price crash risk in their portfolio investment decisions.

This study complements the existing literature on the benefits and costs of hiring generalist CEOs. Our results highlight that the general human capital of CEOs improves the information disclosure decisions of firms and attenuates the tail risk of stock returns. Our findings have implications for agency theory that generalist CEOs' outside job opportunities may reduce agency problems due to managers' career concerns. Our findings also have implications for the design of managerial compensation that corporate boards and other stakeholders should take general managerial skills into account when they align CEOs' interests with shareholders' interests. Although we show a positive effect of generalist CEOs on the disclosure of financial information, we need to be cautious when generalizing our results. As shown in the previous studies, generalist CEOs' tolerance for failure may encourage them to take on more risks. Such risk-taking behaviors may be detrimental to other corporate outcomes.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

BFA | 33

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REFERENCES

- Al Mamun, M., Balachandran, B., & Duong, H. N. (2020). Powerful CEOs and stock price crash risk. Journal of Corporate Finance, 62, 101582.
- Ali, A., & Zhang, W. (2015). CEO tenure and earnings management. Journal of Accounting and Economics, 59, 60–79.
- An, H., & Zhang, T. (2013). Stock price synchronicity, crash risk, and institutional investors. Journal of Corporate Finance, 21, 1–15.
- Andreou, P. C., Fiordelisi, F., Harris, T., & Philip, D. (2022). Institutional ownership and firms' thrust to compete. British Journal of Management, 33, 1346–1370.
- Andreou, P. C., Lambertides, N., & Magidou, M. (2023). A critique of the agency theory viewpoint of stock price crash risk: The opacity and overinvestment channels. *British Journal of Management*, 34, 2158–2815.
- Andreou, P. C., Louca, C., & Petrou, A. P. (2016). CEO age and stock price crash risk. Review of Finance, 21, 1287-1325.
- Arena, C., Michelon, G., & Trojanowski, G. (2018). Big egos can be green: A study of CEO hubris and environmental innovation. British Journal of Management, 29, 316–336.
- Armstrong, C. S., & Vashishtha, R. (2012). Executive stock options, differential risk-taking incentives, and firm value. Journal of Financial Economics, 104, 70–88.
- Bao, D., Fung, S. Y. K., & Su, L. (2018). Can shareholders be at rest after adopting clawback provisions? Evidence from stock price crash risk. Contemporary Accounting Research, 35, 1578–1615.
- Basu, S. (1997). The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics*, 24, 3–37.
- Bauer, A. M., Fang, X., & Pittman, J. A. (2021). The importance of IRS enforcement to stock price crash risk: The role of CEO power and incentives. Accounting Review, 96, 81–109.
- Bebchuk, L., Cohen, A., & Ferrell, A. (2009). What matters in corporate governance? Review of Financial Studies, 22, 783–827.

Bergstresser, D., & Philippon, T. (2006). CEO incentives and earnings management. Journal of Financial Economics, 80, 511–529.

- Betzer, A., Lee, H. S. G., Limbach, P., & Salas, J. M. (2020). Are generalists beneficial to corporate shareholders? Evidence from exogenous executive turnovers. *Journal of Financial and Quantitative Analysis*, 55, 581–619.
- Buchholtz, A. K., & Ribbens, B. A. (1994). Role of chief executive officers in takeover resistance: Effects of CEO incentives and individual characteristics. Academy of Management Journal, 37, 554–579.
- Callen, J. L., & Fang, X. (2013). Institutional investor stability and crash risk: Monitoring versus short-termism? Journal of Banking and Finance, 37, 3047–3063.

Callen, J. L., & Fang, X. (2015). Religion and stock price crash risk. Journal of Financial and Quantitative Analysis, 50, 169–195.

