Generalist CEOs and Credit Ratings*

ZHIMING MA, *Guanghua School of Management, Peking University*

LUFEI RUAN, *Lam Family College of Business, San Francisco State University*†

DANYE WANG, *Stern School of Business, New York University*

HAIYAN ZHANG, *School of Economics and Management, Tsinghua University*

ABSTRACT

A recent trend is that firms prefer to hire generalist CEOs with transferable skills (across firms or industries) over hiring specialist CEOs, but the consequences of this trend are unclear. In this study, we examine whether credit rating agencies consider a CEO's general skills as a credit risk factor when assessing an entity's overall creditworthiness. We predict and find that generalist CEOs are associated with lower credit ratings, suggesting that the presence of generalist CEOs is a significant credit rating factor. We also find that generalist CEOs are likely to take on more risks, which leads to more volatile performance ex post, and our path analyses confirm default risk is a significant mediator between credit ratings and CEOs' general skills. Our results hold in the presence of additional controls (e.g., CEO characteristics and corporate governance), when applying different fixed-effect models and different matching methods, and for a subsample with forced CEO turnover. We also find that the negative relationship is attenuated for R&D-intensive firms and firms in competitive industries. Last, we provide evidence that firms with generalist CEOs face higher borrowing costs, such as bond yields and syndicated loan spreads. Overall, our results contribute to a growing literature on the costs and benefits of hiring generalist CEOs, by providing a full picture of why hiring a generalist CEO may benefit shareholders but also cause misalignments with bondholders' interests.

Keywords: general skills, generalist CEOs, risk-taking, credit ratings, borrowing costs, CEO characteristics

Chefs de la direction généralistes et notations de crédit

généralistes sont susceptibles de prendre davantage de risques, ce qui accroît la volatilité de la performance *a posteriori*, et leurs analyses des pistes causales confirment que les risques d'insolvabilité sont un médiateur important entre les notations de crédit et les compétences de généralistes des chefs de la direction. Les résultats qu'ils obtiennent résistent en présence de contrôles supplémentaires (par exemple, les caractéristiques des chefs de la direction et la gouvernance d'entreprise), lorsqu'ils appliquent différents modèles à effet fixe et différentes méthodes d'appariement, ainsi que pour un sous-échantillon de cas de rotation forcée des chefs de la direction. Les auteurs constatent également que la relation négative est atténuée dans le cas des sociétés à forte intensité d'activités de R&D et des sociétés exerçant leurs activités dans des secteurs concurrentiels. Pour finir, les auteurs font état de données démontrant que les sociétés dont les chefs de la direction sont des généralistes font face à des coûts d'emprunt plus élevés — rendements obligataires et marges sur prêts syndiqués, par exemple. Dans l'ensemble, les résultats de l'étude viennent enrichir les écrits de plus en plus abondants sur les coûts et les avantages du choix de chefs de la direction généralistes, en brossant un portrait complet des raisons pour lesquelles le choix de généralistes peut être avantageux pour les actionnaires mais peut aussi être la source de divergences d'intérêt avec les porteurs d'obligations.

Mots-clés : compétences de généralistes, chefs de la direction généralistes, prise de risques, notations de crédit, coûts d'emprunt, caractéristiques des chefs de la direction

1. Introduction

A firm's credit ratings represent rating agencies' assessments of the firm's overall creditworthiness and the firm's ability to meet its financial obligations (Standard and Poor's 2002). In general, on behalf of bondholders, rating agencies collect and process information to independently assess the likelihood of default when determining a firm's credit ratings. The literature documents many firm-level factors that rating analysts often consider in rating assessments, such as financial ratios (Kaplan and Urwitz 1979), the effectiveness of corporate governance (Ashbaugh-Skaife et al. 2006), and a CEO's compensation contract (Kuang and Qin 2013), among other factors. However, the role of a firm's management with respect to credit ratings has been largely unexplored; in fact, only a few recent papers have examined the effect of CEO attributes on firms' credit ratings (Bonsall et al. 2016; Cornaggia et al. 2017). In this study, we extend the research by examining whether credit rating agencies also consider CEOs' general skills in their rating assessments.

CEOs play a critical role in modern companies; thus, CEO recruiting is a key decision that hugely influences firms' future performance. Researchers emphasize two types of top managers since Becker's (1962) landmark study: generalist CEOs, whose skills are transferable across firms or industries, and specialist CEOs, whose skills are firm- or industry-specific. In other words, a generalist CEO usually has a more diverse career background and industry experience, while a specialist CEO usually has deeper expertise in areas specific to the firm or industry. Although the recent trend is that firms prefer externally hired CEOs to internally promoted ones (Crossland et al. 2014; Ertimur et al. 2018), the evidence about the consequences of hiring generalist CEOs is still ambiguous and somewhat debatable. On the one hand, empirical results suggest that generalist CEOs' broad expertise may improve organizational efficiency, such as reducing organizational communication costs (Ferreira and Sah 2012), spurring firm innovation (Custódio et al. 2017), and performing more complex tasks (Custódio et al. 2013), thus benefiting shareholders (Betzer et al. 2020). These results suggest that generalist CEOs are likely to outperform specialist CEOs in addressing complex modern business issues and adapting to an evolving economic environment. On the other hand, generalist CEOs' transferable skills make it easier for them to move across industries, resulting in career paths being disconnected, to some degree, from the current firm's performance. Thus, the presence of outside options may encourage generalist CEOs to take excessive risks (e.g., overinvestment in high-risk projects), which may lead to more severe agency problems, weaker financial conditions, and a higher probability of failure (Gounopoulos and Pham 2018; May 1995; Mishra 2014). Thus, it is unclear whether a generalist CEO is desirable from the perspective of bondholders. An empirical investigation is therefore warranted to directly examine whether rating agencies perceive generalist CEOs positively or negatively.

We approach this question by considering the impact of a CEO's general skill on bondholders' payoff function. It is well known that bondholders' payoff function is asymmetric in the sense that their maximum payoff is capped, but they are vulnerable to the downside risks of default. Such an asymmetric payoff function naturally suggests that bondholders are risk-averse. Generalist CEOs are usually less risk-averse than specialist CEOs in that a failure in one firm does not necessarily affect generalist CEOs' career paths, as they can easily move across industries, given their diverse industry experience. The existence of outside options naturally provides generalist CEOs with incentives to take on risky projects (Custódio et al. 2017), and such risk-taking incentives can lead to misalignments with bondholders' interests. Therefore, it is likely that generalist CEOs' risk-taking incentives are perceived negatively by bondholders, and we hypothesize a negative association between generalist CEOs and firms' credit rating.

We use a sample of public US firms from 1992 to 2015 and the CEO generality index based on lifetime work experience, following Custódio et al. (2013), to test our hypothesis. We find a negative and significant association between generalist CEOs and firms' credit ratings, suggesting that the presence of generalist CEOs is a significantly negative factor, probably because generalist CEOs' risk-taking incentives might increase firms' chances of default. The economic impact of CEO skills on credit ratings is significant. A one-standard-deviation increase in a CEO's general skills leads to a 0.169-rating-notch decrease in a firm's credit rating. The results are robust to adding firm fixed effects or CEO fixed effects to control for unknown firm or CEO characteristics that may affect bond ratings.

We further find that firms with generalist CEOs tend to take more risks ex post, such as a higher level of leverage and/or intangible investments in the next year, and those firms exhibit more volatile future performance measured by the standard deviation of return on assets (*ROA*) in the next three years. These findings further support the agency problem argument that generalist CEOs' risk-taking incentives might increase firms' chances of default. Path analyses also confirm a highly significant mediated link (by default risks) between credit ratings and CEOs' general skills, suggesting that risk of default is a mediator variable influenced by CEOs' general skills that, in turn, influences firms' credit ratings.

We also conduct multiple robustness tests with different alternative empirical specifications and identification strategies to mitigate potential endogeneity concerns. In addition to the above-mentioned firm and CEO relation between a CEO's attributes and the firm's credit rating (Bonsall et al. 2016; Cornaggia et al. 2017; Kuang and Qin 2013). This study documents a significant and negative association between firms' credit ratings and CEOs' general skills, and this negative association is through a significant mediated link by default risks. This effect is incremental to CEO ability (Bonsall et al. 2016; Cornaggia et al. 2017) and compensation contract incentives (Kuang and Qin 2013), which deepens our understanding of rating analysts' decision making and debt market risk assessment.

