Generalist CEOs and Debt Concentration*

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Abstract

We document a negative relation between CEOs' general skills and corporate debt concentration using a sample of S&P 1500 firms during 2000–2017. This negative relation is robust to numerous alternative measures, alternative specifications, and different identification tests to mitigate endogeneity. Our path analyses suggest that generalist CEOs reduce debt concentration through increasing conditional accounting conservatism and the likelihood of voluntary managerial disclosure. Consistent with the financial information efficiency mechanism, the negative relation between CEO general skills and debt concentration is stronger for firms with more financial constraints, worse internal governance, weaker external monitoring, lower management team ability, more R&D expenses, and lower credit rating. Our findings support the view that generalist CEOs' broader job market opportunities reduce their incentives to hide bad news and their extensive work experience helps them communicate with creditors more efficiently, leading to a less concentrated debt structure.

JEL classification: G30; G32; J24; J53
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1. Introduction

Although CEOs with extensive general managerial skills demand a significant pay premium in the executive labor market (Custódio et al., 2013; Crossland et al., 2014), firms headed by generalist CEOs do not receive advantageous terms in external financing. Since general managerial skills are transferable across industries or firms, generalist CEOs' external job options mitigate their career concerns and encourage them to engage in more risky projects (Custódio et al., 2019). Due to generalist CEOs' risk-taking incentives, firms with generalist CEOs have higher required costs of equity (Mishra, 2014) and lower credit ratings (Ma et al., 2021a). The capital market's negative perception of generalist CEOs in addition to their sought-after experience in the labor market motivates us to further examine their role in corporate financing decisions. It remains unclear whether, and how, generalist CEOs affect firms' ability to borrow from different types of debt creditors. This study examines the link between CEO general skills and the degree of debt concentration measured across debt types.

Earlier theoretical literature shows that a dispersed debt structure leads to coordination and free-riding problems among creditors, especially during debt renegotiation (e.g., Asquith et al., 1994; Bolton and Scharfstein, 1996; Bris and Welch, 2005). A recent study by Zhong (2021) develops a dynamic model of optimal debt concentration and indicates that the number of creditors in equilibrium depends on a dynamic trade-off between the risk of debt rollover failure and the benefits of more pledgeability to pay back creditors. Consistent with the theoretical analyses, empirical evidence suggests that US public firms exhibit a great cross-sectional heterogeneity in the degree of debt concentration (e.g., Rauh and Sufi, 2010; Colla et al., 2013). In line with the coordination perspective, recent empirical studies show that firms with higher accounting quality (Platikanova and Soonawalla, 2020; Li et al., 2021), lower risk-taking incentives in CEO pay (Castro et al., 2020), and weaker country-level creditor protection (John et al., 2021) tend to have less debt concentration.

On the one hand, CEO general skills may help firms borrow debt from diverse sources and with various contractual features. First, using multiple debt types not only increases creditor coordination costs during debt renegotiation (Asquith et al., 1994) but also makes debt renegotiation more difficult due to cross-acceleration and cross-default provisions (Beatty et al., 2012). Li et al. (2021) show that transparent accounting information reduces information asymmetry and facilitates creditor coordination, therefore firms with higher accounting quality borrow from more diversified debt sources. Since generalist CEOs' popularity in the executive labor market naturally offers them a higher tolerance for failure, they have weaker incentives to talk up firms' short-term performance and withhold bad news from outside investors (Custódio et al., 2019; Girardone et al., 2022). Second, generalist CEOs' strong networks built through their diversified professional career enable them to reach agreements with different creditors. Based on a sample of Chinese firms, Xu et al. (2021) find that generalist top executives' social networks help firms enlist more target firms' financial institution shareholders and politically-connected directors after mergers and acquisitions (M&As). Third, generalist CEOs' broad expertise and diverse work experience help firms reduce organizational communication costs (Ferreira and Sah, 2012) and improve the outcomes of complex projects such as corporate restructuring and acquisitions (Custódio et al., 2013; Xu et al., 2021). Therefore, generalist CEOs' extensive cross-sector negotiation and debt restructuring experience help them to better communicate with different creditors, which facilitates debt rollovers and renegotiation and reduces creditors' coordination costs. Last, a dispersed debt structure makes it difficult for multiple creditors to coordinately renegotiate with borrowers, which deters strategic defaults (Bolton and Scharfstein, 1996). Since it takes less time for generalist CEOs to find a new job than specialist CEOs after forced turnovers (Custódio et al., 2019), generalist CEOs have the incentive to choose strategic default even though their firms are still able to service the debt. Borrowing from multiple debt sources can prevent generalist CEOs from choosing strategic defaults.

On the other hand, CEO general skills can deter firms from borrowing from multiple creditors. Since the executive labor market is much more fluid for generalist CEOs, they enjoy high tolerance for failure and have an incentive to take excessive risks. Mishra (2014) argues that generalist CEOs' long-term wealth is less contingent on the future prosperity of their firms, so they tend to invest in risky projects without fearing the rise of bankruptcy risks. Consistent with this view, Ma et al. (2021a) show that firms managed by generalist CEOs have lower credit ratings and higher borrowing costs. Generalist CEOs' risk-taking incentives could also affect firms' debt structure. Bris and Welch's (2005) model indicates that debt concentration in equilibrium depends on the trade-off between in-bankruptcy collection deadweight costs and pre-bankruptcy deadweight agency and signaling costs.[1] Castro et al. (2020) argue that CEOs' risk-taking incentives are positively related to the agency and signaling costs specified in Bris and Welch's (2005) model. Creditors' negative perception of generalist CEOs' risk-taking behavior can be mitigated by a concentrated debt structure, which offers creditors more protection in the case of bankruptcy. Castro et al. (2020) show that firms with a higher Vega or Delta of CEO pay adopt a more concentrated debt structure. In a similar vein, generalist CEOs' risk-taking activities may reduce debt concentration.

How CEO general skills affect debt structure is ultimately an empirical question. To provide systematic evidence on this unresolved issue, we examine the relation between CEO general skills and debt concentration in a sample of S&P 1500 firms from 2000 to 2017, during which the data on firms' debt structure and Custódio et al.'s (2013) general skill index are available. The general skill index reflects five features of a CEO's work experience: the number of positions, companies, and industries in which the CEO has worked, whether the CEO took a CEO position at a different firm, and whether the CEO has worked for a conglomerate firm. To mitigate the concern that our empirical findings are subject to the choice of debt concentration proxies, we employ three measures of debt concentration: a normalized Herfindahl–Hirschman Index based on the percentage of different debt types, an indicator variable that is equal to one if a firm obtains at least 90% debt borrowing from

[1] The former is materialized when firms file bankruptcy and results in less debt concentration, while the latter is materialized before firms file bankruptcy and leads to more debt concentration.

a single debt type, and the number of different debt types. Our baseline regression results show that there is a negative relation between CEO general skills and debt concentration after controlling for a set of firm characteristics and the Fama–French 48 industry and year fixed effects. A one-standard-deviation increase in CEO general skills is associated with a decrease by 4.5% of the average within-firm standard deviation of the normalized Herfindahl–Hirschman Index.

Similar to previous studies investigating the impact of managerial characteristics on corporate practices, our empirical setting needs to address the potential endogeneity concern due to self-selection bias, reverse causality, and omitted variable issues. Specifically, the propensity of a generalist CEO to join a firm and the firm's debt structure could both be driven by some firm-specific and industry-specific variables which are not accounted for in our baseline regressions. We adopt three identification tests to establish a causal relation between CEO general skills and debt concentration: (1) propensity score matching (PSM), (2) entropy balancing matching (EB), and (3) difference-in-difference (DID) test utilizing exogenous CEO turnovers. The negative relation between CEO general skills and debt concentration remains robust in all three identification tests, supporting a causal interpretation of our finding. Although our identification tests cannot fully correct for the endogeneity bias, these tests reduce the likelihood that our main finding is driven by endogenous matching or omitted variables.

Moving on from our identification tests, we next conduct supplementary tests to better understand the potential mechanisms through which CEO general skills are related to debt concentration. Li et al. (2021) show that since higher accounting quality helps reduce creditors' coordination costs, firms with higher accounting quality are able to borrow from diversified lenders. Using a path analysis, we include conditional accounting conservatism and voluntary managerial disclosure as separate mediating variables, measuring firms' financial information quality. We find that CEO general skills are positively related to conditional accounting conservatism and the likelihood of voluntary managerial disclosure. More importantly, we find that the two mediated paths through conditional accounting conservatism and voluntary managerial disclosure significantly explain the decrease in debt concentration.

We also perform cross-sectional analyses to examine whether and how various manager-, firm-, and industry-level variables moderate the negative relation between CEO general skills and debt concentration. If generalist CEOs reduce debt concentration through improving financial information efficiency, this negative relation should exhibit cross-sectional variations with respect to the variables that can affect firms' accounting quality or information asymmetry. In line with this intuition, we find that the negative relation between CEO general skills and debt concentration is indeed more prominent for firms with more financial constraints, worse internal governance, weaker external monitoring, lower management team ability, more R&D expenses, and lower credit rating.

In additional robustness checks, we show that our main finding continues to hold when we replace the CEO general skill index with a generalist CEO indicator variable that is equal to one if the index value is above the annual sample median and zero otherwise, and control for CEOs' risk-taking incentives, age, tenure, gender, ownership, power, as well as CEO fixed effects. Finally, we examine how CEOs' general skills affect firms' choice of individual types of debt. We find that CEOs' general skills are positively related to the likelihood of using senior bonds and notes and other debt.[2]

Our paper's main contribution to the literature is that we uncover a positive role of CEOs' general managerial skills in corporate external borrowing. Recent studies have documented a negative capital market reaction to firms hiring generalist CEOs by showing that CEOs' general managerial skills are positively related to equity and debt borrowing costs (Mishra, 2014; Ma et al., 2021a). Our paper highlights that generalist CEOs help firms to borrow from a diversified base of creditors by mitigating the information asymmetry between firms and creditors. Our finding provides empirical evidence to justify why general managerial skills have become a desirable trait in the US executive labor market (Crossland

[2] "Other debt" refers to the remaining debt in a firm's capital structure which is not classified as an individual debt type by Capital IQ, such as unclassified short-term borrowings, deferred credits, fair value adjustments related to hedging contracts, and trust-preferred securities (Colla et al., 2013).

et al., 2014; Ertimur et al., 2018). Our study also contributes to the literature on the determinants of debt concentration by debt type. Previous studies have focused on how firm-level and country-level characteristics affect a firm's debt structure (e.g., Giannetti, 2019; Platikanova and Soonawalla, 2020; John et al., 2021; Li et al., 2021). At the manager level, Castro et al. (2020) show that CEOs' risk-taking incentives in executive pay increase the degree of debt concentration. We push this strand of research forward by showing that it is important to consider CEOs' general human capital when explaining the cross-sectional variations of debt concentration among US public firms.

The paper proceeds as follows. Section 2 reviews related literature and develops our testable hypothesis. Section 3 discusses the sample selection, measurement of key variables, and research design. Section 4 presents the descriptive statistics and main empirical results. Section 5 provides supplementary analyses and robustness checks. Section 6 concludes the paper.

2. Related literature and hypothesis development

2.1. Prior research on generalist CEOs

In proposing a multi-agent communication model, Ferreira and Sah (2012) show that people holding higher positions in multi-layered hierarchies tend to have more general skills, and the value of general skills increases when organizations are more complex and face more uncertainties. Empirical studies on executive compensation suggest that generalist CEOs receive higher compensation than specialist CEOs (e.g., Murphy and Zabojnik, 2004; Custódio et al., 2013; Frydman, 2019), supporting the view that generalist CEOs' breadth of work experience and broad knowledge beyond their current firms' technology domain increase their labor market value. Generalist CEOs' compensation premium is usually higher when they are hired externally (Custódio et al., 2013; Liu et al., 2021) and when they are appointed to lead challenging projects or manage complex enterprises (Custódio et al., 2013; Brockman et al., 2016).