- Callen, J. L., & Fang, X. (2017). Crash risk and the auditor-client relationship. Contemporary Accounting Research, 34, 1715– 1750.
- Castanias, R. P., & Helfat, C. E. (2001). The managerial rents model: Theory and empirical analysis. *Journal of Management*, 27, 661–678.
- Chen, G., Luo, S., Tang, Y., & Tong, J. Y. (2015). Passing probation: Earnings management by interim CEOs and its effect on their promotion prospects. Academy of Management Journal, 58, 1389–1418.
- Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, 61, 345–381.
- Christensen, T. E., Huffman, A., Lewis-Western, M. F., & Scott, R. (2022). Accruals earnings management proxies: Prudent business decisions or earnings manipulation? *Journal of Business Finance and Accounting*, 49, 536–587.
- Christensen, T. E., Huffman, A., Lewis-Western, M. F., & Valentine, K. (2023). A simple approach to better distinguish real earnings manipulation from strategy changes. *Contemporary Accounting Research*, 40, 406–450.
- Coff, R., & Kryscynski, D. (2011). Drilling for micro-foundations of human capital-based competitive advantages. Journal of Management, 37, 1429–1443.
- Coles, J. L., Daniel, N. D., & Naveen, L. (2014). Co-opted boards, Review of Financial Studies, 27, 1751–1796.
- Crossland, C., Zyung, J., Hiller, N. J., & Hambrick, D. C. (2014). CEO career variety: Effects on firm-level strategic and social novelty. Academy of Management Journal, 57, 652–674.
- Cuñat, V., & Guadalupe, M. (2009a). Executive compensation and competition in the banking and financial sectors. *Journal of Banking and Finance*, 33, 495–504.
- Cuñat, V., & Guadalupe, M. (2009b). Globalization and the provision of incentives inside the firm: The effect of foreign competition. *Journal of Labor Economics*, 27, 179–212.

- Custódio, C., Ferreira, M. A., & Matos, P. (2013). Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics*, 108, 471–492.
- Custódio, C., Ferreira, M. A., & Matos, P. (2019). Do general managerial skills spur innovation? *Management Science*, 65, 459–476.
- Dechow, P., & Dichev, I. (2002). The quality of accruals and earnings: The role of accruals estimation errors, *Accounting Review*, 77, 35–59.

DeFond, M. L., Hung, M., Li, S., & Li, Y. (2015). Does mandatory IFRS adoption affect crash risk? Accounting Review, 90, 265–299.

- DeFond, M., Erkens, D., & Zhang, J. (2016). Do client characteristics really drive the big N audit quality effect? New evidence from propensity score matching. *Management Science*, 63, 3531–3997.
- Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics, 7, 197–226.
- Ertimur, Y., Rawson, C., Rogers, J. L., & Zechman, S. L. (2018). Bridging the gap: Evidence from externally hired CEOs. Journal of Accounting Research, 56, 521–579.
- Ertugrul, M., Lei, J., Qiu, J., & Wan, C. (2017). Annual report readability, tone ambiguity, and the cost of borrowing. Journal of Financial and Quantitative Analysis, 52, 811–836.
- Fang, X., Li, Y., Pittman, J., & Zeng, Y. (2023). Executive team heterogeneity and information suppression: Evidence from stock price crash risk. SSRN. 4375144.
- Fang, X., Pittman, J., & Zhao, Y. (2021). The importance of director external social networks to stock price crash risk. Contemporary Accounting Research, 38, 903–941.
- Feng, M., Ge, W., Luo, S., & Shevlin, T. (2011). Why do CFOs become involved in material accounting manipulations? Journal of Accounting and Economics, 51, 21–36.
- Francis, B., Hasan, I., & Li, L. (2016). Abnormal real operations, real earnings management, and subsequent crashes in stock prices. Review of Quantitative Finance and Accounting, 46, 217–260.
- Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005). The market pricing of accruals quality. *Journal of Accounting and Economics*, 39, 295–327.
- Ferreira, D., & Sah, R. K. (2012). Who gets to the top? Generalists versus specialists in managerial organizations. The RAND Journal of Economics, 43, 577–601.
- Friedman, H. L. (2014). Implications of power: When the CEO can pressure the CFO to bias reports. Journal of Accounting and Economics, 58, 117–141.
- Frydman, C. (2019). Rising through the ranks: The evolution of the market for corporate executives, 1936–2003. Management Science, 65, 4951–4979.
- Galariotis, E., Louca, C., Petmezas, D., & Wang, S. (2022). Agency cost of debt and inside debt: The role of CEO overconfidence. British Journal of Management, 34, 1606–1631.
- Garicano, L., & Rossi-Hansberg, E. (2006). Organization and inequality in a knowledge economy. *Quarterly Journal of Economics*, 121, 1383–1435.
- Gounopoulos, D., & Pham, H. (2018). Specialist CEOs and IPO survival. Journal of Corporate Finance, 48, 217-243.
- Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, 20, 25–46.
- Ham, C., Lang, M., Seybert, N., & Wang, S. (2017). CFO narcissism and financial reporting quality. *Journal of Accounting Research*, 55, 1089–1135.
- Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. Academy of Management Review, 9, 193–206.
- Hanlon, D., Khedmati, M., Lim, E. K., & Truong, C. (2023). Boardroom backscratching and stock price crash risk. *Journal of Business Finance & Accounting*, forthcoming.
- Harris, D., & Helfat, C. (1997). Specificity of CEO human capital and compensation. Strategic Management Journal, 18, 895–920.
- Hermalin, B. E., & Weisbach, M. S. (2012). Information disclosure and corporate governance. Journal of Finance, 67, 195-233.
- Hoberg, G., Phillips, G., & Prabhala, N. (2014). Product market threats, payouts, and financial flexibility. *Journal of Finance*, 69, 293–324.
- Hong, H., & Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. Review of Financial Studies, 16, 487–525.
- Huang, J., & Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics*, 108, 822–839.
- Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R², and crash risk. Journal of Financial Economics, 94, 67–86.
- Jin, L., & Myers, S. C. (2006). r2 around the world: New theory and new tests. Journal of Financial Economics, 79, 257–292.
- Khan, M., & Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics*, 48, 132–150.
- Khurana, I. K., Pereira, R., & Zhang, E. (2018). Is real earnings smoothing harmful? Evidence from firm-specific stock price crash risk. *Contemporary Accounting Research*, 35, 558–587.