Second, our paper extends the literature on the value of hiring generalist and specialist CEOs (e.g., Custódio et al. 2013; Custódio et al. 2017; Ferreira and Sah 2012; Gounopoulos and Pham 2018; Mishra 2014) by providing evidence that both credit agencies and debtholders are likely to view the presence of a generalist CEO as a negative factor. In recent years, companies have seemed to prefer external CEOs, which has resulted in more CEOs with diverse career backgrounds and industry experience (Crossland et al. 2014; Ertimur et al. 2018). Probably due to this increasing demand for general skills, generalist CEOs receive pay premiums relative to specialist CEOs (Custódio et al. 2013; Frydman 2019). Some researchers find that generalist CEOs are valuable in addressing difficult and complex corporate tasks (e.g., Cunat and Guadalupe 2009; Custódio et al. 2013), while others observe that investors view hiring generalist CEOs as costly for firms (e.g., Gounopoulos and Pham 2018; Mishra 2014). These mixed findings have drawn particular attention to whether generalist CEOs' skills and traits explain differences in executive pay (see, e.g., Chang et al. 2010; Falato et al. 2015; Graham et al. 2013). Our findings contribute to the literature by providing evidence that firms with generalist CEOs tend to take more risks ex post and exhibit more volatile future performance, which may hurt debtholders' interests. These results are also consistent with the argument in prior literature that the existence of generalist CEOs' outside options naturally provides them with more risk-taking incentives. We therefore provide a full picture of why hiring a generalist CEO may be desirable from shareholders' perspectives but still lead to less favorable credit ratings and higher debt costs.

The remainder of this paper proceeds as follows. We review the literature and develop our hypothesis in the second section, and we discuss the research design and describe the data in the third section. The fourth section presents the regression results and path analyses. In the fifth and sixth sections, we report the results of the robustness tests and additional tests. We offer conclusions in the final section.

2. Hypothesis development

Credit rating agencies contribute significantly to debt markets because debt contracts (especially interest rates) are frequently determined by a borrower's credit rating. Managers (CFOs) believe that credit ratings are the second most important determinant of corporate debt policy (Graham and Harvey 2001). Moreover, the considerable increase in the corporate bond market calls for a better understanding of the factors that debt market participants consider in assessing default risk. However, until now, market participants have not fully understood which factors credit rating agencies use to determine and issue credit ratings.

A growing number of studies show that rating agencies consider firm-level factors in their analysis and rating recommendations, such as financial information (Kaplan and Urwitz 1979), earnings quality (Francis et al. 2005), accounting conservatism (Ahmed et al. 2002), analyst following (Cheng and Subramanyam 2008), book-tax difference (Ayers et al. 2010), and off-balance sheet financing (Kraft 2015). These studies generally suggest that rating agencies appreciate (discount) firm-level factors that reduce (increase) default risks. Existing literature also suggests that the attributes of a CEO influence a firm's capital structure and default risks and thus should be considered by rating agencies in their assessments. For example, Bonsall et al. (2016) and Cornaggia et al. (2017) document that firms with more capable managers tend to receive higher credit ratings. However, managerial ability is conceptually different from the focus of this paper, which is general skills that have been defined by recent studies (e.g., Custódio et al. 2013) as skills acquired through a lifetime of work experience, especially those gained while holding CEO positions at other firms and conglomerates.

General skills are particularly important in practice. The upper echelons theory (Hambrick and Mason 1984) suggests that CEOs' general skills, such as career experience and socioeconomic background, are closely related to their strategy preferences, and CEOs' strategic choices can partially predict an organization's performance. Managers develop their cognitive knowledge bases through their industry experience and knowledge, which inevitably influence their strategy preference and shape the lenses through which they perceive strategic opportunities as well as problems (Carpenter et al. 2004; Herrmann and Datta 2006; Jensen and Zajac 2004; Wiersema and Bantel 1992). Although such strategy-related knowledge significantly contributes to managers' accumulated skills, it can only be gained tacitly or experientially (Ansoff 1988). Managers who have spent their entire careers in one organization (i.e., specialist CEOs) have a relatively narrow range of knowledge and might not perform well when facing novel problems, such as intensified competition or technology shifts.

However, it is still unclear whether and how CEOs' strategy preferences and general skills affect firms' bond ratings, even though major credit rating agencies all state that they use factors related to managerial quality in credit risk assessments (Moody's Investor Service 2002; Standard and Poor's 2008).[1] On the one hand, generalist CEOs' broad expertise may improve organizational efficiency and thus may be viewed as a signal of high managerial ability in modern business. For example, Ferreira and Sah (2012) find that firms with generalist CEOs incur lower communication costs between CEOs and their subordinates, especially for firms having more unpredictable or complex businesses. Custódio et al. (2013) find that, compared with specialist CEOs, generalist CEOs perform better in more complex tasks, such as restructurings and acquisitions. Custódio et al. (2017) find that generalist CEOs are more likely to prompt firm innovation given their broader knowledge beyond firms' current technological domains.[2]

On the other hand, generalist CEOs may take excessive risks because they are less susceptible to being fired and enjoy a more favorable job market environment. This happens because generalist CEOs' diverse backgrounds facilitate their movement across industries; therefore, failure in one company may not reflect poorly on their abilities, especially when they move to another place or industry. As a result, it is not surprising that generalist CEOs express relatively less concern for their careers and possess less long-term wealth associated with their firm's future performance. Prior studies find that generalist CEOs engage more in job-hopping and get hired more easily (Custódio et al. 2013).[3] Thus, generalist CEOs have more incentives to invest in high-risk projects, without considering the fact that such corporate policies compromise firm value, misaligning their incentives with those of shareholders (Custódio et al. 2017; May 1995; Mishra 2014). For example, May (1995) finds that a specialist CEO who has spent many years in one firm has a negative impact on the variance of the firm's equity return and the firm's leverage. Mishra (2014) finds that, compared with specialist CEOs, generalist CEOs may have different incentives for risk-taking, resulting in more severe agency problems. Similarly, Gounopoulos and Pham (2018) find that generalist CEOs' incentives are less likely to align with the interests of stakeholders and therefore enhance the probability of failure after initial public offerings. In contrast, specialist CEOs' job mobility is more limited, and poor firm performance will negatively

1. For example, Moody's evaluates three key elements—franchise value, financial statement analysis, and management quality—in the fundamental credit rating analysis.
2. However, more general skills do not necessarily result in better firm performance. Custódio et al. (2013) find that the relationship between CEOs' general skills and firm performance is statistically insignificant. Moreover, Gounopoulos and Pham (2018) find that specialists perform better than generalists in newly listed firms.
3. A specialist CEO's job search might be delayed by the prevalent "noncompete clauses," which prevent them from working for competitors in the same industry.

affect their future job opportunities (Custódio et al. 2017). Therefore, specialist CEOs often prefer strategic stability and long-term viable firm performance. To summarize, this line of research reveals a potential difference between generalist and specialist CEOs in regard to their attitudes toward risk-taking as well as their approaches to minimizing risks, suggesting that generalist CEOs relatively lack incentives to reduce risk.

Collectively, top managers' general skills may benefit firms by improving operating efficiency, but may also increase firms' downside risks of default due to their excess risk-taking. As discussed in the credit rating literature, rating agencies collect and process information to provide independent assessments of firms' credit risks on behalf of bondholders, while bondholders are more vulnerable to the downside risks of default because of their asymmetric payoff function. Consequently, rating agencies are more likely to negatively perceive factors that increase default risks. Therefore, we hypothesize a negative association between generalist CEOs and firms' credit rating.