Despite the existence of a generalist pay premium, previous studies document both the positive and negative roles of generalist CEOs in corporate activities. On the bright side, firms managed by generalist CEOs have higher internal capital allocation efficiency (Xuan, 2009), more firm-level strategic novelty in terms of strategic dynamism and strategic distinctiveness (Crossland et al., 2014), better patent-based innovation metrics (Custódio et al., 2019), better operating performance (Betzer et al., 2020), more value creation in M&As (Chen et al., 2021; Xu et al., 2021), higher pay-for-performance sensitivity (Liu et al., 2021), and lower future stock price crash risk (Girardone et al., 2022). These studies reinforce the managerial ability view that general skills are beneficial in leading complex and challenging corporate tasks (Cuñat and Guadalupe, 2009; Custódio et al., 2013). Custódio et al. (2019) and Girardone et al. (2022) also highlight that generalist CEOs' competitiveness in the external labor market increases their tolerance for failure, which mitigates their career concern and reduces their incentives to withhold bad news.

On the dark side, firms operated by generalist CEOs have higher equity financing costs (Mishra, 2014), a higher probability of initial public offering (IPO) failure and a shorter time to survive after IPOs (Gounopoulos and Pham, 2018), lower Tobin's Q (Li and Patel, 2019), less corporate social responsibility activities (Chen et al., 2020), worse credit ratings and higher debt financing costs (Ma et al., 2021a), and higher audit fees (Ma et al., 2021b). This strand of literature emphasizes the possibility that the favorable labor market for CEOs with general managerial skills results in an agency problem – excessive managerial risk-taking. Since generalist CEOs' managerial skills are easily transferable across firms and industries, they have more outside job options and a higher tolerance for failure. When generalist CEOs' long-term interests are not aligned with their firms' future prospects, they tend to invest in risky projects.

2.2. Literature on debt concentration

The theoretical literature on debt structure highlights the trade-off between the costs and benefits of borrowing from multiple creditors (e.g., Bolton and Scharfstein, 1996; Park, 2000; Bris and Welch, 2005; Zhong, 2021; Gan et al., 2022). Bolton and Scharfstein (1996) develop a model of optimal debt structure that focuses on how debt structure affects firms' default negotiations. After balancing debt default determent and the reduction of unavoidable default costs, they predict that firms with low default risk tend to borrow from more creditors. Bris and Welch's (2005) model emphasizes the mutual free-riding problem among multiple creditors when they have to negotiate with financially distressed borrowers. Bris and Welch (2005) show that by borrowing from more creditors, firms take advantage of the failure of creditors' coordination in the event of financial distress, while creditors charge higher interest rates for firms with a diverse debt structure. In a similar vein, Zhong (2021) develops a dynamic model in which firms optimally adjust the number of creditors during repeated short-term debt rollovers, according to the trade-off between the costs of rollover failure and the benefits of better commitment power.[3]

Based on 305 randomly selected non-financial rated public firms, Rauh and Sufi (2010) show that about 75% of their sample firms have multiple debt instruments. However, Colla et al. (2013) provide large sample evidence that 85% firms covered by Capital IQ only utilize one type of debt. A recent strand of empirical studies examines the factors related to debt structure and shows that firms with higher risk-taking incentives in CEO pay (Castro et al., 2020) or operating in countries with stronger creditor protection (John et al., 2021) have a more concentrated debt structure. Other research implies that firms with a lower likelihood of experiencing a severe turnover reduction (Giannetti, 2019), better accrual quality (Platikanova and Soonawalla, 2020) and accounting quality (Li et al., 2021), and more covenants in new debt contracts (Lou and Otto, 2020) have a less concentrated debt structure.

[3]Firms with lower commitment power have worse credibility and more restricted debt financing capacity.

2.3. Hypothesis development

Generalist CEOs' broad expertise is taken as a signal of high managerial ability in modern business. Unlike specific managerial skills that are highly valuable for a certain firm or within a particular industry, general managerial skills are readily transferable across entities and sectors. Consistent with this notion, earlier studies show that generalist CEOs are frequently approached by executive search consultants and have a more favorable external job market (e.g., Giannetti, 2011; Custódio et al., 2013; Crossland et al., 2014). Based on a sample of forced CEO turnovers, Custódio et al. (2019) show that it takes an average of 8 months for generalist CEOs while an average of 20 months for specialist CEOs to find a new job after forced turnovers. Therefore, generalist CEOs have weaker career concerns and fewer incentives to talk up firms' short-term performance (Custódio et al., 2019; Girardone et al., 2022). Pae's (2021) theoretical model implies a negative empirical relation between managerial career concerns and financial reporting quality. Baginski et al. (2018) provide empirical evidence that managers' career concerns encourage them to withhold bad news. Specifically, Girardone et al. (2022) show that firms managed by generalist CEOs are less likely to delay bad news and boost short-term firm performance, leading to lower future stock price crash risk.

Multiple creditors have to coordinate and agree on debt restructuring procedures when borrowers default. Therefore, it is costly for firms with a dispersed debt structure to renegotiate with multiple creditors within the same debt types or across different debt types (e.g., Gertner and Scharfstein, 1991; Asquith et al., 1994; Berglöf and Von Thadden, 1994; Bolton and Scharfstein, 1996; Colla et al., 2013; Ivashina et al., 2016). Li et al. (2021) argue that high-quality accounting information not only reduces information asymmetry between firms and investors but also lowers the coordination costs among creditors of different debt types. High-quality accounting information can assist different lenders to evaluate firm value and facilitate their coordination during debt renegotiations, therefore high accounting quality moderates the risk and potential costs of multi-creditor coordination failures. Even if creditor coordination fails during debt renegotiations, firms with higher quality accounting information are more likely to get their Chapter 11 reorganization plan accepted by their creditors (Warner, 1977; Weiss, 1990) or achieve a higher liquidation value during Chapter 7 liquidation processes (Bolton and Scharfstein, 1996). Li et al. (2021) provide empirical evidence that higher accounting quality is indeed associated with less debt concentration. Since generalist CEOs improve the quality of financial reporting, we predict that firms managed by generalist CEOs tend to choose a less concentrated debt structure.

Generalist CEOs, who have worked in various positions, firms, and industries, may build up strong connections with different financial institutions. In addition, generalist CEOs' diverse working experience helps their firms form reliable strategic alliances with corporate stakeholders, such as suppliers, customers, competitors, and creditors, which improves the effectiveness of information processing and communication (Ma et al., 2021b). Ferreira and Sah (2012) argue that firms with generalist CEOs incur lower communication costs between CEOs and their subordinates. Xu et al. (2021) also show that generalist CEOs enlist more financial institution shareholders and politically-connected independent directors after M&As to enhance the long-term financing of the merged firms. Therefore, the wider network and better communication ability of generalist CEOs can also help their firms to borrow from more creditors. We formally state our null hypothesis as:

> ***H_0:*** *There is a negative association between CEOs' general skills and debt concentration.*

It is important to stress that the broader set of external job options available to generalist CEOs encourages them to take more risks without fearing the effect of risk-taking on the longevity of their firm (Mishra, 2014; Custódio et al., 2019). Consistent with this view, Ma et al. (2021a) find that due to generalist CEOs' risk-taking incentives, firms with generalist CEOs have lower credit ratings and higher debt borrowing costs. Creditors' negative perception of generalist CEOs' risk-taking tendency can be mitigated by a more concentrated debt structure, which offers creditors more protection in the case of firm bankruptcy. As in the spirit of Bris and Welch's (2005) model, the choice of a more concentrated debt structure acts as a valuable signaling mechanism to reassure lenders. Castro et al. (2020) also provide empirical evidence that when CEOs' pay offers more risk-taking incentives, firms rely on fewer debt types. Generalist CEOs' risk-taking tendency generates an ex-ante tension regarding the impact of CEO general skills on debt concentration. It comes down to an empirical question as to whether generalist CEOs have a positive or negative effect on debt concentration. Our alternative hypothesis is formulated as follows:

> $\boldsymbol{H_a}$**:** *There is a positive association between CEOs' general skills and debt concentration.*

3. Sample and research design

3.1. Data sources and sample

We obtain the data on CEOs' general ability index from Custódio et al. (2013) who extend their data to 2016.[4] Following Colla et al. (2013), we collect firm-level debt structure data from Capital IQ, which starts providing debt data from 2001. Therefore, our effective sample for CEOs' general skills and control variables is between 2000 and 2016, while the effective sample for debt concentration variables is between 2001 and 2017. The data on CEO traits are from the ExecuComp database. The data on firm-level accounting and financial variables are from the Compustat database. The data on firm age are from the Center for Research in Security Prices (CRSP). We download the data on co-opted directors from Lalitha Naveen's website and the data on managerial ability scores from Peter Demerjian's website. Firms in the financial industry (SIC codes 6000 to 6999) are excluded from our sample because they are highly levered and their debt structure is fundamentally different from non-financial firms'. We also exclude firms in the highly regulated utility

[4]We would like to thank Cláudia Custódio for sharing the data on the CEOs' general ability index.

industry (SIC codes 4900 to 4999) from our sample. Following the debt concentration literature (e.g., Colla et al., 2013; Li et al., 2021), we drop firm–year observations with zero and missing values of debt and total assets and observations with the value of debt above the value of total assets. We also drop firm–year observations when the differences in their total debt between Compustat reported values and Capital IQ report values are higher than 10% of the Compustat reported values. Our final sample covers 8,704 firm–year observations for 1,412 unique firms. We winsorize all the continuous variables at the 1st and 99th percentile values.

3.2. Dependent variables: Debt concentration

Following Colla et al. (2013) and Li et al. (2021), we construct three measures of debt concentration. Our first measure is the normalized Herfindahl–Hirschman Index (*HHI*) across the seven mutually exclusive types of debt used by a firm. Capital IQ decomposes a firm's total debt into: commercial paper (*CP*), drawn credit lines (*DC*), term loans (*TL*), senior bonds and notes (*SBN*), subordinated bonds and notes (*SUB*), capital leases (*CL*), and other debt (*Other*).[5] Thus, for firm i at the end of fiscal year t, we first calculate $SS_{i,t}$:

$$SS_{i,t} = (\frac{CP_{i,t}}{TD_{i,t}})^2 + (\frac{DC_{i,t}}{TD_{i,t}})^2 + (\frac{TL_{i,t}}{TD_{i,t}})^2 + (\frac{SBN_{i,t}}{TD_{i,t}})^2 + (\frac{SUB_{i,t}}{TD_{i,t}})^2 + (\frac{CL_{i,t}}{TD_{i,t}})^2 + (\frac{Other_{i,t}}{TD_{i,t}})^2 \quad (1)$$

We then normalize $SS_{i,t}$ to obtain $HHI_{i,t}$ so that $HHI_{i,t}$ is between zero and one:

$$HHI_{i,t} = \frac{SS_{i,t} - 1/7}{1 - 1/7} \quad (2)$$

$HHI_{i,t}$ takes the maximum value of one if a firm only employs one type of debt, while $HHI_{i,t}$ takes the minimum value of zero if a firm employs all seven types of debt in equal proportion. An increase in $HHI_{i,t}$ corresponds to firm i having a higher debt concentration in fiscal year t.

[5]Please refer to Colla et al. (2013) for the detailed discussions on these seven debt types.

The second measure of debt concentration is an indicator variable, $Excl90_{i,t}$, which is equal to one if firm i obtains at least 90% of its debt from one single debt type in fiscal year t and zero otherwise. The third measure, $Count_{i,t}$, is the number of different debt types that firm i has in fiscal year t. In line with Li et al. (2021), we only count debt types that are at least 5% of a firm's total debt, which play an economically significant role in the firm's external financing decisions. *Excl90* being equal to one or a lower value of *Count* corresponds to a more concentrated debt structure. *HHI* reflects both the number of debt types and the proportion of each debt type in a firm's debt structure, while *Excl90* and *Count* focus on the number of debt types.

In our empirical analyses below, we employ one-year-ahead debt concentration proxy variables as the dependent variables: $HHI_{i,t+1}$, $Excl90_{i,t+1}$, and $Count_{i,t+1}$.