- Kim, J.-B., Li, Y., & Zhang, L. (2011a). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, 101, 713–730.
- Kim, J.-B., Li, Y., & Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level analysis. Journal of Financial Economics, 100, 639–662.
- Kim, J.-B., Wang, Z., & Zhang, L. (2016). CEO overconfidence and stock price crash risk. Contemporary Accounting Research, 33, 1720–1749.
- Kim, J.-B., & Zhang, L. (2016). Accounting conservatism and stock price crash risk: Firm-level evidence. Contemporary Accounting Research, 33, 412–441.
- Kim, J., Luo, L., & Xie, H. (2018). The bright side of paying dividends: Evidence from stock price crash risk [Technical report. Working paper], City University of Hong Kong and University of Kentucky.
- Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. Journal of Banking and Finance, 43, 1–13.
- Knyazeva, A., Knyazeva, D., & Masulis, R. W. (2013). The supply of corporate directors and board independence. Review of Financial Studies, 26, 1561–1605.
- Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. Journal of Accounting and Economics, 39, 163–197.
- Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? Journal of Accounting Research, 47, 241–276.
- Krishnamurti, C., Chowdhury, H., & Han, H. D. (2021). CEO centrality and stock price crash risk. Journal of Behavioral and Experimental Finance, 31, 100551.
- Li, K., Mai, F., Shen, R., & Yan, X. (2021). Measuring corporate culture using machine learning. *Review of Financial Studies*, 34, 3265–3315.
- Li, M., & Patel, P. C. (2019). Jack of all, master of all? CEO generalist experience and firm performance. The Leadership Quarterly, 30, 320–334.
- Li, S., & Zhan, X. (2019). Product market threats and stock crash risk. Management Science, 65, 4011–4031.
- Li, Y., & Zeng, Y. (2019). The impact of top executive gender on asset prices: Evidence from stock price crash risk. *Journal of Corporate Finance*, 58, 528–550.
- Ma, Z., Ruan, L., Wang, D., & Zhang, H. (2021). Generalist CEOs and credit ratings. Contemporary Accounting Research, 38, 1009– 1036.
- Mackey, A. (2008). The effect of CEOs on firm performance. Strategic Management Journal, 29, 1357–1367.
- Markarian, G., & Parbonetti, A. (2007). Firm complexity and board of director composition. Corporate Governance: An International Review, 15, 1224–1243.
- Miller, D., Xu, X., & Mehrotra, V. (2015). When is human capital a valuable resource? The performance effects of Ivy League selection among celebrated CEOs. Strategic Management Journal, 36, 930–944.
- Mishra, D. R. (2014). The dark side of CEO ability: CEO general managerial skills and cost of equity capital. *Journal of Corporate Finance*, 29, 390–409.
- Murphy, K. J., & Zabojnik, J. (2004). CEO pay and appointments: A market-based ex-planation for recent trends. American Economic Review, 94, 192–196.
- Nagar, V. (1999). The role of the manager's human capital in discretionary disclosure. *Journal of Accounting Research*, 37, 167–181.
- Nagar, V., Nanda, D., & Wysocki, P. (2003). Discretionary disclosure and stock-based incentives. *Journal of Accounting and Economics*, 34, 283–309.
- Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37, 187–204.
- Oyer, P. (2004). Why do firms use incentives that have no incentive effects? Journal of Finance, 59, 1619–1650.
- Parrino, R. (1997). CEO turnover and outside succession A cross-sectional analysis. *Journal of Financial Economics*, 46, 165–197.Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22, 435–480.
- Quigley, T. J., & Hambrick, D. C. (2015). Has the "CEO effect" increased in recent decades? A new explanation for the great rise in America's attention to corporate leaders. *Strategic Management Journal*, 36, 821–830.
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70, 41–55.
- Roychowdhury, S. (2006). Earnings management through real activities manipulation. Journal of Accounting and Economics, 42, 335–370.
- Verrecchia, R. E. (2001). Essays on disclosure. Journal of Accounting and Economics, 32, 97-180.
- Waldman, D. A., Ramirez, G. G., House, R. J., & Puranam, P. (2001). Does leadership matter? CEO leadership attributes and profitability under conditions of perceived environmental uncertainty. *Academy of Management Journal*, 44, 134–143.
- Xing, Y., Zhang, X., & Zhao, R. (2010). What does the individual option volatility smirk tell us about future equity returns? Journal of Financial and Quantitative Analysis, 45, 641–662.