HYPOTHESIS 1. *Generalist CEOs are negatively associated with credit ratings.*

Nevertheless, there are other reasons why we may not observe such an effect. As stated in the literature (Bonsall et al. 2016; Cornaggia et al. 2017), firm characteristics explain most of the variation in credit ratings, and the degree to which rating agencies consider CEO attributes remains uncertain. Furthermore, even if rating agencies evaluate managerial attributes in credit risk assessments, it remains unclear whether attributes that rating agencies use would match with the data from publicly available sources.

3. Sample and research design

Sample and data

We obtain CEOs' general ability data from Custódio et al. (2013) and extend their data with data from BoardEx. We also obtain credit rating data and company financial data from Compustat. The final sample includes 12,675 firm-year observations for 1,272 unique US firms from 1992 to 2015. We winsorize all continuous variables at the top and bottom one percentiles to mitigate the effects of outliers.

CEOs' general skills measure

A CEO's general skills capture the generality of human capital the CEO has accumulated from work experience (Custódio et al. 2013).[4] The construction of this index considers five aspects of a CEO's professional career: the number of past positions, the number of past firms, the number of industries in which the CEO worked, whether the CEO held a CEO position at a different company, and whether the CEO worked for a conglomerate (Custódio et al. 2013). Custódio et al. (2013) use principal component analysis to extract the common components from these five proxies, meaning that a CEO who has diverse working experience, including taking different positions, working in multiple firms or different industries or in a conglomerate firm, or previously serving as a CEO in another firm, is classified as having more general skills. A higher index value reflects a higher level of generality of the CEO's human capital (Custódio et al. 2013).

Credit rating measure

Following related research (Ashbaugh-Skaife et al. 2006; Bonsall et al. 2016; Cornaggia et al. 2017; Kuang and Qin 2013), we define a firm's credit ratings as a numerical translation of the

4. We appreciate Custódio et al.'s (2013) generous sharing of data on General Ability Index (available online at http://jfe.rochester.edu/data.htm).

S&P long-term issuer credit ratings, which increase in credit quality or decrease in credit risk. The ratings range from AAA (highest rating) to D (lowest rating; i.e., defaulting on debt payment), reflecting S&P's assessment regarding the firm's creditworthiness relative to its senior debt obligations. We transform the ratings into numbers from 1 to 22 to conduct the following analyses.

Research design

To explore the relationship between a firm's credit ratings and a CEO's general skills, we use the following model:

$$RATE = \beta_0 + \beta_1\, GA + \sum \beta_i\, Controls_i + \varepsilon. \tag{1}$$

The dependent variable *RATE* is the firm's credit ratings, which increase in credit quality or decrease in credit risk. Our variable of interest, *GA*, is the CEO's general skills, following Custódio et al. (2013). Hypothesis 1 predicts a negative association ($\beta_1 < 0$) between a firm's credit ratings and a CEO's general skills. Following prior studies (Ashbaugh-Skaife et al. 2006; Bonsall et al. 2016; Cornaggia et al. 2017; Kuang and Qin 2013), we control for variables that are found to affect a firm's credit ratings. First, we control for managerial ability (*MASCORE*), an index developed by Demerjian et al. (2012), to show that our variable of interest has an incremental effect. Second, we include two measures to capture financial reporting quality: financial transparency (*TRANSP*) and abnormal accruals (*ACCRUAL*). Third, we control for firm size, profitability, and operational risks: the natural logarithm of total assets (*SIZE*), operating loss (*LOSS*), interest coverage (*COVER*), return on assets (*ROA*), financial leverage (*LEV*), and standard deviation of *ROA* over the prior three years (*ROASTD3*). Fourth, we include variables to proxy for market valuation: the book-to-market ratio (*BMRATIO*) and the standard deviation of daily stock returns over the past year (*STDRET*). Fifth, we control for growth and investment opportunities: capital investments (*CAPINT*) and R&D and advertising intensity (*INTAN*). Finally, we include both industry and year fixed effects in the regressions. Standard errors are corrected for heteroskedasticity and are clustered at the firm level. A detailed definition of all variables is summarized in Appendix 1.

Descriptive statistics and correlation

Table 1 reports the descriptive statistics. Panel A presents the sample distribution by year, showing that our sample is roughly evenly distributed over the period 1992–2015. Panel B presents the descriptive statistics of all variables in our sample. Based on panel B, the median value of the credit rating is 13, indicating that median sample firms have a BBB− credit rating. In addition, the lower quartile of the credit rating is 11, while the higher quartile is 16, suggesting that sample firms' ratings possess adequate variation.

Table 2 shows the correlations among all variables. Column (1) confirms that most control variables are significantly associated with the dependent variable *RATE*.

4. Empirical results

Test of Hypothesis 1

Table 3 reports the estimation results of Hypothesis 1, in which we explore the association between a CEO's general skills and a firm's credit ratings. Column (1) presents the regression results based on equation (1). The coefficient on *GA* is negative and significant ($p < 0.01$, two-tailed), which is consistent with Hypothesis 1, indicating that credit agencies are likely to view CEOs' general skills as a negative factor. To examine the economic significance of the *GA* coefficient estimate, we estimate credit ratings using equation (1), using the full sample and setting the values of all independent variables at their mean levels. The estimated mean rating is 13.28 (untabulated). A one-standard-deviation increase in *GA* (1.00) from its mean value results in a

TABLE 1
Descriptive statistics

Panel A: Sample distribution by year

Year	Freq.	Percent	Year	Freq.	Percent
1992	135	1.07	2004	626	4.94
1993	352	2.78	2005	613	4.84
1994	400	3.16	2006	620	4.89
1995	446	3.52	2007	613	4.84
1996	500	3.94	2008	567	4.47
1997	513	4.05	2009	562	4.43
1998	557	4.39	2010	545	4.3
1999	605	4.77	2011	536	4.23
2000	612	4.83	2012	541	4.27
2001	606	4.78	2013	538	4.24
2002	609	4.80	2014	530	4.18
2003	630	4.97	2015	419	3.31
			Total	12,675	100

Panel B: Descriptive statistics

Variable	*N*	Mean	SD	Q1	Median	Q3
RATE	12,675	13.28	3.37	11.00	13.00	16.00
GA	12,675	0.20	1.00	−0.54	0.05	0.78
MASCORE	12,675	0.01	0.15	−0.09	−0.03	0.06
TRANSP	12,675	−0.11	0.25	−0.10	−0.03	−0.01
ACCRUAL	12,675	0.08	0.64	−0.05	0.00	0.07
SIZE	12,675	8.29	1.27	7.37	8.18	9.13
LOSS	12,675	0.16	0.37	0.00	0.00	0.00
COVER	12,675	14.59	23.88	4.39	7.96	14.12
ROA	12,675	0.04	0.07	0.02	0.05	0.08
BMRATIO	12,675	0.47	0.39	0.24	0.40	0.61
ROASTD3	12,675	0.04	0.05	0.01	0.02	0.04
STDRET	12,675	0.02	0.01	0.02	0.02	0.03
LEV	12,675	0.30	0.16	0.19	0.28	0.38
CAPINT	12,675	0.33	0.23	0.15	0.28	0.48
INTAN	12,675	0.03	0.05	0.00	0.01	0.05

Notes: This table reports the year distribution and the descriptive statistics for the variables used in the analyses. Panel A presents the distribution of the final sample by year. Panel B presents the descriptive statistics for the variables used in the analyses. See Appendix 1 for variable definitions.

0.169-rating-notch decrease in credit ratings. This economic significance for CEOs' general skills is comparable to the economic magnitude of important variables that have been well documented in prior literature, such as firm performance and reporting quality (Ashbaugh-Skaife et al. 2006; Kaplan and Urwitz 1979). A one-standard-deviation increase in return on assets (*ROA*) and in financial transparency (*TRANSP*) from their respective mean values will result in approximately a 0.485- and 0.118-rating-notch increase in credit rating, respectively.[5] In column (2), we use the dummy variable *Generalist_Dummy* to substitute for *GA*. Following Custódio et al. (2013), *Generalist_Dummy* is an indicator variable that equals one if the CEO's general skills are above

5. 0.07 (one-standard-deviation of *ROA*) × 6.925 (coefficient on *ROA*) = 0.485
0.25 (one-standard-deviation of *TRANSP*) × 0.473 (coefficient on *TRANSP*) = 0.118.