3.3. Independent variable: CEOs' general ability

Consistent with the literature on CEOs' general skills, we adopt Custódio et al.'s (2013) general ability index (GAI) to capture the generality of human capital which a CEO has accumulated from her work experience. The index is based on a CEO's work experience in different firms, industries, and non-CEO positions as well as work experience in the CEO position and as a top executive in a conglomerate. Specifically, GAI is constructed based on the following equation:

$$GAI_{i,t} = 0.268X1_{i,t} + 0.312X2_{i,t} + 0.309X3_{i,t} + 0.218X4_{i,t} + 0.153X5_{i,t} \tag{3}$$

where *X1* is the number of top executive positions which a CEO has held until year t, *X2* is the number of firms at which a CEO has worked until year t, *X3* is the number of the four-digit SIC industries in which a CEO has worked until year t, *X4* is an indicator variable which is equal to one if a CEO has held a CEO position at a different firm until year t and zero otherwise, and *X5* is an indicator variable which is equal to one if a CEO has worked for a conglomerate until year t and zero otherwise. The coefficients of *X1*–*X5* in Equation (3) are based on the first factor of the principal component analysis (PCA) of *X1–X5*. *GAI* is standardized to have a mean of zero and a standard deviation of one. $GAI_{i,t}$ reflects the level of a CEO's general managerial skills gathered before year t. Based on CEOs' *GAI*, we define a generalist CEO indicator variable, *GAI_Dummy*, that is equal to one if *GAI* is above its annual sample median and zero otherwise (Custódio et al., 2013).

3.4. Control variables

Following prior literature (e.g., Colla et al., 2013; Castro et al., 2020), we include a set of control variables that potentially determine a firm's debt structure. *Size* is the natural logarithm of market capitalization; *Tangibility* is the ratio of net property, plant, and equipment to total assets; *Leverage* is the ratio of long-term debt to total assets; *MTB* is the ratio of the market value of equity plus the book value of debt to the book value of total assets; *Profitability* is the ratio of earnings before interest, tax, depreciation, and amortization to total assets; *R&D* is research and development expenses scaled by the market value of equity; *Dividend* is cash dividends scaled by the market value of equity; *Rating* is an indicator value that is equal to one if a firm has a Standard and Poor's domestic rating and zero otherwise; *CF_Volatility* is the standard deviation of operating cash flows scaled by total assets over the past five years; *Firm_Age* is the natural logarithm of the number of years that a firm has been in CRSP; and *Z-Score* is modified Altman's (1968) *Z-Score*. These variables control for bankruptcy costs, incentives to monitor debt borrowing, and access to debt markets, which are related to a firm's debt financing decisions. Detailed definitions of all variables are illustrated in Appendix A.

4. Main results

4.1. Summary statistics and univariate analyses

We present the summary statistics for our sample in Table 1. The number of observations, means, standard deviations, 25th percentiles, medians, and 75th percentiles of the variables used in our main analyses are reported from left to right. Regarding the three debt concentration proxy variables, the mean values of *HHI*, *Excel90*, and *Count* are 0.727, 0.511, and 1.772, respectively. These statistics indicate that 51.1% of our sample firm–year observations have at least 90% of their debt from one debt type, and an average firm–year observation in our sample has at least 5% of their total debt financed through 1.7 different sources. The standard deviations of the three debt concentration proxy variables are 0.254, 0.500, and 0.804, respectively. The summary statistics of our debt concentration proxy variables are consistent with those reported in Colla et al. (2013) and Li et al. (2021).

The mean and standard deviations of GAI are -0.084 and 0.884, which are close to the standardized mean of zero and the standardized standard deviation of one. The average *Size* is 7.649, equivalent to $2.099 billion market capitalization, and the average *Firm_Age* is 2.690, equivalent to 15 years, indicating that our sample is tilted toward larger and older firms. The average *Rating* is 0.966, suggesting that 96.6% of our sample firms have a Standard and Poor's domestic credit rating. The means (standard deviations) of *Tangibility*, *Leverage*, *MTB*, *Profitability*, *R&D*, *Dividend*, *CF_Volatility*, and *Z-Score* are 0.271 (0.216), 0.212 (0.145), 3.216 (3.233), 0.138 (0.075), 0.020 (0.036), 0.010 (0.015), 0.034 (0.027), and 2.005 (1.156), respectively. The summary statistics of our control variables are generally consistent with the previous studies based on the Execucomp and Capital IQ databases.

Table 2 presents the Pearson correlation matrix. As expected, HHI_{t+1} and $Excel90_{t+1}$ are highly positively correlated, while they are highly negatively related to $Count_{t+1}$. We find that the pairwise correlations between GAI_t and HHI_{t+1} and between GAI_t and *Ex-*

cel90$_{t+1}$ are negative and statistically significant, while the pairwise correlation between GAI_t and $Count_{t+1}$ is positive and statistically significant, which provide preliminary support on our hypothesis H_0. The largest pairwise correlation among our control variables, in terms of absolute values, is 0.53 between *Z-Score* and *Profitability*, suggesting that multicollinearity is not a serious concern in our empirical analyses.

4.2. Baseline regression analyses

To provide formal evidence on the relation between CEO general skills and debt concentration, we employ the following baseline regression:

$$Debt\ Concentration_{i,t+1} = \beta_0 + \beta_1 GAI_{i,t} + \Gamma' Controls_{i,t} + \theta_j + \mu_t + \epsilon_{i,t} \tag{4}$$

where the dependent variable *Debt Concentration*, measured in year $t+1$, is one of three debt concentration proxy variables: *HHI*, *Excel90*, and *Count*. *HHI* is bounded between zero and one, *Excel90* is an indicator variable, and *Count* takes an integer value between one and seven. Therefore, in estimating Equation (4), we employ both a Tobit and ordinary least squares (OLS) regressions when *HHI* is the dependent variable, a Probit regression when *Excel90* is the dependent variable, and a Poisson regression when *Count* is the dependent variable. All the independent variables are measured in year t. The independent variable of interest is *GAI*. Besides the control variables discussed in Section 3.4, we control for the Fama–French 48 industry (θ_j) and year (μ_t) fixed effects.

Table 3 presents the estimated coefficients in our baseline regression. The t-statistics and z-statistics below the coefficients are based on robust standard errors clustered by firm. In column (1), we estimate an ordinary least squares (OLS) regression for HHI_{t+1}. The estimated coefficient on GAI_t is negative and statistically significant at the 5% level, indicating that when a firm's CEO has a higher general ability index, the firm tends to have less debt concentration. We next estimate a Tobit model for HHI_{t+1} censored at zero and one, and report the average marginal effects in column (2). The estimate implies that a one-standard-deviation increase in GAI_t is associated with a decrease by 4.5% (=0.884*-0.013/0.254) of the average within-firm standard deviation of *HHI*. For comparison, a one-standard-deviation change in *Tangibility* or *MTB* is associated with a change in *HHI* by 8.9% (=0.216*-0.105/0.254) or 5.1% (=3.233*0.004/0.254) of the average within-firm standard deviation, respectively. The estimated coefficients on the control variables are generally in line with the findings of previous studies (e.g., Castro et al., 2020; Li et al., 2021). The coefficients of *MTB*, *R&D*, *Dividend*, and *CF_Volatility* are positive and statistically significant, while the coefficients of *Tangibility*, *Leverage*, and *Firm_Age* are negative and statistically significant.

In column (3) of Table 3, we replace the dependent variable HHI_{t+1} with $Excel90_{t+1}$ and report the average marginal effects estimated by a Probit model. The average marginal effect of GAI_t on $Excel90_{t+1}$ is negative and statistically significant at the 5% level, indicating that when a firm's CEO has a higher general ability index, the firm is less likely to obtain at least 90% of its debt from one debt type. A one-standard-deviation increase in GAI_t is associated with a decrease of 1.9% (=0.884*-0.022) in the probability of an average firm obtaining at least 90% of its debt from one debt type, which is equivalent to 3.7% (=0.019/0.511) of *Excel90*'s sample mean. In column (4), the dependent variable is $Count_{t+1}$, and the average marginal effects estimated by a Poisson model are reported. The average marginal effect of GAI_t on $Count_{t+1}$ is positive and statistically significant at the 5% level, suggesting that when a firm's CEO has a higher general ability index, the firm is more likely to borrow from different debt sources. A one-standard-deviation increase in GAI_t is associated with 0.034 (=0.884*0.039) additional debt types. Overall, the empirical evidence documented in Table 3 supports our hypothesis H_0 that CEO general skills are negatively related to debt concentration.

4.3. Mitigating endogeneity

Our baseline analysis is vulnerable to potential endogeneity between CEO general skills and debt concentration, for several reasons. First, generalist CEOs may not be randomly assigned to firms in the top executive labor market. One may argue that firms with less debt concentration are more likely to hire generalist CEOs. It is also likely that generalist CEOs self-select into firms that diversify across multiple debt types. Although the independent variables in Equation (4) are lagged by one year relative to debt concentration proxies, the reverse causality concern makes it questionable to identify a causal relation between CEO general skills and debt concentration. Second, even if we control for the observable firm characteristics, the industry fixed effects, and the year fixed effects in Equation (4), there might exist unobservable heterogeneity when omitted unobservable variables are related to both a firm's selection of a generalist CEO and its debt structure. For example, both the selection of a generalist CEO and a lower degree of debt concentration may be simultaneously driven by corporate culture. In this section, we adopt three econometric identification methods to mitigate potential endogeneity threats: a PSM approach, an EB matching approach, and a DID framework.

4.3.1. Propensity score matching

Since firms managed by generalist CEOs may differ from those managed by specialist CEOs in terms of firm characteristics, the appointments of generalist CEOs could be endogenously determined. To control for the observed dissimilarity between firms with generalist and specialist CEOs, we conduct PSM in which a treatment group composed of firm–years with generalist CEOs is matched with a control group composed of firm–years with specialist CEOs. The PSM strategy ensures that there are no significant differences in terms of observed firm-level characteristics between firm–years in the treatment and control group. The PSM method mitigates the endogenous mutual selection between firms and generalist CEOs, and helps to improve causal inference.

We first estimate the propensity score (probability) that a firm appoints a generalist CEO, using a Probit regression with the dependent variable being *GAI_Dummy* and the independent variables being the same as the control variables included in Equation (4). We tabulate the Probit regression results in column (1) of Panel A of Table 4. *Size*, *Leverage*, *R&D*, *Dividend*, and *CF_Volatility* are positively related to the likelihood that a firm hires a generalist CEO, while *Tangibility* is negatively related to the likelihood that a firm hires a generalist CEO. Based on the estimated propensity scores, we employ the nearest-neighbor matching approach without replacement. Specifically, each firm with a generalist CEO in a year is matched to a firm with a specialist CEO in the same year and with the smallest difference in their propensity scores. We also require that the maximum difference in the propensity scores between a treated observation and a matched control observation does not exceed 1% in absolute value.[6]

To verify the efficiency of our PSM method, we first re-estimate the Probit regression for a sample composed of the treated and control firm–years. The estimated coefficients are reported in column (2) of Panel A of Table 4. All the estimated coefficients are statistically insignificant at the 10% level. The pseudo R^2 decreases from 0.084 in column (1) to 0.027 in column (2). Second, we investigate the differences in the observable firm characteristics between the observations in the treatment and control groups. Panel B of Table 4 shows that the differences in all the firm characteristics between the treatment and control groups are statistically insignificant at the 10% level, suggesting that our PSM is efficient. The two diagnostic tests indicate that our PSM removes all observable differences between the observations in the treatment and control group other than the difference in the presence of generalist CEOs. Therefore, any difference in debt concentration between the treatment and control group is more likely due to the presence of generalist CEOs than the differences in the other observable firm characteristics.

Finally, we estimate Equation (4) in the PSM sample and tabulated the results in Panel C of Table 4. We report the OLS regression coefficients in column (1) and the average treatment effects of the Tobit, Probit, and Poisson regressions in columns (2)–(4), respectively. Panel C shows that the estimated coefficient or average treatment effects of GAI_t in the PSM sample are statistically significant, and have the same sign as those

[6] Our PSM results remain robust if we use a caliper width of 0.005 or an alternative *GAI_Dummy* being equal to one if *GAI* is above its annual sample top quartile and zero otherwise.

reported in Table 3. The coefficient and the average treatment effects of *GAI* in our PSM tests are also comparable in magnitude to those reported in Table 3. Our findings reinforce that firms with generalist CEOs have a more diversified debt structure than matched firms with specialist CEOs.