Xu, N., Li, X., Yuan, Q., & Chan, K. C. (2014). Excess perks and stock price crash risk: Evidence from China. Journal of Corporate Finance, 25, 419–434.

Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics*, *99*, 216–233. Yonker, S. E. (2017). Geography and the market for CEOs. *Management Science*, *63*, 609–630. Zhu, W. (2016). Accruals and price crashes. *Review of Accounting Studies*, *21*, 349–399.

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APPENDIX A

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36

TABLE A1 Variables definitions.

Variables	Definitions	Sources
Main crash risk variables		
NCSKEW	The negative coefficient of skewness, defined as the negative ratio of the third moment of firm-specific weekly returns to the cubed sample standard deviation over a fiscal year (Chen et al., 2001), where a firm-specific weekly return is the natural logarithm of one plus the residual estimated from an extended market model	CRSP
DUVOL	The natural logarithm of the ratio of the standard deviation of firm-specific weekly returns in the "down-week" sample to the standard deviation in the "up-week" sample over a fiscal year, where "down-(up-)weeks" are those with firm-specific weekly returns below (above) the annual mean (Chen et al., 2001)	CRSP
CEO-level variables		
GAI	The index of general managerial ability that incorporates five aspects of a CEO's lifetime career experience, including the past number of (i) positions, (ii) firms and (iii) industries in which the CEO worked; (iv) whether the CEO held a CEO position at a different company and (v) whether the CEO worked for a conglomerate firm (Custódio et al., 2013). The index is the first factor of the PCA of the five proxies	BoardEx
GAI_Dummy	An indicator variable that equals one if a CEO's GAI is above the 75th percentile in a fiscal year, and zero otherwise (Custódio et al., 2013)	BoardEx
CEO_Equity_Inc	The incentive ratio for a CEO's option holdings, defined as Onepct/(Onepct + Salary + Bonus), where Onepct is the dollar change in the value of a CEO's option holdings resulting from a 1% increase in the firm's stock price (Bergstresser & Philippon, 2006)	ExecuComp
CEO_Age	CEO age	ExecuComp
CEO_Tenure	The number of years in the current CEO position	ExecuComp