TABLE 2
Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*RATE*														
(2)	*GA*	**0.081**													
(3)	*MASCORE*	**0.324**	**0.044**												
(4)	*TRANSP*	**0.144**	0.016	**−0.034**											
(5)	*ACCRUAL*	**0.032**	0.017	0.021	0.014										
(6)	*SIZE*	**0.502**	**0.248**	**0.263**	**0.107**	**0.066**									
(7)	*LOSS*	**−0.393**	0.005	**−0.149**	**−0.053**	−0.01	**−0.127**								
(8)	*COVER*	**0.291**	**−0.032**	**0.258**	0.004	0.008	**0.116**	**−0.192**							
(9)	*ROA*	**0.489**	−0.009	**0.264**	**0.039**	**0.028**	**0.153**	**−0.712**	**0.36**						
(10)	*BMRATIO*	**−0.225**	**−0.086**	**−0.173**	**0.033**	**−0.037**	**−0.093**	**0.169**	**−0.146**	**−0.253**					
(11)	*ROASTD3*	**−0.345**	0.008	**−0.024**	**−0.119**	−0.005	**−0.184**	**0.401**	**−0.073**	**−0.452**	**−0.029**				
(12)	*STDRET*	**−0.533**	**−0.074**	**−0.095**	**−0.29**	**−0.025**	**−0.3**	**0.415**	**−0.123**	**−0.441**	**0.219**	**0.427**			
(13)	*LEV*	**−0.401**	**−0.029**	**−0.214**	**−0.027**	0.02	**−0.156**	**0.237**	**−0.462**	**−0.31**	**−0.102**	**0.14**	**0.189**		
(14)	*CAPINT*	−0.017	**−0.079**	**−0.133**	**0.047**	**−0.031**	**0.047**	**0.063**	**−0.118**	**−0.072**	**0.123**	0.005	**0.04**	**0.154**	
(15)	*INTAN*	**0.134**	**0.069**	**0.293**	**−0.073**	**0.043**	**0.023**	**0.033**	**0.202**	**0.082**	**−0.232**	**0.144**	0.022	**−0.138**	**−0.293**

Notes: This table presents the Pearson correlation matrix. Numbers in bold indicate significance at the 1% level (two-sided) or lower. See Appendix 1 for variable definitions.

the 75th percentile in a given year, and zero otherwise. The result of column (2) is similar to that of column (1).

Although we have already controlled for factors that are known to affect a firm's credit ratings, unknown firm characteristics affecting credit ratings may be missing. Prior literature and anecdotal evidence suggest that credit ratings might be affected by firm effects. These firm effects might be time-invariant, in the sense that they vary across firms but are constant over time. For example, firm-specific political costs, which cannot be fully proxied by size or other variables, may affect the risk of default and thus may drive the firm's credit rating. Therefore, we adopt fixed-effect methods to solve omitted variable problems.

Column (3) of Table 3 reports the results controlling for firm fixed effects, in which only the impact of within-firm changes on *RATE* is taken into account; thus, the observed relationship between *RATE* and *GA* is not caused by firm-specific unobserved variables. Column (4) of Table 3 reports the results controlling for CEO fixed effects, in which the coefficient on *GA* captures only the difference in *RATE* with a shift from specialist to generalist leadership or vice versa. The coefficients on *GA* remain negative and significant in both columns ($p < 0.01$ in column (3) and $p < 0.05$ in column (4), two-tailed), indicating that our main results are not likely to be driven by unobservable firm and CEO characteristics. The economic impact of *GA* on credit ratings remains significant. A one-standard-deviation increase in *GA* (1.00) from its mean value is associated with a 0.105-rating-notch decrease in column (3) and a 0.18-rating-notch decrease in column (4).

For the control variables, the coefficient on *MASCORE* is positive and significant ($p < 0.01$ in columns (1)–(3) and $p < 0.05$ in column (4), two-tailed), which is consistent with the findings in prior literature that firms with more capable managers tend to have low default risk and thus higher credit ratings (Bonsall et al. 2016; Cornaggia et al. 2017). The coefficients on *TRANSP*, *SIZE*, *COVER*, *ROA*, and

TABLE 3
Main results

	RATE			
Variable	(1)	(2)	(3)	(4)
GA	−0.169***		−0.105***	−0.180**
	(−4.78)		(−3.24)	(−2.45)
Generalist_Dummy		−0.342***		
		(−4.21)		
MASCORE	0.956***	0.967***	0.604***	0.448**
	(3.00)	(3.04)	(2.93)	(2.51)
TRANSP	0.473***	0.467***	0.147***	0.144***
	(6.38)	(6.31)	(3.01)	(2.99)
ACCRUAL	−0.017	−0.018	0.012	−0.005
	(−0.62)	(−0.66)	(0.55)	(−0.26)
SIZE	1.091***	1.078***	1.110***	0.862***
	(24.58)	(24.35)	(13.14)	(10.64)
LOSS	−0.042	−0.044	−0.020	−0.026
	(−0.46)	(−0.48)	(−0.32)	(−0.47)
COVER	0.009***	0.009***	0.004***	0.001
	(4.05)	(4.11)	(3.00)	(1.40)
ROA	6.925***	6.930***	3.685***	3.300***
	(11.26)	(11.26)	(8.45)	(7.86)
BMRATIO	−0.769***	−0.765***	−0.391***	−0.358***
	(−7.59)	(−7.49)	(−4.57)	(−4.29)
ROASTD3	−1.393**	−1.451**	−0.737	−1.192**
	(−1.99)	(−2.07)	(−1.23)	(−2.15)
STDRET	−98.189***	−97.807***	−53.631***	−41.644***
	(−22.87)	(−22.77)	(−15.60)	(−12.40)
LEV	−4.166***	−4.170***	−3.524***	−3.329***
	(−13.95)	(−13.97)	(−12.38)	(−11.68)
CAPINT	0.650**	0.686**	2.088***	1.231***
	(2.26)	(2.38)	(4.84)	(2.77)
INTAN	1.842	1.771	2.704*	3.736***
	(1.60)	(1.54)	(1.73)	(2.77)
Constant	8.886***	9.134***	7.258***	8.509***
	(10.40)	(10.52)	(10.35)	(7.74)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes		Yes
Firm FE			Yes	
CEO FE				Yes
Observations	12,675	12,675	12,675	12,675
R^2	0.724	0.724	0.911	0.945

Notes: This table reports coefficients from the estimation of the following model:

$$RATE = \beta_0 + \beta_1 \times GA\ (Generalist\_Dummy) + \sum \beta_i \times Controls + \varepsilon.$$

See Appendix 1 for variable definitions. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include different fixed effects (e.g., year and industry fixed effects in columns (1) and (2); year and firm fixed effects in column (3); year, industry, and CEO fixed effects in column (4)), and standard errors are heteroskedasticity-robust and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

A one-standard-deviation increase in *GA* (1.00) from its mean value increases *FUT1_LEV* to 0.2301 (a 0.7% increase), *FUT1_INTAN* to 0.0385 (a 0.8% increase), *FUT1_LOSS* to 0.1669 (a 4.8% increase), and *FUT3_ROASTD* to 0.0408 (a 2.8% increase).

2016; Lu et al. 2011) and conduct path analyses to determine if there is an indirect link in which the risk of default is a mediator variable influenced by CEOs' general skills that, in turn, influences firms' credit ratings. Following prior literature (e.g., Charitou et al. 2011; Franzen et al. 2007), we use Ohlson's O-score and Altman's Z-score to proxy for default risk. Table 5 reports the results of the path analyses. In column (1), we use the next year's Ohlson's O-score (*FUT1_OScore*) to proxy for default risks; a higher *OScore* indicates a higher risk of default. In column (2), we use the next year's Z-score (*FUT1_ZScore*) to proxy for default risks; a lower *ZScore* indicates a higher risk of default. In both columns, both direct and mediated paths are negative and highly significant. The percentage of the total effect of *GA* on *RATE* are approximately 92% and 81%, respectively, which are attributable to the direct path, while approximately 8% and 19%, respectively, are attributable to the mediated path. We also find similar results when we use the current year's O-score and Z-score as mediators (results untabulated). Taken together, the results in Table 5 suggest that the mediated link (via default risks) between credit ratings and CEOs' general skills is reliably nonzero.