4.3.2. Entropy balancing matching

The PSM method stochastically balances the covariates between treatment and control groups. In this section, we re-estimate our baseline regression using an EB matching sample. EB is a matching method that reweights observations in control groups by imposing constraints in adjusting the first, second, as well as third moments of the covariates' distributions to achieve a great extent of covariate balances between treatment and control groups (Hainmueller, 2012). The EB matching method keeps all observations in treatment and control groups, while the PSM method throws away "unmatched" observations. Unlike the PSM method, the EB matching method does not rely on any specific research design to achieve the covariate balance, which mitigates the concern that the post-matching results are sensitive to model specification (DeFond et al., 2017).

Specifically, firm–years with *GAI_Dummy* being equal to one are assigned in the treatment group and those with *GAI_Dummy* being equal to zero are assigned in the control group. We adopt three balance conditions that the mean, variance, and skewness of the covariates must be the same between the treatment and control group.[7] The covariates are the control variables included in Equation (4). Panel A of Table 5 illustrates the efficiency of EB matching. After the matching, the mean, variance, and skewness of the firm characteristics are indeed the same between the treatment and control group. Panel B of Table 5 reports the results of estimating Equation (4) on the EB matching sample. The coefficient of *GAI* in column (1) and the average treatment effects of *GAI* in columns (2)–(4) are statistically significant and have the same sign as those reported in Table 3. The coefficient and the average treatment effects of *GAI* in our EB tests are about 50% in

[7] Our results remain robust if we conduct EB matching based on only the mean and variance of covariates.

magnitudecompared to those reported in our baseline and PSM tests.

Following the advice of Hainmueller (2012), we further examine whether EB matching improves the model estimation by assigning extremely large weights on some observations in the control group, emphasizing potential outliers in the weighted regressions. The average weight ratio among the control sample is 0.98, indicating that our EB matching does not put weight on more control observations on average than a one-to-one match. The maximum assigned weight is 8.65 and only about 2.07% of the control observations have weights exceeding 3, suggesting that the extreme weight issue is moderate. We refine our analysis by trimming observations with weights above 3 or 1 before re-running the EB program, and verify that our EB test results remain robust, which mitigates any lingering concern about the extreme weights.

4.3.3. Difference-in-differences

Our third identification strategy to address endogeneity is a DID analysis. We utilize exogenous CEO turnovers to single out the effect of generalist CEOs on debt concentration. In line with Custódio et al. (2013), we classify a CEO as a generalist if *GAI_Dummy* is equal to one and a specialist if *GAI_Dummy* is equal to zero. Our DID strategy compares the debt concentration for two groups of firm–years with and without treatment, i.e., a transition from specialist CEOs to generalist CEOs. Thus, it increases the likelihood that any change in debt concentration before and after the specialist-to-generalist transitions is due to the impact of treatment instead of the unobserved firm heterogeneity.

To ensure that the CEO turnovers are not driven by firms' intention to change their debt financing policy, we exclude endogenous CEO turnovers from our DID sample. Following the literature on CEO turnovers, we search for the names of departing CEOs or new CEOs on Factiva. We read the articles mentioning these CEO names and manually identify why a CEO transition occurred, e.g., dismissed for performance-related issues, retirement, death, an internal transition, or left for other businesses. We first classify a CEO transition as endogenous if she is sacked, resigns due to corporate strategies, or resigns due to board intervention (Parrino, 1997; Li and Zeng, 2019). If a CEO's transition is not due to the aforementioned three reasons, we estimate a departing CEO's age in the CEO transition year based on the Execucomp data. If a departing CEO's age is below 60 and we could not identify the reasons for the CEO's departure as death, health issues, leaving for other businesses, retirement within six months, and convincing reasons that are irrelevant to firm operation, we take the CEO transition as endogenous (Parrino, 1997; Li and Zeng, 2019). After identifying the endogenous CEO transitions, we exclude them from our CEO transition sample and take the remaining CEO transitions as exogenous. If a firm's debt concentration changes during an exogenous CEO turnover, it is unlikely that the change in debt concentration is due to unobserved confounding factors. This is because the likelihood that the unobserved confounding factors coincidentally change during the exogenous CEO turnover year but are unrelated to the turnover is very low.

Among the exogenous CEO transition sample, we define an indicator variable, *Transition*, which is equal to one if the transition is from a specialist CEO to a generalist CEO and zero otherwise. We follow Huang and Kisgen (2013) and require that firms have at least two years of non-missing data on all regressors before CEO turnovers. We also require a new CEO to remain in the position for three years so that we can observe the effect of the new CEO's debt financing policy. Our DID sample includes firm–years three years before and after exogenous CEO turnovers, excluding the turnover firm–years (Huang and Kisgen, 2013; Li and Zeng, 2019). Specifically, we estimate the following two regressions:

$$\begin{aligned} HHI_{i,t+1} =& \beta_0 + \beta_1 Transition_i \times Post_{i,t} + \beta_2 Transition_i + \beta_3 Post_{i,t} + \\ & \Gamma' Control\ Variables_{i,t} + \mu_t + \theta_j + \epsilon_{i,t} \end{aligned} \tag{5}$$

$$\begin{aligned} HHI_{i,t+1} =& \beta_0 + \beta_1 Transition_i \times Post_{i,t} + \beta_2 Post_{i,t} + \Gamma' Control\ Variables_{i,t} \\ & + \mu_t + \nu_i + \epsilon_{i,t} \end{aligned} \tag{6}$$

where i indexes firm, t indexes year, j indexes industry, $Transition_i$ is an indicator variable for an exogenous specialist-to-generalist CEO transition, $Post_{i,t}$ is an indicator variable that is equal to one if firm–year t is after the exogenous CEO turnover and zero otherwise, and $Control\ variables_{i,t}$ are a set of control variables included in baseline regression Equation (4). The independent variable of interest is the interaction term, $Transition_i \times Post_{i,t}$, which compares the changes in debt concentration over time between firms experiencing specialist-to-generalist CEO transitions and those experiencing other CEO transitions. In Equation (5), we control for the year (mu_t) and Fama–French 48 industry (θ_j) fixed effects. In Equation (6), we control for the year (μ_t) and firm (ν_i) fixed effects. When the firm fixed effects are controlled for, the separated term, $Transition_i$, is omitted in the DID regression (Huang and Kisgen, 2013).

Table 6 reports the results of our DID tests using OLS regressions. The estimated coefficients on $Transition_i \times Post_{i,t}$ are negative and statistically significant at the 10% level in columns (1) and (2). These results suggest that after specialist-to-generalist CEO transitions, firms have a lower degree of debt concentration than after other CEO transitions. For example, column (1) shows that on average, firms' debt concentration proxy HHI is 7.2% lower over three years after specialist-to-generalist CEO transitions than it is after the other CEO transitions.

Overall, we continue to find a negative relation between CEO general skills and debt concentration after confronting the potential endogeneity threat in our PSM, EB matching, and DID identification tests.

5. Supplementary tests

5.1. Path analysis

In this section, we employ a path analysis to establish informational efficiency as a mechanism underlying the relation between CEO general skills and debt concentration. Specifically, we investigate whether enhanced informational efficiency, the mediator variable driven by the presence of generalist CEOs, leads to a decrease in debt concentration.[8] Generalist CEOs with diverse professional experiences and a copious history of previous jobs have better employability in the external labor market, so they have fewer career concerns and less pressure to deliver short-term performance than specialist CEOs (Custódio et al., 2013, 2019). We expect that generalist CEOs recognize operating losses in a more timely fashion and are more eager to signal their private information by communicating with corporate stakeholders than specialist CEOs. Bris and Welch's (2005) optimal debt concentration model predicts that when a firm's quality is known to its creditors, the firm can have less debt concentration and avoid the costs associated with higher creditor concentration. Firms with a more transparent information environment attract more diversified creditors and enhance debt pricing efficiency, in turn reducing pre-bankruptcy deadweight costs and signaling costs originating from firms' debt structure.

To perform the path analysis, we estimate a structural equation model (SEM) of the direct effect of CEO general skills on debt concentration, along with CEO general skills' indirect effect on debt concentration through information efficiency as a mediating variable. The SEM estimation is composed of two regressions: a regression of debt concentration on CEO general skills and the mediating variable, information efficiency, and a regression of information efficiency on CEO general skills, with both regressions controlling for a list of variables included as control variables in Equation (4). The indirect effect of CEO general skills on debt concentration is estimated as the product of the effect of CEO general skills on the mediating variable and the effect of the mediating variable on debt concentration. We adopt Sobel's (1982) test statistics to determine the statistical significance of the direct and indirect effects.

We adopt two mediator variables as the proxies for a firm's information efficiency. First, we employ Khan and Watts's (2009) conditional accounting conservatism, *C-Score*, which measures the asymmetric earnings timeliness with respect to accounting gains ver-

[8]Due to data availability, we do not observe CEOs' personal link with both existing creditors and potential creditors for our sample firms. Therefore, we cannot directly test whether generalist CEOs' network with creditors is a mediator variable leading to a less concentrated debt structure.

sus losses. A firm with a higher *C-Score* recognizes its losses in a more timely way than its gains. Firms with more accounting conservatism practice are less likely to withhold information on expected losses (Watts, 2003). Panel A of Table 7 shows that CEO general skills have a negative and statistically significant direct effect on debt concentration, consistent with our main finding. In the mediated path analyses, we find that CEO general skills have a positive and statistically significant relation with conditional accounting conservatism, and accounting conservatism has a significantly negative effect on debt concentration. More importantly, we find that the total indirect effect of CEO general skills on debt concentration, through conditional accounting conservatism as a mediating variable, is statistically significant for all three proxies for debt concentration.

Second, we use voluntary managerial disclosure, *Mgr_disclosure*, as our second mediator variable. *Mgr_disclosure* is equal to one if a firm's managers voluntarily issue an earnings forecast during a given fiscal year and zero otherwise. Previous studies suggest that managers choose to disclose their earnings forecast voluntarily to reduce information asymmetry between insiders and investors (e.g., Marquardt and Wiedman, 1998; Lang and Lundholm, 2000; He, 2018; Kim, 2022). Panel B of Table 7 presents the results of our path analysis using *Mgr_disclosure* as a mediating variable. In the SEM, CEO general skills have a negative and statistically significant direct effect on debt concentration. The results of the mediated path analyses indicate that CEO general skills have a positive and statistically significant effect on the likelihood of managerial voluntary disclosure, and managerial voluntary disclosure has a negative effect on debt concentration. The total indirect effect of CEO general skills on debt concentration, through managerial voluntary disclosure as a mediating variable, is statistically significant for all three proxies for debt concentration.

Taken together, the results tabulated in Table 7 suggest that there exists a reliable mediated link via information efficiency between CEO general skills and debt concentration.

5.2. Cross-sectional analyses

In this section, we explore a list of factors that may induce cross-sectional differences in the empirical relation between CEO general skills and debt concentration: i) financial constraints, ii) co-opted directors, iii) product market competition, iv) managerial ability, v) R&D expenses, and vi) credit rating. We adopt sub-sample analyses and use seemingly unrelated regressions to compare the coefficients between two sub-samples.[9] It is difficult to find an omitted variable that biases our main finding equally in all the six cross-sectional dimensions, so our six heterogeneity tests help to provide further support for our casual inference of the negative effect of CEO general skills on debt concentration.

5.2.1. Financial constraints

Since financially constrained firms have restricted access to external financing and have to rely on limited internal funds, generalist CEOs' ability to secure funding from more sources should play a more important role for firms with financial constraints than those without financial constraints. In addition, earlier literature shows that firms with financial constraints have worse financial reporting quality (e.g., Linck et al., 2013; Andreou et al., 2021). Hence, we conjecture that the negative relation between CEO general skills and debt concentration is more prominent when firms are financially constrained.