TABLE A1 (Continued)

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IABLEA1 (Continu	ied)	
Variables	Definitions	Sources
CEO_Gender	An indicator variable that equals one if a CEO is female, and zero otherwise	ExecuComp
CEO_External_Hire	An indicator variable that equals one if a CEO is hired outside the incumbent company, and zero otherwise	BoardEx
CEO_lvy_League	An indicator variable that equals one if a CEO attended an Ivy League university (i.e., Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania and Yale University) at any academic level, and zero otherwise	BoardEx
CEO_Army	An indicator variable that equals one if a CEO has military experience, and zero otherwise	BoardEx
CEO_TC	The natural logarithm of CEO total compensation	ExecuComp
BST	An indicator variable that equals one if a firm's CEO and board of directors engage in backscratching, and zero otherwise	Incentive Lab, BoardEx and ExecuComp
Other firm-level variable	es	
DTURN	Detrended stock turnover, defined as the difference between the average monthly share turnover over fiscal year $t - 1$ and the average monthly share turnover over fiscal year t , where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding over the month (Kim et al., 2011a)	CRSP
SIGMA	The standard deviation of firm-specific weekly returns over a fiscal year (Kim et al., 2011a)	CRSP
RET	The mean of firm-specific weekly returns over a fiscal year, multiply by 100 (Kim et al., 2011a)	CRSP
SIZE	Firm size, defined as the natural logarithm of market capitalization at the end of a fiscal year (Kim et al., 2011a)	Compustat
МТВ	Market-to-book ratio, defined as the ratio of the market value of equity to the book value of equity at the end of a fiscal year (Kim et al., 2011a)	Compustat
LEV	Financial leverage, defined as the ratio of the sum of current liabilities and long-term debt to the lag total assets, measured at the end of a fiscal year (Kim et al., 2011a)	Compustat
ROE	Return on equity, defined as the ratio of net income divided by the lagged book value of equity, measured at the end of a fiscal year	Compustat
OPAQUE	The absolute value of the annual performance-adjusted discretionary accruals developed by Kothari et al. (2005)	Compustat
CASH_ETR	The cash taxes paid scaled by pretax book income after removing the effects of special items, set as missing when the denominator is zero or negative	Compustat

(Continues)

TABLE A1 (Continued)

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38

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Variables	Definitions	Sources
KURT	The kurtosis of firm-specific weekly returns over a fiscal year	CRSP
AUDIT_Tenure	An indicator variable that equals one if the number of consecutive years that an auditor has been employed by a firm in a fiscal year is greater than five, and zero otherwise	Audit analytics
DIVIDEND	An indicator variable that equals one if a firm has a positive dividend payout over a fiscal year, and zero otherwise	Compustat
BIG4	An indicator that equals one if a firm is audited by one of the Big Four auditors (or their predecessors), and zero otherwise	Compustat
ANALYST_Num	The natural logarithm of one plus the number of analysts that issue earnings forecasts for a firm in the fiscal year	IBES
LONG	The percentage of shares outstanding held by "dedicated" and "quasi-indexer" institutional investors at the end of a fiscal year	13f and BB
SHORT	The percentage of shares outstanding held by "transient" institutional investors at the end of a fiscal year	13f and BB
TIGHT	An indicator variable that equals one if the annual unemployment rate in the MSA where a firm's headquarter locates is less than the annual sample median, and zero otherwise	BLS
CEO AGE	An indicator variable that equals one if a CEO's age is above the sample median, and zero otherwise	ExecuComp
COMPLEXITY	An indicator variable that equals one if the percentage of a firm's sales with respect to the total sales within the industry (<i>Sales-to-Ind</i>) is larger than the annual sample median of Sales-to-Ind, and zero otherwise	Compustat
FLUIDITY	An indicator variable that equals one if product market fluidity developed by Hoberg et al. (2014) is greater than the annual sample median, and zero otherwise	HP
DISTANCE	An indicator variable that equals one if the distance between the county where a firm is headquartered and the closest SEC regional or national office is within 100 km, and zero otherwise	EDGAR 10-K
CSCORE	A firm-year measure of conditional accounting conservatism introduced by Khan and Watts (2009)	Compustat
REM	The sum of the values of three real earnings management measures developed by Roychowdhury (2006): abnormal operating cash flow, abnormal production costs, and abnormal discretionary expenses	Compustat