5. Robustness tests

Additional controls

Our level tests in Table 3 show that a CEO's general skill has an effect on a firm's credit rating that is incremental to the effect of managerial ability, mitigating concerns about whether a CEO's general skills can be captured by managerial ability. However, it is still unclear whether a CEO's general skills have an effect on a firm's credit rating that is incremental to the effects of other CEO attributes, such as gender, tenure, age, and compensation incentives, and corporate governance fac-

TABLE 5
Path analyses

	Risk measure			
	(1) *FUT1_OScore*		(2) *FUT1_ZScore*	
	Coefficient	z-stat	Coefficient	z-stat
Direct path				
p(GA, RATE)	−0.158***	−4.45	−0.139***	−3.96
percentage	91.86		81.29	
Indirect path				
p(GA, Risk) = a	0.047***	2.50	−0.097***	−4.28
p(Risk, RATE) = b	−0.295***	−9.20	0.326***	11.45
Total indirect path (=a × b)	−0.014**	−2.37	−0.032***	−4.01
percentage	8.14		18.71	
Controls	Yes		Yes	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
Observations	12,323		12,304	

Notes: This table reports path analyses of the links between credit ratings and CEOs' general skills—a direct link and a link mediated by default risks. Specifically, we estimate the following structural equation models:

$RATE = \beta$

before the matching, most of these differences become insignificant after the matching, suggesting that our matching process is efficient. Table 6, column (1), presents the regression results of equation (1) based on the PSM sample. The coefficient on *Generalist_Dummy* is negative and significant ($p < 0.01$, two-tailed), which is consistent with the prediction of Hypothesis 1.

Panel C of Table 11 in Appendix 2 illustrates the matching efficiency of EB. While the mean and variance between the treatment and the control groups are significantly different before matching, they become exactly the same after matching. Table 6, column (2), presents the regression results of equation (1) based on the EB matching sample. The coefficient on *Generalist_Dummy* is significantly negative ($p < 0.01$, two-tailed), which is consistent with the prediction of Hypothesis 1.

Collectively, the results of Table 6 suggest that the potential appointment of generalist CEOs to firms with a higher default risk (i.e., a lower credit rating) does not explain our main findings. Therefore, our results are not likely to be driven by observable differences in firm characteristics.

Forced CEO turnover subsample

We recognize that the negative association between firm ratings and a CEO's general skills could arise from a higher demand for a generalist CEO's talent among firms with low credit ratings, which leads to a reverse causality issue. To address this possibility, we next conduct a change

TABLE 6
PSM and EB matching

	RATE	
Variable	PSM (1)	EB (2)
Generalist_Dummy	−0.350***	−0.319***
	(−3.74)	(−3.78)
MASCORE	1.216***	1.160***
	(3.17)	(3.15)
TRANSP	0.558***	0.504***
	(4.27)	(5.16)
ACCRUAL	0.049	0.040
	(1.16)	(1.12)
SIZE	0.967***	0.991***
	(18.99)	(20.28)
LOSS	−0.139	−0.177
	(−0.90)	(−1.45)
COVER	0.011***	0.012***
	(3.23)	(3.33)
ROA	7.090***	6.962***
	(7.88)	(9.23)
BMRATIO	−0.824***	−0.817***
	(−4.78)	(−5.52)
ROASTD3	−2.481**	−2.282***
	(−2.40)	(−2.65)
STDRET	−103.213***	−104.789***
	(−16.34)	(−19.39)
LEV	−4.261***	−4.510***
	(−9.52)	(−10.97)
CAPINT	1.029**	1.008***
	(2.45)	(2.61)
INTAN	2.724*	2.480**
	(1.89)	(1.97)
Constant	10.247***	9.918***
	(7.24)	(7.42)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	5,360	11,034
R^2	0.724	0.727

Notes: This table reports coefficients from the estimation of the following model using the matching samples:

$$RATE = \beta_0 + \beta_1 \times Generalist\_Dummy + \sum \beta_i \times Controls + \varepsilon.$$

Column (1) presents the regression results of the PSM sample. The matching sample is constructed using a nearest-neighbor PSM with a caliper width of 0.05 and with replacement. The propensity scores are calculated by a probit model in which the dependent variable is *Generalist_Dummy*. Column (2) presents the regression results of the EB matching sample. See Appendix 2 for the first-stage results of PSM and the matching efficiency of PSM and EB matching. See Appendix 1 for variable definitions. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include year and industry fixed effects, and standard errors are heteroskedasticity-robust and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 7
Forced CEO turnover analysis

Variable	Forced CEO turnover sample $\Delta RATE$
ΔGA	−0.169**
	(−2.02)
$\Delta MASCORE$	1.997*
	(1.70)
$\Delta TRANSP$	0.280
	(0.74)
$\Delta ACCRUAL$	−0.195
	(−1.31)
$\Delta SIZE$	1.514*
	(1.94)
$\Delta LOSS$	−0.073
	(−0.23)
$\Delta COVER$	−0.009
	(−1.02)
ΔROA	1.692
	(0.75)
$\Delta BMRATIO$	−1.145***
	(−2.83)
$\Delta ROASTD3$	−8.698*
	(−1.87)
$\Delta STDRET$	−8.494
	(−0.46)
ΔLEV	−4.728*
	(−1.86)
$\Delta CAPINT$	−0.903
	(−0.73)

(The table is continued on the next page.)

analysis using a subsample of forced CEO turnover, following Jenter and Kanaan (2015), who classify forced turnover as removal of the CEO for reasons other than bad firm performance, such as CEOs who were terminated due to policy differences or left under pressure. This subsample of forced turnover, which was not caused by bad firm performance, further alleviates the reverse causality concern that firms with low credit ratings need to hire generalist CEOs to improve their operational efficiency.[6] These exogenous turnovers also address the issue of endogenous matching between CEOs and firms, which is likely to distort inferences regarding CEOs' value (Betzer et al. 2020). Table 7 reports the test results. The coefficient on ΔGA is negative and significant ($p < 0.05$, two-tailed), which is consistent with our expectation, suggesting that ratings worsen when firms hire new CEOs with relatively higher general skills than those of the forced-out CEOs. Furthermore, our analyses of forced CEO turnover may also alleviate potential concerns that time-variant effects influence our results, adding more confidence that our main results are not likely to be driven by time-variant unobservable differences in firm and CEO characteristics.

6. We thank Jenter and Kanaan (2015) and Peters and Wagner (2014) for generously sharing their CEO forced-turnover data. We check the change in fundamentals before and after the CEO turnovers and find no statistically significant differences between the two consecutive years.

TABLE 7 (continued)

Variable	Forced CEO turnover sample $\Delta RATE$
$\Delta INTAN$	7.286
	(0.85)
Constant	−2.259***
	(−3.91)
Year FE	Yes
Industry FE	Yes
Observations	113
R^2	0.762

Notes: This table reports coefficients from the estimation of the following model:

$$\Delta RATE = \beta_0 + \beta_1 \times \Delta GA + \sum \beta_i \times \Delta Controls + \varepsilon.$$

The prefix Δ denotes changes in the underlying variables. We focus on the forced CEO turnover subsample following Jenter and Kanaan (2015) and Peters and Wagner (2014), and we further require that the announcement date of the forced CEO turnover be within the last fiscal year of the CEO in place. See Appendix 1 for variable definitions. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include year and industry fixed effects, and standard errors are heteroskedasticity-robust and clustered at the firm level. t-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

6. Other tests

Cross-sectional analysis of firm characteristics

We next investigate whether the negative relationship between credit ratings and CEOs' general skills is heterogeneous across different types of firms. In particular, we study whether this negative relationship can be mitigated if generalist CEOs' risk-taking behaviors are desirable in certain types of firms. For example, prior studies (e.g., Aghion et al. 2005; Bloom and Van Reenen 2007; Bloom et al. 2016) document that high market competition fosters innovation, given that firms in neck-and-neck sectors benefit more from innovation that helps them "escape" competition. In this case, generalist CEOs' risk-taking behavior, especially their tendency to spur firm innovation as documented by Custódio et al. (2017), could be relatively more beneficial. Hence, we expect that the negative relationship should be attenuated for firms in highly competitive industries and/or innovative firms. We use a Herfindahl-Hirschman Index (HHI) to measure industry competition: a low (high) index indicates relatively high (low) competition. *LowHHI* is an indicator variable that equals one if a firm's HHI is below the sample year tertile, and zero otherwise. In addition, we use R&D expenditure to measure firms' innovation intensity: *HighRD* is an indicator variable that equals one if a firm's R&D expense (scaled by total assets) is above the sample year tertile, and zero otherwise. We expect positive coefficients on the interaction terms *LowHHI*×*GA* and *HighR&D*×*GA*, suggesting that the negative relationship between credit ratings and CEOs' general skills is mitigated by firms' innovation intensity.