We employ Whited and Wu's (2006) *WW-Index* as the proxy for firms' external finance constraints:

$$\begin{aligned} \textit{WW-Index}_{i,t} = & -0.091 * (CF_{i,t}/TA_{i,t}) - 0.062 * DIVPOS_{i,t} + 0.021 * (LTD_{i,t}/TA_{i,t}) \\ & - 0.044 * ln(TA_{i,t}) + 0.102 * ISG_{i,t} - 0.035 * SG_{i,t} \end{aligned} \tag{7}$$

[9] We adopt the sub-sample analyses instead of including an interaction term between GAI_t and one of the six sub-sample classification variables in our baseline regression. The interaction term method requires two stringent assumptions that are unlikely to be true in our sample. First, the control variables' coefficients are the same between the two sub-samples. Second, the distributions of the residual terms are the same between the two sub-samples.

where $CF_{i,t}$ is cash flow, $TA_{i,t}$ is total assets, $DIVPOS_{i,t}$ is an indicator variable that takes the value of one if firm i pays cash dividends and zero otherwise, $LTD_{i,t}$ is long-term debt, $ISG_{i,t}$ is firm i's three-digit industry sales growth, and $SG_{i,t}$ is firm i's sales growth. The coefficients in *WW-Index* are estimated by Whited and Wu (2006), based on the generalized method of moments estimation of an investment Euler equation of a structural model.

In Panel A of Table 8, we divide our sample into two sub-samples based on the annual median of *WW-Index*. Firms with a high (low) value of *WW-Index* are more financially constrained. We then repeat our analyses in Table 3 in the high and low sub-samples separately. For brevity, we only report the coefficients on *GAI* in columns (1) and (2) and the average treatment effects of *GAI* in columns (3)–(8). The same set of control variables, industry fixed effects, and year fixed effects are controlled for as in our baseline regressions. The negative effects of *GAI* on debt concentration are only statistically significant in the sub-samples of firms with a high value of *WW-Index*. The differences in the coefficients and the average treatment effects of *GAI* are statistically significant between the two sub-samples.

5.2.2. Corporate governance

Previous studies have argued that good corporate governance mechanisms mitigate information asymmetry problems and protect debtholders' rights, which in turn reduce the cost of debt financing (e.g., Sengupta, 1998; Ashbaugh-Skaife et al., 2006). Moreover, Schauten and van Dijk (2010) find that better financial disclosure quality would help firms to get access to debt financing only when shareholder right is weakly protected. As a result, we expect that generalist CEOs' ability to borrow from diversified lenders would play a more important role for firms with weaker corporate governance.

We use the variable *Co-Opt* proposed by Coles et al. (2014) to measure internal corporate governance. *Co-Opt* is the ratio of the number of co-opted directors to the total number of board directors, where co-opted directors are those who are appointed after the incumbent CEOs take office. Coles et al. (2014) show that firms with a higher value of *Co-Opt* have less effective board monitoring since co-opted directors tend to be loyal to the CEOs. Based on the annual sample median of *Co-Opt*, we split our sample into firms with better internal corporate governance (low *Co-Opt*) and worse internal corporate governance (high *Co-Opt*). Panel B of Table 8 shows that the negative impact of *GAI* on debt concentration is only statistically significant for the high *Co-Opt* sub-samples. The absolute values of the coefficients and the average treatment effects of *GAI* are larger for the sub-samples of firms with worse internal corporate governance than for those with better internal corporate governance. The differences in the coefficients and the average treatment effects of *GAI* are statistically significant between the two sub-samples.

In a similar vein, we use *HHI_Sales*, defined as the Herfindahl–Hirschman index based on firms' total sales over a fiscal year within the same Fama–French 48 industry (Chen et al., 2015), to measure external monitoring. Product market competition exerts a predation threat to underperforming firms, which encourages managers to work harder and helps to mitigate the agency problem (Giroud and Mueller, 2010, 2011). Li (2010) also finds that product market competition improves the quality of corporate financial disclosure and alleviates information asymmetry between firms and investors. We partition our sample into high and low sub-samples based on the annual sample median of *HHI*. Firms operating in an industry with a high value of *HHI_Sales* have low market competition and hence weak external monitoring. Panel C of Table 8 shows that the negative impact of *GAI* on debt concentration is only statistically significant in the sub-samples of firms with a high value of *HHI_Sales*. The absolute values of the coefficients and the average treatment effects of *GAI* are larger for the sub-samples of firms in industries with less external monitoring than for those in industries with more external monitoring. The differences in the coefficients and the average treatment effects of *GAI* are statistically significant between the two sub-samples.

The results in Panel B and C support the notion that the negative relation between CEO general skills and debt concentration is more prominent for firms with weaker corporate governance.

5.2.3. Managerial ability

We also examine whether the effect of CEO general skills on debt concentration varies with the ability of management teams. Demerjian et al. (2012) construct a managerial ability index, *MA-Score*, which evaluates management teams' efficiency in transforming corporate resources into revenues. Bonsall IV et al. (2017) find that firms with a higher value of *MA-Score* experience lower volatility in future cash flows and stock returns, which in turn results in a higher credit rating for these firms. Bui et al. (2018) also show that firms with a persistently superior *MA-Score* have lower debt financing costs. Besides facilitating external debt borrowing, Baik et al. (2011) find that high-ability management teams not only are more likely to issue management earnings forecasts but also issue more accurate forecasts. Since high-ability management teams facilitate firms' external debt financing, we expect that the negative effect of CEO general skills on debt concentration should be more pronounced for firms with a lower value of *MA-Score*.

We separate our sample into high and low sub-samples based on the annual sample median of *MA-Score*. Panel D of Table 8 shows that the negative effect of GAI on debt concentration is only statistically significant in the sub-samples of firms with a low *MA-Score*. The absolute values of the coefficients and the average treatment effects of GAI are larger for the sub-samples of firms with a lower *MA-Score* than for those with a higher *MA-Score*. The differences in the coefficients and the average treatment effects of GAI are statistically significant between the two sub-samples, except for columns (5) and (6).

5.2.4. R&D expenses

Due to information asymmetry, the risk of innovation failure and the uncertain pay-offs of innovation activities reduce R&D intensive firms' access to external debt financing (Mann, 2018). It is also difficult for outside lenders to value R&D intensive firms' intangible capital, so intangible capital is often not accepted as the collateral in R&D intensive firms' debt negotiation (Hochberg et al., 2018). If generalist CEOs improve firms' information disclosure efficiency and are able to effectively communicate with potential lenders, the negative effect of CEO general skills on debt concentration should be more pronounced for firms with more R&D expenses.

In Panel E of Table 8, we divide our sample into firms with high and low R&D expenses according to the annual sample median of *R&D*. Consistent with our expectation, the negative effect of *GAI* on debt concentration is only statistically significant in the sub-samples of firms with high R&D expenses. The absolute values of the coefficients and the average treatment effects of *GAI* are larger for the sub-samples of firms with high R&D expenses than for those with low R&D expenses. The differences in the coefficients and the average treatment effects of *GAI* are statistically significant between the two sub-samples, except for columns (5) and (6).

5.2.5. Credit rating

Colla et al. (2013) find that the degree of debt concentration is the highest for firms with lower than CCC+. We further examine whether the relation between CEO general skills and debt concentration varies with respect to firms' credit rating. We adopt Badoer and James's (2016) classification and define an investment grade indicator variable, *IG_Rating_Dummy*, which is equal to one if a firm has a long-term credit rating by S&P of BBB− or higher or if it has a short-term credit rating by S&P of A−3 or higher and zero otherwise. Firms with an investment-grade credit rating have better access to external borrowing.

We partition our sample firms into investment grade if *IG_Rating_Dummy* is equal to one and non-investment grade if *IG_Rating_Dummy* is equal to zero. Panel F of Table 8 shows that the negative effect of *GAI* on debt concentration is only statistically significant in the sub-samples of firms with *IG_Rating_Dummy* being equal to zero. The absolute values of the coefficients and the average treatment effects of *GAI* are larger for the sub-samples of firms with a lower credit rating than for those with a higher credit rating. The differences in the coefficients and the average treatment effects of *GAI* are statistically significant between the two sub-samples, except for columns (5) and (6).

5.3. Alternative measure of generalist CEOs

Our empirical analyses so far rely on Custódio et al.'s (2013) general ability index (GAI). In this section, we use the indicator variable *GAI_Dummy* to substitute for GAI. Following Custódio et al. (2013), we classify CEOs with a GAI score above the annual median as generalists (*GAI_Dummy*= 1) and CEOs with a GAI score below the annual median as specialists (*GAI_Dummy*= 0). The coefficients on *GAI_Dummy* capture the difference in debt concentration between firms managed by generalist CEOs and those managed by specialist CEOs, after controlling for other debt concentration determinants, as well as the year and Fama–French fixed effects. Table 9 shows the results of our baseline regression after replacing GAI with *GAI_Dummy*. Overall, the effects of *GAI_Dummy* on debt concentration proxy variables are similar to those tabulated in Table 3, suggesting that firms with generalist CEOs tend to choose a more diversified debt structure than firms with specialist CEOs.

5.4. Controlling for managerial traits

In our baseline regression, we follow the literature in selecting and specifying controls for the determinants of debt concentration (e.g., Colla et al., 2013; Castro et al., 2020). Previous studies suggest that a firm's external financing decisions are related to CEO personal characteristics, such as pay-for-performance sensitivity (John and John, 1993; Castro et al., 2020), age (Serfling, 2014), tenure (Berger et al., 1997), gender (Datta et al., 2021), firm ownership (Mehran et al., 1999), and dominance (Korkeamäki et al., 2017). These variables potentially affect managerial risk-taking incentives and the agency problem related to debt financing. Particularly, Castro et al. (2020) show that risk-taking incentives in CEO compensation are positively related to debt concentration. To further isolate the direct impact of CEO general skills on debt concentration, we explicitly control for these

CEO traits and the CEO fixed effects.

In columns (1)–(4) of Table 10, we extend our baseline regression by controlling for *CEO_Delta*, *CEO_Vega*, *CEO_Age*, *CEO_Tenure*, *CEO_Gender*, *CEO_Ownership*, and *CEO_Power*. The detailed definitions of these control variables are provided in Appendix A. In column (5), we adopt a high-dimensional fixed effects model which includes the year, Fama–French 48 industry, and CEO fixed effects. As advocated in Gormley and Matsa (2014), controlling for the CEO fixed effects helps to mitigate the potential endogeneity concern due to unobserved heterogeneity across CEOs. Table 10 shows that our main finding remains robust after controlling for CEO managerial characteristics and the CEO fixed effects.

5.5. CEOs' general skills and debt types

Our analyses so far focus on the effect of CEOs' general skills on the three debt concentration measures. To understand how CEOs' general skills affect firms' use of a specific debt type, we follow the classification of Capital IQ described in Section 3.2 and define seven debt type indicator variables: *CP_Dummy*, *DC_Dummy*, *TL_Dummy*, *SBN_Dummy*, *SUBN_Dummy*, *CL_Dummy*, and *Other_Dummy*. These indicator variables are equal to one if a firm uses the corresponding types of debt and zero otherwise. We then adopt Probit regressions and regress these indicator variables on *GAI* and the control variables used in our baseline regression.

Table 11 reports the results. The coefficients of GAI_t are not statistically significant in columns (1)–(3), (5), and (6), suggesting that CEOs' general skills do not significantly affect the probabilities that firms use commercial paper, drawn credit lines, term loans, subordinated bonds and notes, and capital leases. The coefficients of GAI_t are positive and statistically significant in columns (4) and (7), indicating that CEOs' general skills are positively associated with the probability that firms use senior bonds and notes and other debt.

6. Conclusions

The value of general managerial skills is well recognized in the literature. However, the impact of generalist CEOs on corporate debt structure decisions is ambiguous. On the one hand, asymmetric information theory suggests that firms managed by generalist CEOs have a less concentrated debt structure, because generalist CEOs who worry less about their careers improve financial reporting quality, mitigating the concern over coordination costs faced by multiple creditors in the event of financial distress. Agency theory, on the other hand, argues that in response to generalist CEOs' willingness to carry on risky projects, debt structure should become more concentrated rather than dispersed to facilitate creditors' coordination. Our paper aims to shed light on the question of whether and how CEOs' general managerial skills affect corporate debt structure.

Using a sample of 8,704 firm–year observations for 1,412 unique US firms over 2000–2017, we document robust evidence that CEO general managerial skills are negatively related to corporate debt structure. Our mediation analyses lend support to the asymmetric information theory by showing that CEO general managerial skills reduce debt concentration through two mediating variables, conditional accounting conservatism and managerial voluntary disclosure. Finally, our cross-sectional tests show that the impact of CEO general managerial skills on debt concentration is more pronounced for firms that are more financially constrained, have weaker corporate governance, are managed by management teams with a weaker ability, invest more in R&D, and have lower credit ratings, as expected by the asymmetric information theory.

