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Brand capital and debt choice☆

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ABSTRACT

This paper investigates the effect of brand capital on firms' choices of debt structure. Using a sample of publicly listed U.S. firms between 2001 and 2019, we find that firms with higher levels of brand capital rely less on bank debt financing. This finding is robust to the use of alternative regression models and alternate measures of brand capital and bank debt financing. Employing an industry-level positive shock to brand capital as a quasi-natural experiment, we demonstrate that such a shock negatively affects firms' reliance on bank debt. Our cross-sectional analyses reveal that the effect of brand capital on bank debt is more pronounced for firms with high information asymmetry, weak corporate governance mechanisms, and poor financial conditions. We also find that brand capital-intensive firms raise funds from the public debt market and issue more (or less) unsecured (or secured) debt. Taken together, we show that brand capital has an important bearing on corporate financing decisions.

1. Introduction

This study investigates the relationship between brand capital and debt choice. Debt stands as a crucial source of financing for corporations, with U.S.-domiciled firms raising over $2.5 trillion in new debt capital in 2020 alone, comprising bonds, syndicated debt, and various types of loans. In contrast, equity markets saw a mere $335 billion secured during the same period.[1] Firms that choose to use debt to finance their projects can borrow from banks or issue debt in the public market, also known as debt choice. Existing literature suggests that corporate debt choice is affected by various factors such as corporate disclosure quality (Dhaliwal, Khurana, & Pereira, 2011), analyst coverage (Li, Lin, & Zhan, 2019), external governance mechanisms (Bharath & Hertzel, 2019), state ownership (Boubakri & Saffar, 2019), product market competition (Boubaker, Saffar, & Sassi, 2018), and corporate ownership and control rights (Lin, Ma, Malatesta, & Xuan, 2013). However, the influence of firm-specific brand capital (i.e., an intangible asset encompassing consumers' awareness, impressions, loyalty, and recognition of a product, service, or organisation (Belo, Gala, Salomao, & Vitorino, 2022, Belo, Lin, & Vitorino, 2014, Hasan, Taylor, & Richardson, 2022, Pillai, 2012)) on debt choice remains unexplored.[2] This study aims to bridge this gap in the literature.

The motivation for this study stems from the growing recognition that brand capital constitutes a sizable share of corporate value. For

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[1] Figures are obtained from https://www.federalreserve.gov/data/corpsecure/current.htm.

[2] While there is no unified definition of brand capital, consistent with Belo et al. (2014), we define brand capital as a production factor within the firm's operating profit function, as it bolsters sales by fostering increased customer loyalty and visibility.

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instance, Belo et al. (2022) show that brand capital accounts for 6%–25% of firms' market value. *The Economist* reported that "brands account for more than 30% of the stock market value of companies in the S&P 500 index."[3] *Forbes* estimated that the top 100 most valuable brands in 2020 were collectively worth \$2.5 trillion.[4] Notably, financial intermediaries also emphasize the importance of brands, as evidenced by the downgrading of Volkswagen's credit rating by Fitch Ratings and Standard & Poor's (S&P) following the 2015 emission crisis. In response to this crisis, Volkswagen had to secure a \$21.2 billion bank loan to navigate the challenges, demonstrating the critical role of brand capital in maintaining financial strength and managing reputational damage.[5] Against this backdrop, our central research question revolves around the impact of brand capital on firms' access to public debt and, by extension, its potential to reduce dependence on bank debt. This study aims to empirically address this question, shedding light on a crucial aspect of corporate financing decisions.

A firm's debt choice depends on the pertinent costs and benefits.[6] Theoretical arguments have been proposed to explain firms' debt choice, taking into account several critical factors such as information asymmetry, monitoring ability and efficiency, and debt contract flexibility (Denis & Mihov, 2003; Dhaliwal et al., 2011; Diamond, 1984, 1991; Fama, 1985; Li et al., 2019).

First, the information asymmetry argument posits that banks, as private lenders, hold closer relationships with borrowers, affording them superior access to private borrower information compared with public debt investors (Fama, 1985). Banks are adept at efficiently gathering and processing information, resulting in lower information collection and processing costs for bank debtholders (Diamond, 1991). Consequently, informationally opaque firms prefer bank loans to overcome higher adverse selection costs (Bharath, Sunder, & Sunder, 2008). Increased information asymmetry prompts firms to switch from public bonds to bank loans (Li et al., 2019). Firms tend to rely more on bank debt when public disclosure is costly (Dhaliwal et al., 2011).