Table 8 reports the cross-sectional test results. Consistent with our expectation, the coefficients on the interaction terms, *LowHHI*×*GA* and *HighR&D*×*GA*, are both positive and significant (respectively, $p < 0.01$ and $p < 0.05$, two-tailed), suggesting that higher market competition and/or firms' R&D intensity increase the benefits of generalist CEOs' risk-taking behaviors (especially their tendency to spur firm innovation) and thus weaken the negative association between credit ratings and CEOs' general skills. The coefficients on *GA* are negative and significant in both columns ($p < 0.01$, two-tailed), which is consistent with Hypothesis 1. The coefficients on the control variables in both columns are similar to the results in Table 3.

Borrowing costs

We next push our research forward to analyzing broader debt market effects. Specifically, we examine the borrowing cost of firms with generalist CEOs, such as bond yields and the spreads of syndicated loans. Hypothesis 1 suggests that generalist CEOs may take excessive risks in their operations, which increases firms' risk of default; thus, it is natural to expect that lenders will be more likely to charge higher interest premiums on firms with generalist CEOs, thereby resulting

TABLE 8
Cross-sectional test

	RATE	
Variable	(1)	(2)
GA	−0.227***	−0.225***
	(−5.48)	(−5.44)
LowHHI	0.099	
	(1.27)	
LowHHI×GA	0.167***	
	(2.89)	
HighR&D		0.393***
		(2.85)
HighR&D×GA		0.184**
		(2.58)
MASCORE	0.962***	0.992***
	(3.04)	(3.12)
TRANSP	0.465***	0.469***
	(6.30)	(6.40)
ACCRUAL	−0.018	−0.014
	(−0.66)	(−0.50)
SIZE	1.092***	1.082***
	(24.71)	(24.75)
LOSS	−0.048	−0.041
	(−0.53)	(−0.46)
COVER	0.009***	0.009***
	(4.11)	(4.12)
ROA	6.896***	6.901***
	(11.25)	(11.36)
BMRATIO	−0.772***	−0.738***
	(−7.59)	(−7.37)
ROASTD3	−1.417**	−1.405**
	(−2.03)	(−2.01)
STDRET	−97.851***	−97.774***
	(−22.92)	(−22.94)
LEV	−4.155***	−4.111***
	(−13.92)	(−13.85)
CAPINT	0.642**	0.738***
	(2.23)	(2.59)

(The table is continued on the next page.)

TABLE 8 (continued)

	RATE	
Variable	(1)	(2)
INTAN	1.767	0.303
	(1.53)	(0.24)
Constant	8.905***	8.863***
	(10.47)	(11.02)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	12,675	12,675
R^2	0.725	0.726

Notes: This table reports coefficients from the estimation of the following models:

$$RATE = \beta_0 + \beta_1 \times GA + \beta_2 \times LowHHI + \beta_3 \times LowHHI \times GA + \sum \beta_i \times Controls + \varepsilon,$$

$$RATE = \beta_0 + \beta_1 \times GA + \beta_2 \times HighR\&D + \beta_3 \times HighR\&D \times GA + \sum \beta_i \times Controls + \varepsilon.$$

In column (1), *LowHHI* is a dummy variable that equals one if a firm's HHI is below the sample year tertile (suggesting relatively high competition), and zero otherwise. In column (2), *HighR&D* is a dummy variable that equals one if a firm's R&D expense (scaled by total assets) is above the sample year tertile, and zero otherwise. See Appendix 1 for the definitions of other variables. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include year and industry fixed effects. The standard errors are heteroskedasticity-robust and clustered at the firm level. *t*-statistics are reported in parentheses. ** and *** represent significance levels of 5% and 1%, respectively.

in higher bond yields and/or loan spreads. To investigate the relationship between bond yields and CEOs' general skills, we use the following model:

$$Bond\_Yield = \lambda_0 + \lambda_1\, GA + \sum \lambda_i\, Controls_i + \varepsilon. \tag{2}$$

The dependent variable *Bond_Yield* is the difference between the issue's offering yield and the yield on a benchmark treasury security expressed in basis points (Beaver et al. 2006); we obtain data on the bond yields from Mergent FISD.[7] *Controls* include both firm-specific characteristics, which we use in the main analysis, and bond-related factors used in prior studies (e.g., Beaver et al. 2006; Bonsall et al. 2016), such as bond size (*Bond_AMOUNT*), maturity (*Bond_MATURITY*), a below investment-grade rating (*JUNK*), the presence of credit enhancements (*ENHANCE*), and shelf registration status (*SHELF*). A detailed definition of bond-related variables is summarized in the Table 9 notes. As discussed above, we expect a positive association ($\lambda_1 > 0$) between bond yields and CEOs' general skills. Table 9 presents the result of equation (2). Consistent with our expectation, the coefficient on *GA* is significantly positive ($p < 0.05$, two-tailed), suggesting that debtholders require an interest premium to compensate for the risks associated with generalist CEOs' risk-taking behaviors. To examine the economic significance of the *GA* coefficient estimate, we estimate *Bond_Yield* using equation (2), employing the full sample and setting the values of all independent variables at their mean levels. The estimated mean *Bond_Yield* is 192.32 (untabulated). A one-standard-deviation increase in *GA* (1.00) from its

7. We dropped bond issuances without S&P ratings and/or bonds with special features (e.g., convertible bonds, asset backed and secured lease obligation bonds). After merging with the general ability index, we obtain 4,440 bond issuances.

mean value increases *Bond_Yield* by 5.508, representing a 2.9% increase. The coefficients on the control variables are generally consistent with the related literature.

We next investigate the relationship between the spread of syndicated loans and CEOs' general skills, using the following model:

$$Loan\_Spread = \lambda_0 + \lambda_1\, GA + \sum \lambda_i\, Controls_i + \varepsilon. \quad (3)$$

The dependent variable *Loan_Spread* is the natural logarithm of the all-in-drawn-spread reported by DealScan. Following prior studies (e.g., Chen et al. 2016; De Franco et al. 2017), we also include the current ratio (*CURRENT*) and sales growth (*SALES_G*) in addition to the firm-specific characteristics that we controlled in the main analysis. Furthermore, we control for loan-specific factors, including the number of financial covenants (*FCOVENANT*), loan size

TABLE 9
Bond yields

Variable	Dependent variable defined as *Bond_Yield*
GA	5.508**
	(2.50)
MASCORE	−3.344
	(−0.27)
TRANSP	−11.409
	(−1.18)
ACCRUAL	−0.317
	(−0.14)
SIZE	−22.825***
	(−11.13)
LOSS	35.912***
	(3.47)
COVER	0.038
	(0.48)
ROA	−218.903***
	(−3.96)
BMRATIO	71.271***
	(7.69)
ROASTD3	29.240
	(0.41)
STDRET	2,247.728***
	(6.18)
LEV	69.799***
	(3.12)
CAPINT	6.734
	(0.41)
INTAN	−2.696
	(−0.04)
Bond_AMOUNT	11.708***
	(3.56)
Bond_MATURITY	18.159***
	(11.20)

(The table is continued on the next page.)