Appendix A

Table A1. Variable definitions

This table provides variable definitions and corresponding data sources. ExecuComp refers to Standard and Poor's Executive Compensation database, CRSP refers to the Center for Research in Security Prices, IBES refers to the Institutional Brokers' Estimate System, LN refers to Lalitha Naveen's website, and PD refers to Peter Demerjian's website.

Variable	Definition	Source
Proxies for debt concentration		
HHI	$HHI_{i,t} = \frac{SS_{i,t}-1/7}{1-1/7}$ and $SS_{i,t} = (\frac{CP_{i,t}}{TD_{i,t}})^2 + (\frac{DC_{i,t}}{TD_{i,t}})^2 + (\frac{TL_{i,t}}{TD_{i,t}})^2 + (\frac{SBN_{i,t}}{TD_{i,t}})^2 + (\frac{SUB_{i,t}}{TD_{i,t}})^2 + (\frac{CL_{i,t}}{TD_{i,t}})^2 + (\frac{Other_{i,t}}{TD_{i,t}})^2$, where *CP*, *DC*, *TL*, *SBN*, *SUB*, *CL*, and *Other* denote the amounts of seven types of debt recorded in Compustat Capital IQ: commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt. *TD* denotes the total amount of debt (Colla et al., 2013).	Capital IQ
Excl90	An indicator variable that is equal to one if a firm obtains at least 90% of its debt from one debt type and zero otherwise (Colla et al., 2013).	Capital IQ
Count	The number of different debt types in a firm's total debt. To focus on economically significant debt types, we only count debt types that are at least 5% of the firm's total debt (Li et al., 2021).	Capital IQ
Manager-level variables		
GAI	The index of general managerial ability, which is the first factor of the principal component analysis of five aspects of a CEO's past work experience: number of positions, number of firms, number of industries, CEO experience dummy, and conglomerate experience dummy (Custódio et al., 2013).	BoardEx
GAI_Dummy	An indicator variable that is equal to one if a CEO's *GAI* is above the annual median of *GAI* and zero otherwise (Custódio et al., 2013).	BoardEx
CEO_Delta	Dollar change in a CEO's wealth associated with 1% increase in the firm's stock price, scaled by the CEO's total compensation (Coles et al., 2006; Ham et al., 2017).	ExecuComp

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Variable	Definition	Source
CEO_Vega	Dollar change in a CEO's wealth associated with 1% increase in the standard deviation of the firm's stock return, scaled by the CEO's total compensation (Coles et al., 2006; Ham et al., 2017).	ExecuComp
CEO_Age	CEO age, measured as the natural logarithm of a CEO's age.	ExecuComp
CEO_Tenure	CEO tenure, measured as the natural logarithm of one plus the number of years as the firm's CEO.	ExecuComp
CEO_Gender	An indicator variable that is equal to one if a CEO is female and zero otherwise.	ExecuComp
CEO_Ownership	The percentage of a firm's shares owned by the CEO (Castro et al., 2020).	ExecuComp
CEO_Power	The ratio of a CEO's total compensation to the sum of five highest paid executives' total compensation (Castro et al., 2020).	ExecuComp
Firm-level variables		
Size	The natural logarithm of market capitalization (millions).	Compustat
Tangibility	The ratio net property, plant, and equipment to total assets.	Compustat
Leverage	The ratio of long-term debt to total assets.	Compustat
MTB	The ratio of the market value of equity plus the book value of debt to the book value of total assets.	Compustat
Profitability	The ratio of earnings before interest, tax, depreciation, and amortization to total assets.	Compustat
R&D	Research and development expenses scaled by the market value of equity. *R&D* is equal to zero if research and development expenses are missing.	Compustat
Dividend	Cash dividends scaled by the market value of equity. *Dividend* is equal to zero if cash dividends are missing.	Compustat
Rating	An indicator variable that is equal to one if a firm has a Standard and Poor's domestic credit rating.	Compustat
CF_Volatility	The standard deviation of operating cash flows scaled by total assets over the past five years.	Compustat
Firm_Age	The natural logarithm of the number of years that a firm has been in CRSP.	CRSP
Z-Score	Modified Altman's (1968) *Z-Score*: $(1.2 * WC + 1.4 * RR + 3.3 * EBIT + 0.999 * Sales)/TA$, where WC is working capital, RR is retained earnings, $EBIT$ is earnings before interest and taxes, and TA is total assets. Following Graham et al. (2008), we exclude the ratio of the market value of equity to the book value of total debt from the original *Z-score* formula because a similar term, *MTB*, is included in our regression specifications as a control variable.	Compustat

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Variable	Definition	Source
C-Score	A proxy for accounting conservatism estimated from a rolling 5-year panel developed by Khan and Watts (2009).	Compustat
Mgr_Disclosure	An indicator variable that is equal to one if a firm's managers voluntarily issue an earnings forecast during a given fiscal year and zero otherwise (Kim, 2022).	IBES
WW-Index	Whited and Wu's (2006) financial constraint index: $-0.091*(CF/TA) - 0.062*DIVPOS + 0.021*(LTD/TA) - 0.044*ln(TA) + 0.102*ISG - 0.035*SG$, where *CF* is cash flow, *TA* is total assets, *DIVPOS* is an indicator variable that takes the value of one if a firm pays cash dividends and zero otherwise, *LTD* is long-term debt, *ISG* is a firm's three-digit industry sales growth, and *SG* is a firm's sales growth.	Compustat
Co-Opt	The ratio of the number of co-opted directors to the number of board directors. A co-opted director is a director who joins the board after the current CEO assumes office (Coles et al., 2006).	LN
HHI_Sales	The sum of the squared market shares in percentages of all firms in an industry, where a firm's market share is based on its share of sales within a Fama–French 48 industry (Chen et al., 2015).	Compustat
MA-Score	An index of managerial ability based on managers' efficiency in transforming corporate resources into revenues, relative to their industry peers (Demerjian et al., 2012).	PD
IG_Rating_Dummy	An indicator variable that is equal to one if a firm has a long-term credit rating by S&P of BBB– or higher or if it has a short-term credit rating by S&P of A-3 or higher and zero otherwise (Badoer and James, 2016).	Compustat
R&D_Dummy	An indicator variable that is equal to one if a firm has non-zero R&D expenses in a year and zero otherwise (Hayes et al., 2012).	Compustat
CP_Dummy	An indicator variable that is equal to one if a firm uses commercial paper and zero otherwise.	Capital IQ
DC_Dummy	An indicator variable that is equal to one if a firm uses drawn credit lines and zero otherwise.	Capital IQ
TL_Dummy	An indicator variable that is equal to one if a firm uses term loans and zero otherwise.	Capital IQ
SBN_Dummy	An indicator variable that is equal to one if a firm uses senior bonds and notes and zero otherwise.	Capital IQ
SUBN_Dummy	An indicator variable that is equal to one if a firm uses subordinated bonds and notes and zero otherwise.	Capital IQ
CL_Dummy	An indicator variable that is equal to one if a firm uses capital leases and zero otherwise.	Capital IQ

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Variable	**Definition**	**Source**
Other_Dummy	An indicator variable that is equal to one if a firm uses other debt and zero otherwise.	Capital IQ

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Table 1. Summary statistics

This table presents the summary statistics for the key variables used in our empirical analyses. Our sample consists of 1,412 unique firms and 8,704 firm–year observations, with available data on the CEO general ability index and other variables. The sample period for generalist CEO variables and control variables is from 2000 to 2016 and the sample period for debt concentration variables is from 2001 to 2017. Variable names, the number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile are reported from left to right, in sequence for each variable. Variable definitions are provided in Appendix A.

Variables	Obs.	Mean	S.D.	p25	Median	p75
Debt concentration						
HHI_{t+1}	8,704	0.727	0.254	0.481	0.799	0.983
$Excl90_{t+1}$	8,704	0.511	0.500	0.000	1.000	1.000
$Count_{t+1}$	8,704	1.772	0.804	1.000	2.000	2.000
Generalist CEO						
GAI_t	8,704	-0.084	0.884	-0.779	-0.244	0.475
GAI_Dummy_t	8,704	0.495	0.500	0.000	0.000	1.000
Control variables						
$Size_t$	8,704	7.649	1.526	6.594	7.502	8.585
$Tangibility_t$	8,704	0.271	0.216	0.107	0.201	0.379
$Leverage_t$	8,704	0.212	0.145	0.100	0.202	0.305
MTB_t	8,704	3.216	3.233	1.572	2.319	3.564
$Profitability_t$	8,704	0.138	0.075	0.095	0.133	0.178
$R\&D_t$	8,704	0.020	0.036	0.000	0.000	0.026
$Dividend_t$	8,704	0.010	0.015	0.000	0.003	0.016
$Rating_t$	8,704	0.966	0.180	1.000	1.000	1.000
$CF\_Volatility_t$	8,704	0.034	0.027	0.017	0.027	0.042
$Firm\_Age_t$	8,704	2.690	0.417	2.485	2.773	2.996
$Z\text{-}Score_t$	8,704	2.005	1.156	1.318	1.968	2.681

Table 2. Correlation matrix

This table presents pairwise Pearson correlations for all variables used in our main empirical analyses. The correlation coefficients in bold are statistically significant at higher than the 10% level. Variable definitions are provided in Appendix A.

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
HHI_{t+1}	A	**1.00**														
$Excl90_{t+1}$	B	**0.89**	**1.00**													
$Count_{t+1}$	C	**-0.87**	**-0.78**	**1.00**												
GAI_t	D	**-0.04**	**-0.03**	**0.04**	**1.00**											
$Size_t$	E	0.00	0.00	**0.03**	**0.25**	**1.00**										
$Tangibility_t$	F	**-0.13**	**-0.14**	**0.16**	**-0.10**	**0.03**	**1.00**									
$Leverage_t$	G	**-0.28**	**-0.24**	**0.26**	**0.09**	**0.02**	**0.19**	**1.00**								
MTB_t	H	**0.04**	**0.05**	**-0.03**	**0.07**	**0.29**	**-0.07**	**0.15**	**1.00**							
$Profitability_t$	I	**0.04**	**0.03**	**-0.03**	**-0.06**	**0.27**	**0.16**	**-0.10**	**0.33**	**1.00**						
$R\&D_t$	J	**0.12**	**0.12**	**-0.12**	**0.10**	**-0.16**	**-0.26**	**-0.05**	**-0.05**	**-0.30**	**1.00**					
$Dividend_t$	K	0.01	0.02	0.01	**0.11**	**0.13**	**0.09**	**0.10**	0.00	**0.07**	**-0.11**	**1.00**				
$Rating_t$	L	-0.02	-0.02	0.01	0.01	**0.06**	0.02	**-0.02**	**-0.05**	0.00	0.01	**0.03**	1.00			
$CF\_Volatility_t$	M	**0.15**	**0.14**	**-0.14**	**-0.03**	**-0.28**	-0.01	**-0.17**	**0.06**	**-0.07**	**0.20**	**-0.09**	0.00	**1.00**		
$Firm\_Age_t$	N	**-0.04**	**-0.04**	**0.04**	**0.11**	**0.21**	-0.01	-0.01	-0.02	**0.04**	**-0.05**	**0.18**	**0.12**	**-0.11**	**1.00**	
$Z\text{-}Score_t$	O	**0.03**	**0.04**	**-0.04**	**-0.10**	**0.06**	**-0.08**	**-0.29**	**0.07**	**0.53**	**-0.32**	**0.12**	**0.03**	**-0.08**	**0.15**	**1.00**