(Continues)

TABLE A1 (Continued)



TABLEA1 (Continued)		
Variables		Definitions	Sources
PCA_REM		First component from a PCA of AbnLowExp, AbnLowCFO, AbnHighProd, LitigiousCircuit, LitigiousIndustry and PastAM (Christensen et al., 2023)	Compustat
PAC_AREM		First principal component from a principal component analysis of one accruals earnings management measure and three real earnings management measures (Christensen et al., 2022)	Compustat
SALES_Vol		The standard deviation of sales scaled by total assets over the past 5 years (Ham et al., 2017)	Compustat
SALES_Growth		The percentage change in sales over the previous year (Ham et al., 2017)	Compustat
CF_Vol		The standard deviation of operating cash flows scaled by total assets over the last 5 years (Ham et al., 2017)	Compustat
AGE		The number of years since a firm first appeared in Compustat (Ham et al., 2017)	Compustat
INTEGRITY		Weighted-frequency count of integrity-related words in the earnings call conference transcripts over 3 years (Li et al., 2021)	LMSY
TEAMWORK		Weighted-frequency count of teamwork-related words in the earnings call conference transcripts over 3 years (Li et al., 2021)	LMSY
INNOVATION		Weighted-frequency count of innovation-related words in the earnings call conference transcripts over 3 years (Li et al., 2021)	LMSY
RESPECT		Weighted-frequency count of respect-related words in the earnings call conference transcripts over 3 years (Li et al., 2021)	LMSY
QUALITY		Weighted-frequency count of quality-related words in the earnings call conference transcripts over 3 years (Li et al., 2021)	LMSY
THRUST_TO_C	COMPETE	Decile rank of thrust to compete computed each fiscal year based on the Fama–French (1997) 48 industry classification	SEC EDGAR
BOARD_Size		The natural logarithm of the number of board directors	BoardEx
DIRECTOR_Tenu	re	The natural logarithm of the average director tenure	BoardEx
IND_Director_Ra	tio	The ratio of the number of independent board directors to the total number of board directors	BoardEx
Female_Director_	Ratio	The ratio of the number of female board directors to the total number of board directors	BoardEx
СООРТ		The ratio of the number of co-opted independent directors to the total number of board directors (Coles et al., 2014)	LN
			(Continue

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FANG ET AL.

40 | JBFA

TABLEA1 (Continued)

Variables	Definitions	Sources
DUALITY	An indicator variable that equals one if a firm has a CEO	ExecuComp
FOUNDER	as the Chairman of the board, and zero otherwise An indicator variable that equals one if a firm has a CEO as the founder of the firm, and zero otherwise	ExecuComp
CEO_STK_Ownership	A CEO's equity ownership	ExecuComp
EINDEX	Bebchuk et al. (2009)'s entrenchment index	RiskMetrics
COUNT	The number of firm-specific weekly returns exceeding 3.2 standard deviations below the mean of firm-specific weekly return over a fiscal year, minus the number of firm-specific weekly returns exceeding 3.2 standard deviations above the mean of firm-specific weekly return over the fiscal year (Kim et al., 2011a)	CRSP

Note: This table provides variable definitions and corresponding data sources. CRSP refers to the Center for Research in Security Prices, ExecuComp refers to Standard and Poor's Executive Compensation database, IBES refers to the Institutional Brokers Estimate System, 13f refer to the Thompson Reuters Institutional Managers Holdings database, BLS refers to the website of the US Bureau of Labor Statistics, BB refers to Brian Bushee's personal website, HP refers to the Hoberg-Phillips Data Library, EDGAR 10-K refers to the annual financial statements from the Electronic Data Gathering, Analysis and Retrieval database, LMSY refers to Li et al. (2021), and LN refers to Lalitha Naveen's website.

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