Second, the monitoring or governance argument suggests that due to the concentrated ownership of debt claims, banks encounter fewer free-rider problems and possess a strong incentive and ability to monitor borrowers, mitigating managerial opportunistic behaviours and moral hazard problems (Bharath et al., 2008; Liao, 2015). In contrast, diffusing public debt ownership exacerbates free-rider problems, weakening the incentive of public bondholders to participate in costly monitoring programmes (Diamond, 1984, 1991; Houston & James, 1996). This argument implies that firms with varying monitoring requirements should turn to banks or issue public debt accordingly (Denis & Mihov, 2003).

Finally, the debt renegotiation argument emphasises that a firm's ability to restructure and renegotiate debt contracts plays a significant role in debt choice (Morellec, Valta, & Zhdanov, 2015). Concentrated ownership of debt claims makes bank debt easier to renegotiate than public debt in the event of a covenant violation (Gilson, John, & Lang, 1990; Roberts & Sufi, 2009). Hence, firms facing high ex-ante financial distress risk prefer private loans to public debt (Bolton & Freixas, 2000).

Expanding on these arguments, we propose that brand capital negatively affects bank debt for three primary reasons. First, brand capital serves as a valuable source of information about a firm's cash flow, profitability, competitiveness, and product quality (e.g., Aaker, 1996; Belo et al., 2014; Larkin, 2013; Pillai, 2012). For instance, brand capital credibly signals information about a firm's unobservable quality to potential investors (Chemmanur & Yan, 2009). Recent evidence suggests that brand capital lowers managers' incentives for earnings manipulation and restatements (Ismail, Huseynov, Jain, & McInish, 2021). Consequently, corporations with higher brand capital are less likely to hoard bad news (Hasan et al., 2022). This superior information environment reduces information gathering and processing costs for stakeholders (Hasan & Taylor, 2023), in turn reducing adverse selection costs in public debt markets. As a result, firms with substantial brand capital tend to rely more on public debt and less on bank debt.

Second, brand capital's role in improving corporate visibility and subjecting firms to heightened scrutiny reduces the incentives and opportunities for managerial opportunism (Frieder & Subrahmanyam, 2005; Grullon, Kanatas, & Weston, 2004). Firms with brand capital are also concerned with maintaining their reputational capital. Studies show that brand capital reduces self-serving managerial activities, financial misreporting, and bad news hoarding (Hasan et al., 2022; Ismail et al., 2021). The debt choice literature posits that firms with more agency problems borrow from private lenders due to their superior monitoring incentives and ability, whereas public lenders have fewer incentives to lend to such firms due to their monitoring disadvantages (Denis & Mihov, 2003). Thus, the governance role of brand capital suggests that the higher visibility and disciplinary power of brand capital reduce the monitoring disadvantage (advantage) of public (bank) debt investors and enhance the attractiveness of public debt to borrowing firms. In addition, increased corporate visibility arising from stronger brands may improve the liquidity of firms' public debt, leading to a preference for public debt over private debt. We, therefore, expect brand capital-intensive firms to rely less (more) on bank (public) debt.

Third, brand capital enhances firms' sales, profitability, and cash flow by improving corporate visibility, credibility, customer loyalty, and satisfaction (Aaker & Jacobson, 1994; Hasan et al., 2022). Studies show that brands reduce cash flow volatility, distress risk, and market friction, thus improving corporate credit ratings (Larkin, 2013; Rego, Billett, & Morgan, 2009). Similarly, Huang, Yang, and Zhu (2021) document that brand equity reduces equity holders' risk, as evidenced by lower stock return volatility during the COVID-19 crash. The debt choice literature suggests that firms with ex-ante financial distress risk prefer private borrowing, as bank debt is often easier to renegotiate than public debt (Denis & Mihov, 2003; Roberts & Sufi, 2009). To the extent that brand capital improves operational efficiency and debt management capacity and reduces firms' default risk, we expect firms with high brand capital to rely less (more) on bank (public) debt.[7]

Nonetheless, one might anticipate a positive relationship between brand capital and bank debt. Particularly, as brand capital is a form of intangible asset and lacks the attributes of physical capital, it is not accepted as collateral, reducing firms' debt capacity (Falato, Kadyrzhanova, Sim, & Steri, 2022; Mauer, Villatoro, & Zhang, 2022). Moreover, brand capital may increase information complexity (Gu & Wang, 2005), potentially limiting firms' access to public debt. However, banks, given their close relationship with borrowers, are better equipped to assess the value of brand capital and, therefore, provide private debt to these firms, suggesting a positive link between brand capital and bank debt.