Table 3. CEOs' general skills and debt concentration

This table presents the estimates of the panel regressions of future debt concentration on the CEO general ability index (GAI_t) and control variables. The sample covers 8,704 firm–year observations with non-missing values for the regression variables during 2000–2016. The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is GAI_t. In columns (1)–(4), the model specifications are OLS, Tobit, Probit, and Poisson, respectively. We report the regression coefficients in column (1) and average treatment effects in columns (2)–(4). The coefficients of year and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	OLS HHI_{t+1} **(1)**	Tobit HHI_{t+1} **(2)**	Probit $Excl90_{t+1}$ **(3)**	Poisson $Count_{t+1}$ **(4)**
GAI_t	-0.013**	-0.013**	-0.022**	0.039**
	(-2.39)	(-2.54)	(-2.15)	(2.32)
$Size_t$	0.002	0.003	0.004	0.016
	(0.49)	(-0.74)	(0.54)	(1.23)
$Tangibility_t$	-0.105***	-0.101***	-0.219***	0.447***
	(-2.89)	(-3.13)	(-3.18)	(3.86)
$Leverage_t$	-0.438***	-0.440***	-0.717***	1.210***
	(-12.86)	(-13.94)	(-11.48)	(11.54)
MTB_t	0.004***	0.004***	0.008***	-0.011**
	(2.72)	(3.15)	(2.76)	(-2.35)
$Profitability_t$	0.101	0.116	0.132	-0.413
	(1.34)	(1.62)	(0.89)	(-1.58)
$R\&D_t$	0.511***	0.483***	0.942***	-1.384***
	(3.54)	(3.46)	(3.25)	(-2.85)
$Dividend_t$	1.307***	1.155***	2.569***	-3.149***
	(4.17)	(4.15)	(4.41)	(-3.16)
$Rating_t$	-0.026	-0.029	-0.044	0.043
	(-1.26)	(-1.42)	(-1.14)	(0.64)
$CF\_Volatility_t$	0.735***	0.809***	1.627***	-2.271***
	(4.74)	(5.30)	(5.22)	(-4.28)
$Firm\_Age_t$	-0.035***	-0.037***	-0.076***	0.126***
	(-2.69)	(-3.07)	(-3.06)	(3.15)
$Z\text{-}Score_t$	-0.002	-0.003	0.004	0.006
	(-0.29)	(-0.56)	(0.34)	(0.30)
Constant	0.854***			
	(13.76)			
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,704	8,704	8,704	8,704
Pseudo or Adjusted R^2	0.144	0.327	0.093	0.017

Table 4. Propensity score matching

Panel A. Pre-match propensity score and post-match diagnostic regressions. This panel presents the pre-match propensity score regression results (column (1)) and the post-match diagnostic regression results (column (2)). Our sample covers firm–year observations with non-missing values for all variables during 2000–2016. In columns (1) and (2), the dependent variables are GAI_Dummy_T that is equal to one if a CEO's general ability index is above the annual median and zero otherwise. The independent variables are the control variables reported in Table 3. We use a one-to-one match without replacement and require that the difference between the propensity score of a firm with a generalist CEO and a matched firm with a specialist CEO in the same year does not exceed 1% in absolute value. The coefficients of the year and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	Pre-match GAI_Dummy_t **(1)**	Post-match GAI_Dummy_t **(2)**
$Size_t$	0.236***	0.004
	(9.64)	(0.16)
$Tangibility_t$	-0.812***	-0.158
	(-3.43)	(-0.65)
$Leverage_t$	0.762***	0.014
	(3.66)	(0.06)
MTB_t	-0.013	-0.002
	(-1.59)	(-0.24)
$Profitability_t$	-0.373	-0.117
	(-0.73)	(-0.21)
$R\&D_t$	2.155**	-0.214
	(2.44)	(-0.21)
$Dividend_t$	7.063***	-1.343
	(3.93)	(-0.68)
$Rating_t$	-0.155	0.062
	(-1.27)	(0.48)
$CF\_Volatility_t$	4.262***	0.344
	(4.66)	(0.34)
$Firm\_Age_t$	0.086	0.009
	(1.06)	(0.10)
$Z\text{-}Score_t$	-0.061	0.021
	(-1.53)	(0.47)
Constant	-1.648***	0.170
	(-2.95)	(0.28)
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	8,704	6,014
Pseudo R^2	0.084	0.027

Panel B. Firm characteristics in the matched sample. This panel presents the univariate comparisons of firm characteristics between firms with *GAI_Dummy* being equal to one and matched firms with *GAI_Dummy* being equal to zero. In columns (1)–(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. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

	Generalist CEO (N=3,007) **(1)**	Specialist CEO (N=3,007) **(2)**	Difference **(3)**	T-statistics **(4)**
$Size_t$	7.588	7.622	-0.035	-0.947
$Tangibility_t$	0.267	0.266	0.001	0.159
$Leverage_t$	0.213	0.214	-0.001	-0.342
MTB_t	3.169	3.200	-0.030	-0.379
$Profitability_t$	0.137	0.136	0.000	0.234
$R\&D_t$	0.020	0.020	0.000	0.396
$Dividend_t$	0.010	0.010	0.000	-0.781
$Rating_t$	0.967	0.964	0.003	0.706
$CF\_Volatility_t$	0.034	0.034	0.000	0.243
$Firm\_Age_t$	2.693	2.686	0.007	0.620
$Z\text{-}Score_t$	2.017	2.014	0.003	0.116

Panel C. Propensity score matching estimator. This panel presents the results of our baseline regression in the PSM sample. The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is GAI_t. In columns (1)–(4), the model specifications are OLS, Tobit, Probit, and Poisson, respectively. The control variables are the same as those reported in Table 3. We report the regression coefficients in column (1) and average treatment effects in columns (2)–(4). The coefficients of the control variables, year fixed effects, and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	OLS HHI_{t+1} **(1)**	Tobit HHI_{t+1} **(2)**	Probit $Excl90_{t+1}$ **(3)**	Poisson $Count_{t+1}$ **(4)**
GAI_t	-0.014**	-0.014**	-0.027**	0.051***
	(-2.41)	(-2.51)	(-2.47)	(2.92)
Constant	0.871***			
	(11.36)			
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	6,014	6,014	6,014	6,014
Pseudo or Adjusted R^2	0.147	0.334	0.101	0.019

Table 5. Entropy balancing matching

Panel A. Covariate balance. This panel presents the descriptive statistics for the covariates before and after reweighting to achieve covariate balance between the treatment and control group. Firm–year observations are assigned in the treatment (control) group if *GAI_Dummy* is equal to one (zero). *GAI_Dummy* is equal to one if a CEO's general ability index is above the annual median and zero otherwise. All variables are defined in Appendix A.

	Treatment (N=4,352)			$\text{Control}_{\text{before matching}}$ (N=4,352)			$\text{Control}_{\text{after matching}}$ (N=4,352)		
Variables	Mean **(1)**	Var **(2)**	Skew **(3)**	Mean **(4)**	Var **(5)**	Skew **(6)**	Mean **(7)**	Var **(8)**	Skew **(9)**
$Size_t$	7.962	2.457	0.184	7.343	2.013	0.411	7.962	2.457	0.184
$Tangibility_t$	0.254	0.038	1.165	0.289	0.054	1.008	0.254	0.038	1.165
$Leverage_t$	0.222	0.020	0.455	0.203	0.022	0.560	0.222	0.020	0.455
MTB_t	3.393	11.875	3.410	3.044	8.999	3.926	3.393	11.874	3.410
$Profitability_t$	0.136	0.005	0.183	0.140	0.006	0.114	0.136	0.005	0.183
$R\&D_t$	0.023	0.002	2.613	0.017	0.001	2.978	0.023	0.002	2.613
$Dividend_t$	0.012	0.000	2.076	0.009	0.000	2.549	0.012	0.000	2.076
$Rating_t$	0.969	0.030	-5.401	0.964	0.035	-4.969	0.969	0.030	-5.401
$CF\_Volatility_t$	0.035	0.001	2.352	0.034	0.001	2.234	0.035	0.001	2.352
$Firm\_Age_t$	2.709	0.164	-0.953	2.671	0.183	-0.886	2.709	0.164	-0.953
$Z\text{-}Score_t$	1.913	1.242	-0.193	2.096	1.411	-0.237	1.913	1.242	-0.193

Panel B. Entropy balancing matching estimator. This panel presents the results of our baseline regression estimated in the EB matching sample. The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is GAI_t. In columns (1)–(4), the model specifications are OLS, Tobit, Probit, and Poisson, respectively. The control variables are the same as those reported in Table 3. We report the regression coefficients in column (1) and average treatment effects in columns (2)–(4). The coefficients of the control variables, year fixed effects, and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. ∗ ∗ ∗, ∗∗, and ∗ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	OLS HHI_{t+1} **(1)**	Tobit HHI_{t+1} **(2)**	Probit $Excl90_{t+1}$ **(3)**	Poisson $Count_{t+1}$ **(4)**
GAI_t	-0.007**	-0.007**	-0.012*	0.024**
	(-2.20)	(-2.40)	(-1.85)	(2.17)
Constant	0.773***			
	(20.14)			
Control variables	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,704	8,704	8,704	8,704
R^2	0.145			
F-statistics	25.248***	25.863***	13.734***	21.704***

Table 6. Difference-in-differences regressions

This table presents the DID regression results of the impact of generalist CEOs on future debt concentration. The sample covers firm–year observations three years before and three years an exogenous CEO turnover, excluding the turnover year. The sample period for generalist CEO variables and control variable is from 2000 to 2016 and the sample period for debt concentration variables is from 2001 to 2017. Following Huang and Kisgen (2013), we require that firms have at least two years of non-missing data for all variables before the executives' transition. The dependent variable is a proxy for debt concentration: HHI_{t+1}. $Transition$ is equal to one if a firm experiences a specialist-to-generalist CEO transition and zero otherwise. $Post_t$ is equal to one if year t is after the CEO transition and zero otherwise. We control for the year and Fame–French 48 industry fixed effects in column (1) and control for the year and firm fixed effects in column (2). The coefficients of the fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

	HHI_{t+1}	
Variables	**(1)**	**(2)**
$Transition \times Post_t$	-0.072*	-0.071*
	(-1.66)	(-1.79)
$Transition$	-0.001	
	(-0.02)	
$Post_t$	0.077**	0.014
	(2.40)	(0.43)
$Size_t$	-0.013	-0.064**
	(-1.15)	(-2.15)
$Tangibility_t$	0.106	-0.439**
	(1.00)	(-2.10)
$Leverage_t$	-0.539***	-0.469***
	(-4.46)	(-3.04)
MTB_t	0.016**	0.005
	(2.31)	(0.70)
$Profitability_t$	-0.122	0.603
	(-0.45)	(1.61)
$R\&D_t$	0.694	-1.338***
	(1.23)	(-2.73)
$Dividend_t$	-0.962	-1.045
	(-1.02)	(-1.24)
$Rating_t$	-0.142	0.078
	(-1.41)	(0.87)
$CF\_Volatility_t$	1.288**	1.294*
	(2.00)	(1.93)
$Firm\_Age_t$	-0.012	-0.090
	(-0.15)	(-0.53)
$Z\text{-}Score_t$	0.001	-0.139***
	(0.03)	(-3.07)
Constant	0.895***	1.621***
	(4.31)	(2.88)
Industry fixed effects	Yes	No
Year fixed effects	Yes	Yes
Firm fixed effects	No	Yes
Observations	513	513
Adjusted R^2	0.287	0.130

Table 7. Path analyses

This table presents the estimation of a structural equation model of the direct effect of the CEO general ability index (GAI_t) on debt concentration, as well as the indirect effect of GAI_t on debt concentration through mediating variables. The mediating variable is *C-Score* in Panel A and *Mgr_disclosure* in Panel B. The indirect effect of GAI_t on debt concentration is the product of the effect of GAI_t on the mediating variable and the effect of the mediating variable on debt concentration. Debt concentration is measured by HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The control variables the same as those reported in Table 3. All regressions include the year and Fama–French 48 industry fixed effects.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 significance of the indirect effect is estimated using Sobel's (1982) test statistics. The z-statistics of other coefficient estimates are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