TABLE 9 (continued)

Variable	Dependent variable defined as *Bond_Yield*
JUNK	159.211***
	(19.82)
ENHANCE	−0.033
	(−0.00)
SHELF	−16.411***
	(−3.32)
Constant	−99.764*
	(−1.81)
Year FE	Yes
Industry FE	Yes
Observations	4,440
R^2	0.715

Notes: This table reports coefficients from the estimation of the following model:

$$Bond\_Yield = \lambda_0 + \lambda_1 \times GA + \sum \lambda_i \times Controls + \varepsilon.$$

Bond_Yield is a bond's offering yield minus the benchmark treasury yield reported by Mergent FISD. *Bond_AMOUNT* is the natural logarithm of a bond's offering amount. *Bond_MATURITY* is the natural logarithm of a bond's maturity. *JUNK* is a dummy variable that equals one (zero) if a bond's rating is below (above) the investment grade. *ENHANCE* is a dummy variable that equals one if a bond issuance has credit enhancements, and zero otherwise. *SHELF* is a dummy variable that equals one if a bond issuance is a shelf registration, and zero otherwise. See Appendix 1 for the definitions of other variables. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include year and industry fixed effects. The standard errors are heteroskedasticity-robust and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

TABLE 10
Syndicated loan spreads

Variable	Dependent variable defined as *Loan_Spread*
GA	0.020**
	(2.54)
MASCORE	0.013
	(0.17)
SIZE	−0.085***
	(−9.57)
LEV	0.746***
	(15.20)
CURRENT	−0.023***
	(−2.85)
MB	−0.003***
	(−2.67)
ROA	−1.748***
	(−11.52)

(The table is continued on the next page.)

TABLE 10 (continued)

Variable	Dependent variable defined as *Loan_Spread*
ZSCORE	−0.022**
	(−2.12)
CAPINT	0.053
	(0.85)
FCOVENANT	0.038***
	(5.89)
SALES_G	0.006
	(0.23)
Loan_AMOUNT	−0.151***
	(−17.69)
Loan_MATURITY	0.065***
	(5.55)
INS_IN	0.284***
	(13.45)
REVOLVER	−0.093***
	(−7.37)
COLLATERAL	0.433***
	(25.02)
PPINDEX	−0.110***
	(−6.79)
Constant	8.146***
	(44.78)
Year FE	Yes
Industry FE	Yes
Loan Purpose FE	Yes
Observations	15,222
R^2	0.683

Notes: This table reports coefficients from the estimation of the following model:

$$Loan\_Spread = \lambda_0 + \lambda_1 \times GA + \sum \lambda_i \times Controls + \varepsilon.$$

Loan_Spread is the natural logarithm of the all-in-drawn spread reported by DealScan. *FCOVENANT* is the number of financial covenants. *CURRENT* is the current ratio, measured as current assets divided by current liabilities. *SALES_G* is the sales growth, measured as the percentage change in sales from year $t-1$ to year t. *Loan_AMOUNT* is the natural logarithm of a bank loan's amount. *Loan_MATURITY* is the natural logarithm of a bank loan's maturity. *INS_IN* is a dummy variable that is equal to one if the loan is an institutional term loan, and zero otherwise. *REVOLVER* is a dummy variable that is equal to one if the loan is a revolver, and zero otherwise. *COLLATERAL* is a dummy variable that is equal to one if the loan is backed by collateral, and zero otherwise. *PPINDEX* is a dummy variable that is equal to one if the loan contract includes a performance pricing provision, and zero otherwise. See Appendix 1 for the definitions of other variables. All continuous variables are winsorized at the top and bottom one percentiles. Regressions include year, industry, and loan purpose fixed effects. The standard errors are heteroskedasticity-robust and clustered at the firm level. *t*-statistics are reported in parentheses. ** and *** represent significance levels of 5% and 1%, respectively.

(*Loan_AMOUNT*), maturity (*Loan_MATURITY*), institutional term loan (*INS_IN*), revolver loan (*REVOLVER*), the presence of collateral (*COLLATERAL*), and the presence of performance pricing provisions (*PPINDEX*). A detailed definition of current ratio, sales growth, and loan-specific variables is summarized in the Table 10 notes. As discussed above, we expect a positive association ($\lambda_1 > 0$) between loan spreads and CEOs' general skills.

We obtain loan facilities data from the Thomson Reuters LPC DealScan database. To merge loan facilities data with Compustat, we use the DealScan-Compustat link that is constructed and maintained by Michael Roberts and Wharton Research Data Services (WRDS). After merging with the general ability index, we obtain 15,222 bank facilities.

Table 10 presents the result of equation (3). Consistent with our expectation, the coefficient on *GA* is significantly positive (*p*

Appendix 1

Variable definitions

Variable	Definition
RATE	A numerical translation of the S&P's long-term issuer credit ratings in the range of 1–22, where 22 represents AAA and 1 represents default[a]
MASCORE	Managerial ability score, from Demerjian et al. (2012)
GA	CEO general ability index, from Custódio et al. (2013) and BoardEx
Generalist_Dummy	A dummy variable that equals one if a CEO's *GA* is above the 75th percentile in a given year, and zero otherwise (Custódio et al. 2013)
TRANSP	Financial transparency, measured as negative one multiplied by the squared residual from the cross-sectional regression $ARET = b_0 + b_1(NIBX) + b_2(LOSS) + b_3(NIBX \times LOSS) + b_4(\Delta NIBX) + e$, where the regression is estimated for all firms within a 3-, 2-, or 1-digit SIC code (conditional on having at least 10 firms in each SIC group) for a given year, and *ARET* = the market-adjusted return over the fiscal year, *NIBX* = net income before extraordinary items scaled by the beginning-of-year market value of equity, *LOSS* = one if *NIBX* is negative (and zero otherwise), and $\Delta NIBX$ = change in net income before extraordinary items scaled by the beginning-of-year market value of equity (see Cheng and Subramanyam 2008; Gu 2007)
ACCRUAL	Abnormal accruals, estimated using the cross-sectional Jones model (Jones 1991)
SIZE	Firm size, measured as the natural logarithm of total assets
LOSS	A dummy variable that equals one if a firm has a negative net income before extraordinary items, and zero otherwise
COVER	Interest coverage, measured as the operating income before depreciation divided by the interest expense
ROA	Return on assets, measured as the net income before extraordinary items divided by total assets
BMRATIO	Book-to-market ratio, measured as the book value of a firm's year-end equity divided by the market value of the firm's equity
ROASTD3	Standard deviation of *ROA* over the prior three years
STDRET	Standard deviation of daily stock returns over the past year
LEV	Leverage, measured as the sum of short-term debt and long-term debt divided by total assets
CAPINT	Property, plant, and equipment net of depreciation deflated by total assets
INTAN	The sum of R&D expenditure and advertising expense scaled by total assets (Cheng and Subramanyam 2008)
LogDelta	The natural logarithm of the CEO compensation delta
LogVega	The natural logarithm of the CEO compensation vega

Notes: [a]S&P's long-term issuer credit ratings include AAA, AA+, AA, AA−, A+, A, A−, BBB+, BBB, BBB−, BB+, BB, BB−, B+, B, B−, CCC+, CCC, CCC−, CC, C, D.

Appendix 2

TABLE 11
First-stage regression of PSM and matching efficiency of PSM and EB matching

Panel A: First-stage regression of PSM

Variable	Dependent variable defined as *Generalist_Dummy*
MASCORE	−0.181
	(−0.90)
TRANSP	−0.070
	(−1.21)
ACCRUAL	−0.018
	(−0.70)
SIZE	0.207***
	(6.58)
LOSS	0.077
	(1.18)
COVER	−0.003**
	(−1.99)
ROA	−0.499
	(−1.16)
BMRATIO	−0.141*
	(−1.81)
ROASTD3	1.111**
	(2.14)
STDRET	3.171
	(1.05)
LEV	−0.442**
	(−1.97)
CAPINT	−0.506**
	(−2.39)
INTAN	1.260
	(1.61)
LogDelta	−0.013
	(−0.44)
LogVega	0.082***
	(3.24)
Constant	−1.663***
	(−4.14)
Year FE	Yes
Industry FE	Yes
Observations	11,018
Pseudo R^2	0.074

Panel B: Matching efficiency of PSM

Variables	Treatment (1)	Control–Prematching (2)	Difference (2)−(1)	Control–Postmatching (3)	Difference (3)−(1)
MASCORE	0.016	0.002	−0.014***	0.017	0.001
TRANSP	−0.115	−0.113	0.002	−0.115	0.000

(The table is continued on the next page.)