Following the literature (e.g., Belo et al., 2014; Belo et al., 2022; Hasan et al., 2022; Ismail et al., 2021; Vitorino, 2014), we measure brand capital through advertising expenditures, employing the

[3] https://www.economist.com/business/2014/08/30/what-are-brands-for

[4] https://www.forbes.com/the-worlds-most-valuable-brands/#57fb6854119c

[5] https://www.reuters.com/article/us-volkswagen-emissions-debt-idUSKBN13N1KS

[6] We acknowledge that reducing the cost of public debt alone may not automatically make it less expensive than bank funding. The decision-making process involves numerous factors, including transaction costs, the flexibility of covenants, the amount of debt offerings, credit quality, the firm's strategic goals, risk considerations, the relationship with lenders, and the possibility of rent extraction by banks (Denis & Mihov, 2003; Diamond, 1991).

[7] While our study does not explicitly explore entrepreneurs' preferences among different sources of external financing, we rely on established literature that examines the choice among bank debt, non-bank private debt, and public debt. In particular, Denis and Mihov (2003) document that firms with the highest credit quality borrow from public sources, firms with medium credit quality borrow from banks, and firms with the lowest credit quality borrow from non-bank private lenders. Extending these findings, we contend that entrepreneurs, particularly those with strong brand capital, may strategically opt for public debt over bank funding due to potential benefits associated with public debt, such as a broader investor base and favourable terms.

perpetual inventory method. Our sample consists of 20,280 U.S. firm–-years (3315 unique public firms) over the 2001–2019 period. Our main results show that brand capital is negatively associated with firms' reliance on bank debt, consistent with the anticipated role of brand capital in mitigating information asymmetry while enhancing monitoring and financial conditions. This result is economically meaningful. To illustrate, a one-standard-deviation increase in brand capital (*BRAND/MVE*) translates to a 3.74% (5.47%) decline in reliance on bank debt financing relative to the sample mean (median). Our documented outcomes are robust to the use of alternative regression models, diverse scaling approaches for brand capital and bank debt, variations in depreciation rates for calculating brand capital, and the inclusion of additional control variables.

Next, we conduct a series of tests to mitigate endogeneity concerns, addressing potential issues arising from omitted variable bias and reverse causality. Following recent studies (e.g., Baker, Boulton, Braga-Alves, & Morey, 2021; Chapman, Miller, & White, 2019; Gao & Huang, 2020), we first implement the impact threshold for a confounding variable and utilise Oster (2019) bound estimates to gauge the magnitude of omitted variable bias in our estimation. The findings from both analyses consistently indicate that omitted variable bias does not significantly impact our results. Second, we employ a two-stage regression procedure following Lewbel (2012) and a two-step system generalized method-of-moments (GMM) approach. Importantly, our findings remain robust and unchanged. Third, to further address endogeneity concerns, we leverage entropy balancing estimates, consistently obtaining results that support our main conclusions. Finally, we introduce an industry-level positive shock to brand capital as a quasi-natural experiment, revealing a negative impact on firms' reliance on bank debt. This supports the notion of a causal relationship between brand capital and debt choice. In addition, a placebo test, replacing actual treatment firms with randomly assigned treatment samples, yields an insignificant reduction in bank debt, providing further robustness to our findings.

Subsequently, we investigate how the relationship between brand capital and debt structure varies across the cross-section of firms. Considering the information asymmetry-based argument as the driving force behind the inverse link between brand capital and bank debt, we expect this relationship to be more salient when information asymmetry is high. Our findings consistently demonstrate that the role of brand capital in reducing bank debt is exacerbated in opaque firms. Moreover, aligning with the monitoring and renegotiation-based argument of brand capital as the basis for the negative relationship with bank debt, we expect this relationship to be exacerbated in poorly governed and financially constrained firms. Our results confirm these expectations: the negative link between brand capital and bank debt is more evident for firms with weak corporate governance and poor financial conditions, while being less pronounced for those with strong governance and sound financial standing. These cross-sectional analyses not only offer additional insights into the channels explaining the documented relationship but also alleviate concerns about alternative explanations for our findings (Chen, Hasan, Saffar, & Zolotoy, 2021). Finally, our additional analyses reveal that brand capital-intensive firms tend to raise funds from the public debt market and issue a higher proportion of unsecured debt relative to secured debt.