	HHI_{t+1}		$Excl90_{t+1}$		$Count_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A. Accounting conservatism: *C-Score*.						
	Coeff.	z-stat.	Coeff.	z-stat.	Coeff.	z-stat.
Direct path						
P(*GAI*, Debt Concentration)	-0.012**	-2.15	-0.056**	-1.96	0.020**	2.07
Mediated path						
P(*GAI*, *C-Score*)=a	0.001***	3.31	0.001***	3.31	0.001***	3.31
P(*C-Score*, Debt Concentration)=b	-0.780***	-4.14	-4.087***	-3.80	1.365***	4.23
Total indirect path for *C-Score* (=a×b)	-0.001***	-2.74	-0.005**	-2.54	0.002***	2.85
Control variables	Yes		Yes		Yes	
Industry fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Observations	8,448		8,448		8,448	
Panel B. Manager voluntary disclosure: *Mgr_disclosure*.						
	Coeff.	z-stat.	Coeff.	z-stat.	Coeff.	z-stat.
Direct path						
P(*GAI*, Debt Concentration)	-0.012***	-4.20	-0.021***	-3.46	0.021***	3.91
Mediated path						
P(*GAI*, *Mgr_disclosure*)=a	0.001***	4.29	0.001***	4.29	0.024***	4.29
P(*Mgr_disclosure*, Debt Concentration)=b	-0.000	-1.59	-0.001*	-1.78	0.029***	2.71
Total indirect path for *Mgr_disclosure* (=a×b)	-0.001***	-2.74	-0.005**	-2.54	0.001**	2.25
Control variables	Yes		Yes		Yes	
Industry fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Observations	8,704		8,704		8,704	

Table 8. Cross-sectional analyses

This table examines the cross-sectional variations of the impact of the CEO general ability index (GAI_t) on debt concentration. In Panels A–E, we divide our sample into two sub-samples based on financial constraints measured by *WW-Index* (Whited and Wu, 2006), co-opted board directors measured by *Co-Opt* (Coles et al., 2006), product market competition measured by *HHI_Sales* (Chen et al., 2015), managerial ability measured by *MA-Score* (Demerjian et al., 2012), and R&D expenses measured by *R&D*, respectively. Firm–year observations are in the high (low) sub-samples if the corresponding proxy variables are above (below) their annual median. In Panel F, we divide our sample into two sub-samples based on *IG_Rating_Dummy*. *IG_Rating_Dummy* is equal to one if a firm has a long-term credit rating by S&P of BBB− or higher or if it has a short-term credit rating by S&P of A−3 or higher and zero otherwise (Badoer and James, 2016). The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is GAI_t. The model specifications are OLS, Tobit, Probit, and Poisson, from left to right. We report the regression coefficients in columns (1) and (2) and average treatment effects in columns (3)–(8). The control variables are the same as those reported in Table 3. The coefficients of the control variables, year fixed effects, and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

	OLS HHI_{t+1}		Tobit HHI_{t+1}		Probit $Excl90_{t+1}$		Poisson $Count_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Panel A. Financial constraints: *WW-Index*.								
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
GAI_t	0.001	-0.023***	0.001	-0.020***	-0.001	-0.038***	0.012	0.057***
	(0.20)	(-3.34)	(0.11)	(-3.28)	(-0.04)	(-3.00)	(0.53)	(2.84)
Constant	0.664***	0.930***						
	(7.39)	(16.41)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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	OLS HHI_{t+1}		Tobit HHI_{t+1}		Probit $Excl90_{t+1}$		Poisson $Count_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,355	4,349	4,355	4,349	4,355	4,337	4,355	4,349
Pseudo or Adjusted R^2	0.138	0.165	0.507	0.292	0.093	0.114	0.017	0.020
p-value for difference in coefficients or marginal effects	0.000***		0.000***		0.002***		0.021**	
Panel B. Co-opted board directors: *Co-Opt.*								
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
GAI_t	-0.002	-0.026***	-0.002	-0.023***	-0.001	-0.051***	0.005	0.071***
	(-0.19)	(-2.84)	(-0.32)	(-2.79)	(-0.06)	(-3.11)	(0.20)	(2.64)
Constant	0.931***	0.896***						
	(11.13)	(13.07)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,455	3,238	3,455	3,238	3,449	3,230	3,455	3,238
Pseudo or Adjusted R^2	0.134	0.166	0.346	0.400	0.095	0.112	0.018	0.022
p-value for difference in coefficients or marginal effects	0.001***		0.002***		0.000***		0.004***	
Panel C. Product market competition: *HHI_Sales.*								
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
GAI_t	-0.007	-0.020***	-0.007	-0.019***	-0.012	-0.034**	0.025	0.059***
	(-0.95)	(-2.74)	(-1.05)	(-2.85)	(-0.87)	(-2.39)	(1.05)	(2.63)
Constant	0.887***	0.824***						
	(11.85)	(10.83)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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	OLS HHI_{t+1}		Tobit HHI_{t+1}		Probit $Excl90_{t+1}$		Poisson $Count_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,447	4,257	4,447	4,257	4,447	4,257	4,447	4,257
Pseudo or Adjusted R^2	0.144	0.149	0.335	0.347	0.096	0.104	0.019	0.018
p-value for difference in coefficients or marginal effects	0.034**		0.025**		0.061*		0.077*	
Panel D. Managerial ability: *MA-Score*.								
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
GAI_t	-0.020***	-0.006	-0.019***	-0.005	-0.030**	-0.012	0.074***	0.007
	(-2.68)	(-0.92)	(-2.89)	(-0.92)	(-2.28)	(-0.96)	(3.41)	(0.36)
Constant	0.871***	0.800***						
	(11.32)	(12.10)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,321	4,312	4,321	4,312	4,321	4,304	4,321	4,312
Pseudo or Adjusted R^2	0.160	0.116	0.424	0.274	0.108	0.087	0.019	0.016
p-value for difference in coefficients or marginal effects	0.021**		0.012**		0.151		0.000***	
Panel E. R&D expenses: *R&D*.								
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
GAI_t	-0.009	-0.020***	-0.008	-0.019***	-0.021	-0.026*	0.024	0.056***
	(-1.06)	(-2.71)	(-1.06)	(-2.88)	(-1.43)	(-1.86)	(0.93)	(2.74)
Constant	0.835***	0.889***						
	(9.17)	(12.53)						

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	OLS HHI_{t+1}		Tobit HHI_{t+1}		Probit $Excl90_{t+1}$		Poisson $Count_{t+1}$	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,449	4,255	4,449	4,255	4,449	4,233	4,449	4,255
Pseudo or Adjusted R^2	0.159	0.147	0.387	0.349	0.103	0.101	0.021	0.017
p-value for difference in coefficients or marginal effects	0.065*		0.050**		0.665		0.099**	
Panel F. Credit rating: *IG_Rating_Dummy*.								
	= 0	= 1	= 0	= 1	= 0	= 1	= 0	= 1
GAI_t	-0.016**	-0.002	-0.014**	-0.002	-0.024**	-0.007	0.046**	0.010
	(-2.36)	(-0.19)	(-2.33)	(-0.27)	(-2.01)	(-0.39)	(2.35)	(0.34)
Constant	1.018***	0.536***						
	(11.75)	(3.72)						
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,004	2,700	6,004	2,700	6,004	2,696	6,004	2,700
Pseudo or Adjusted R^2	0.197	0.115	0.338	1.540	0.128	0.096	0.024	0.017
p-value for difference in coefficients or marginal effects	0.030**		0.035**		0.203		0.099*	

Table 9. Alternative measure of generalist CEOs

This table reports the estimates of the panel regressions of future debt concentration on an alternative CEO general ability measure (GAI_Dummy_t) and control variables. The sample covers 8,704 firm–year observations with non-missing values for the regression variables during 2000–2016. The independent variable of interest is GAI_Dummy_t, which is equal to one if a CEO's general ability index is above the annual median and zero otherwise. The control variables are the same as those reported in Table 3. In columns (1)–(4), the model specifications are OLS, Tobit, Probit, and Poisson, respectively. We report the regression coefficients in column (1) and average treatment effects in columns (2)–(4). The coefficients of the control variables, year fixed effects, and Fama–French 48 industry fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

	OLS	Tobit	Probit	Poisson
	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
Variables	**(1)**	**(2)**	**(3)**	**(4)**
GAI_Dummy_t	-0.017*	-0.015*	-0.030*	0.054**
	(-1.85)	(-1.85)	(-1.77)	(1.96)
Constant	0.874***			
	(14.17)			
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	8,704	8,704	8,704	8,704
Pseudo or Adjusted R^2	0.143	0.325	0.093	0.017

Table 10. Controlling for managerial traits

This table reports the estimates of the panel regressions of future debt concentration on the CEO general ability index (GAI_t), managerial traits, and control variables. The sample covers firm–year observations with non-missing values for the regression variables during 2000-2016. In columns (1)–(4), we control for *CEO_Delta*, *CEO_Vega*, *CEO_Age*, *CEO_Tenure*, *CEO_Gender*, *CEO_Ownership*, and *CEO_Power*. In column (5), we add the CEO fixed effects. The other control variables are the same as those reported in Table 3. In columns (1)–(5), the model specifications are OLS, Tobit, Probit, Poisson, and OLS respectively. We report the regression coefficients in columns (1) and (5) and average treatment effects in columns (2)–(4). The coefficients of the other control variables, Fama–French 48 industry fixed effects, year fixed effects, and CEO fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The t-statistics or z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	OLS HHI_{t+1} **(1)**	Tobit HHI_{t+1} **(2)**	Probit $Excl90_{t+1}$ **(3)**	Poisson $Count_{t+1}$ **(4)**	OLS HHI_{t+1} **(5)**
GAI_t	-0.016**	-0.014***	-0.028**	0.040**	-0.036*
	(-2.56)	(-2.59)	(-2.48)	(2.16)	(-1.75)
CEO_Delta_t	-0.008	-0.006	-0.016	0.006	-0.006
	(-0.60)	(-0.49)	(-0.62)	(0.16)	(-0.37)
CEO_Vega_t	0.314**	0.301***	0.511**	-0.973**	0.229*
	(2.47)	(2.62)	(2.01)	(-2.36)	(1.82)
CEO_Age_t	0.001	-0.009	0.039	0.169	-0.064
	(0.03)	(-0.21)	(0.46)	(1.15)	(-0.12)
CEO_Tenure_t	0.003	0.004	-0.002	-0.015	0.020
	(0.42)	(0.64)	(-0.18)	(-0.64)	(0.96)
CEO_Gender_t	0.070**	0.072***	0.145***	-0.265***	0.000
	(2.57)	(2.61)	(2.79)	(-2.83)	(0.00)
$CEO\_Ownership_t$	0.054	0.032	0.146	0.118	0.072
	(0.35)	(0.23)	(0.46)	(0.28)	(0.47)
CEO_Power_t	-0.014	-0.014	-0.027	0.042	-0.007
	(-1.19)	(-1.34)	(-1.18)	(1.06)	(-0.64)
Constant	0.833***				1.21
	(4.54)				(0.56)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
CEO fixed effects	No	No	No	No	Yes
Observations	7,166	7,166	7,162	7,166	6,703
Pseudo or Adjusted R^2	0.154	0.370	0.102	0.019	0.545

Table 11. CEOs' general skills and debt types

This table presents the estimates of the Probit regressions of future debt type indicators on the CEO general ability index (GAI_t) and control variables. The sample covers 8,704 firm–year observations with non-missing values for the regression variables during 2000–2016. The dependent variables are seven debt type indicator variables: CP_Dummy_{t+1}, DC_Dummy_{t+1}, TL_Dummy_{t+1}, SBN_Dummy_{t+1}, $SUBN\_Dummy_{t+1}$, CL_Dummy_{t+1}, and $Other\_Dummy_{t+1}$. The control variables are the same as those reported in Table 3. We report the average treatment effects in columns (1)–(7). The coefficients of the control variables, Fama–French 48 industry fixed effects, and year fixed effects are suppressed for brevity in the respective columns. All variables are defined in Appendix A. The z-statistics reported in parentheses are based on robust standard errors clustered by firm. $***$, $**$, and $*$ indicate the significance level at 1%, 5%, and 10%, respectively.

Variables	CP_Dummy_{t+1} **(1)**	DC_Dummy_{t+1} **(2)**	TL_Dummy_{t+1} **(3)**	SBN_Dummy_{t+1} **(4)**	$SUBN\_Dummy_{t+1}$ **(5)**	CL_Dummy_{t+1} **(6)**	$Other\_Dummy_{t+1}$ **(7)**
GAI_t	-0.001	0.006	0.001	0.017*	-0.009	0.006	0.011**
	(-0.25)	(0.50)	(0.11)	(1.87)	(-1.20)	(0.49)	(1.98)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8431	8704	8704	8653	8613	8672	8517
Pseudo R^2	0.377	0.100	0.065	0.258	0.253	0.075	0.145