TABLE 11 (continued)

Panel B: Matching efficiency of PSM

Variables	Treatment (1)	Control–Prematching (2)	Difference (2)−(1)	Control–Postmatching (3)	Difference (3)−(1)
ACCRUAL	0.093	0.083	−0.010	0.080	−0.013
SIZE	8.707	8.161	−0.546***	8.687	−0.020
LOSS	0.166	0.155	−0.011	0.149	−0.017
COVER	14.119	14.770	0.651	15.042	0.923
ROA	0.042	0.043	0.001	0.045	0.003*
BMRATIO	0.419	0.478	0.058***	0.425	0.006
ROASTD3	0.037	0.035	−0.002*	0.036	−0.001
STDRET	0.024	0.025	0.001***	0.023	−0.001
LEV	0.283	0.297	0.013***	0.280	−0.003
CAPINT	0.308	0.337	0.029***	0.312	0.004
INTAN	0.039	0.032	−0.007***	0.039	0.000
LogDelta	5.956	5.610	−0.346***	5.880	−0.076**
LogVega	4.837	4.304	−0.534***	4.796	−0.041

Panel C: Matching efficiency of EB matching

	Treatment		Control-Before matching		Difference		Control-After matching	
Variables	Mean (1)	Variance (2)	Mean (3)	Variance (4)	(3)−(1)	(4)−(2)	Mean (5)	Variance (6)
MASCORE	0.016	0.024	0.003	0.021	−0.013***	−0.003***	0.016	0.024
TRANSP	−0.115	0.066	−0.114	0.062	0.001	−0.004**	−0.115	0.066
ACCRUAL	0.093	0.447	0.083	0.413	−0.01	−0.034	0.093	0.447
SIZE	8.707	1.631	8.161	1.532	−0.546***	−0.099**	8.707	1.631
LOSS	0.166	0.139	0.155	0.131	−0.012	−0.008*	0.166	0.139
COVER	14.120	430.600	14.760	591.700	0.645	161.1***	14.120	430.500
ROA	0.042	0.005	0.043	0.005	0.001	0.000	0.042	0.005
BMRATIO	0.419	0.128	0.477	0.150	0.058***	0.022***	0.419	0.128
ROASTD3	0.037	0.003	0.035	0.002	−0.002*	−0.001***	0.037	0.003
STDRET	0.024	0.000	0.025	0.000	0.001***	0.000**	0.024	0.000
LEV	0.283	0.023	0.297	0.024	0.013***	0.001*	0.283	0.023
CAPINT	0.309	0.045	0.337	0.052	0.028***	0.007***	0.309	0.045
INTAN	0.039	0.002	0.032	0.002	−0.008***	0.000	0.039	0.002
LogDelta	5.956	1.912	5.611	1.911	−0.345***	−0.001	5.956	1.911
LogVega	4.837	2.322	4.303	2.206	−0.534***	−0.116*	4.837	2.322

Notes: Panel A presents the first-stage results of PSM. Panel B presents the matching efficiency of PSM. Panel C presents the matching efficiency of EB matching. All variables are defined in Appendix 1. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

References

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics* 120 (2): 701–28.

Ahmed, A. S., B. K. Billings, R. M. Morton, and M. Stanford-Harris. 2002. The role of accounting conservatism in mitigating bondholder-shareholder conflicts over dividend policy and in reducing debt costs. *The Accounting Review* 77 (4): 867–90.

Ansoff, I. H. 1988. *The new corporate strategy*. New York: John Wiley & Sons.

Ashbaugh-Skaife, H., D. W. Collins, and R. LaFond. 2006. The effects of corporate governance on firms' credit ratings. *Journal of Accounting and Economics* 42 (1–2): 203–43.

Ayers, B. C., S. K. Laplante, and S. T. McGuire. 2010. Credit ratings and taxes: The effect of book-tax differences on ratings changes. *Contemporary Accounting Research* 27 (2): 359–402.

Beaver, W. H., C. Shakespeare, and M. T. Soliman. 2006. Differential properties in the ratings of certified versus non-certified bond-rating agencies. *Journal of Accounting and Economics* 42 (3): 303–34.

Becker, G. S. 1962. Investment in human capital: A theoretical analysis. *Journal of Political Economy* 70 (5 Part 2): 9–49.

Betzer, A., M. Ibel, H. S. Lee, P. Limbach, and J. M. Salas. 2020. Are generalists beneficial to corporate shareholders? Evidence from sudden deaths. *Journal of Financial and Quantitative Analysis* 55 (2): 581–619.

Bloom, N., M. Draca, and J. Van Reenen. 2016. Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies* 83 (1): 87–117.

Bloom, N., and J. Van Reenen. 2007. Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics* 122 (4): 1351–408.

Bonsall, S. B., E. R. Holzman, and B. P. Miller. 2016. Managerial ability and credit risk assessment. *Management Science* 63 (5): 1425–49.

Carpenter, M. A., M. A. Geletkanycz, and W. G. Sanders. 2004. Upper echelons research revisited: Antecedents, elements, and consequences of top management team composition. *Journal of Management* 30 (6): 749–78.

Chang, Y. K., S. Dasgupta, and G. Hilary. 2010. CEO ability, pay, and firm performance. *Management Science* 56 (10): 1633–52.

Charitou, A., N. Lambertides, and G. Theodoulou. 2011. Dividend increases and initiations and default risk in equity returns. *Journal of Financial and Quantitative Analysis* 46 (5): 1521–43.

Chen, P. F., S. He, Z. Ma, and D. Stice. 2016. The information role of audit opinions in debt contracting. *Journal of Accounting and Economics* 61 (1): 121–44.

Cheng, M., and K. R. Subramanyam. 2008. Analyst following and credit ratings. *Contemporary Accounting Research* 25 (4): 1007–44.

Cornaggia, K. J., G. V. Krishnan, and C. Wang. 2017. Managerial ability and credit ratings. *Contemporary Accounting Research* 34 (4): 2094–2122.

Crossland, C., J. Zyung, N. Hiller, and D. Hambrick. 2014. CEO career variety: Effects on firm-level strategic and social novelty. *Academy of Management Journal* 57 (3): 652–74.

Cunat, V., and M. Guadalupe. 2009. Globalization and the provision of incentives inside the firm: The effect of foreign competition. *Journal of Labor Economics* 27 (2): 179–212.

Custódio, C., M. A. Ferreira, and P. Matos. 2013. Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics* 108 (2): 471–92.

Custódio, C., M. A. Ferreira, and P. Matos. 2017. Do general managerial skills spur innovation? *Management Science* 65 (2): 459–76.

De Franco, G., O. K. Hope, and H. Lu. 2017. Managerial ability and bank-loan pricing. *Journal of Business Finance & Accounting* 44 (9–10): 1315–37.

DeFond, M. L., C. Y. Lim, and Y. Zang. 2016. Client conservatism and auditor-client contracting. *The Accounting Review* 91 (1): 69–98.

Demerjian, P., B. Lev, and S. McVay. 2012. Quantifying managerial ability: A new measure and validity tests. *Management Science* 58 (7): 1229–48.

Ertimur, Y., C. Rawson, J. L. Rogers, and S. L. C. Zechman. 2018. Bridging the gap: Evidence from externally hired CEOs. *Journal of Accounting Research* 56 (2): 521–79.

Falato, A., D. Li, and T. Milbourn. 2015. Which skills matter in the market for CEOs? Evidence from pay for CEO credentials. *Management Science* 61 (12): 2845–69.

Fama, E. F., and J. D. MacBeth. 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81 (3): 607–36.

Ferreira, D., and R. K. Sah. 2012. Who gets to the top? Generalists versus specialists in managerial organizations. *RAND Journal of Economics* 43 (4): 577–601.