Our findings significantly contribute to existing research in several ways. First, we expand upon the literature exploring firms' debt choice. While prior studies explore factors substituting for the monitoring roles of bank lenders, such as external governance mechanisms (Bharath & Hertzel, 2019), outside blockholder monitoring (Boubaker et al., 2018; Liao, 2015), and product market competition (Boubaker et al., 2018), our research introduces a new dimension by highlighting the distinctive role of brand capital. By demonstrating that brand capital-intensive firms strategically reduce reliance on bank debt, we offer a comprehensive perspective on how intangible assets, especially brand capital, shape corporate financing decisions. This enriches the existing knowledge on debt choices, emphasising the collective impact of informational, monitoring, and financial aspects related to brand capital.

Second, our study extends the burgeoning literature on intangible assets, focusing specifically on brand capital. In the realm of emerging finance research, the recognition that brand capital can mitigate debtholders' risk (Hasan & Taylor, 2023; Larkin, 2013) and serve as a mechanism to prevent managerial opportunistic behaviours (Hasan et al., 2022; Ismail et al., 2021) has gained traction. Our contribution lies in revealing the vital role of brand capital in shaping firms' choices between bank loans and public debt issuance. Our findings suggest a distinct preference among firms with elevated brand capital for opting for public debt financing rather than relying on bank loans, thus enhancing the understanding of how intangible assets, particularly brand capital, shape financing decisions.[8] This exploration adds depth to the emerging field of intangible asset research, providing a comprehensive view of its impact on corporate financial strategies.

Finally, our research contributes to the existing knowledge on how brand capital creates value for shareholders. While marketing literature traditionally highlights the benefits of brand capital (Ailawadi, Lehmann, & Neslin, 2003; Madden, Fehle, & Fournier, 2006; Rego et al., 2009), our study goes beyond, revealing that brand capital positively influences shareholder value through firms' financing decisions. Specifically, our findings underscore the contrast between the substantial interest rate premiums required by banks and the credit risk implied by the public debt market (Schwert, 2020). This insight highlights the strategic advantage of brand capital in financing choices, emphasising its impact on shareholder value. In doing so, our research aligns with and extends the understanding of the multifaceted benefits of brand capital within the broader context of corporate finance and shareholder value.

In a recent study, Mauer et al. (2022) examine how brand equity affects corporate capital structure. The authors find that brand equity is associated with lower equity and debt but has no impact on debt maturity. The distinctions between our study and Mauer et al. (2022) are significant in multiple aspects. First, while Mauer et al. (2022) provide a comprehensive examination of the relationship between brand capital and corporate capital structure, our study specifically explores how brand capital influences the choices between bank loans and public debt issuance. This targeted focus allows us to discern distinct patterns in firms' financing decisions. Second, in contrast to Mauer et al. (2022), which employ the pecking order theory to elucidate that firms with elevated brand capital exhibit greater debt capacity but use less debt overall, our study explores specific mechanisms—information asymmetry, governance mechanisms, and financial conditions— through which brand capital exerts its influence on debt choice. This comprehensive exploration provides a more nuanced understanding of the multifaceted mechanisms through which brand capital impacts a firm's financial strategy. Essentially, both studies contribute valuable insights into the intricate relationship between brand-related factors and financial decisions, with our research providing a more focused examination of the specific channels through which brand capital influences firms' debt choice.

The remainder of the paper is organised as follows. Section 2 explains the research methodology. Section 3 presents empirical results and robustness checks. Section 4 presents cross-sectional analyses and additional tests. Section 5 concludes the study.

[8] To provide a practical illustration, consider Amazon's issuance of £10 billion in senior unsecured bonds in 2017 to fund the acquisition of Whole Foods Market. Despite having a substantial cash balance at the time, Amazon strategically chose to issue bonds. This decision aligns with our findings, providing a real-world scenario where a firm with significant brand capital opted for public debt over other financing options.

2. Research methodology

2.1. Data and sample

We began our sample with all U.S. public firms listed in the Capital IQ database for the 2001–2019 period. Our sample starts in 2001 because Capital IQ provides debt structure data from this date onwards.[9] We then merge the sample with the Compustat data file. We drop financial service industry firms (Standard Industrial Classification [SIC]: 6000–6999), those with zero total debt, and those with missing required data.[10] This sampling procedure yields a final sample of 20,280 firm-years, representing 3315 unique U.S. firms.

For our sensitivity and additional analyses, we collect CEO-level data from Execucomp, analyst data from the Institutional Brokers Estimate System, and institutional shareholding data from the 13F database.

2.2. Main variables

2.2.1. Dependent variable: Bank debt

Following prior studies (Boubaker et al., 2018; Boubaker, Rouatbi, & Saffar, 2017; Boubakri & Saffar, 2019; Lin et al., 2013), we capture a firm's debt choice using the ratio of bank debt to total debt (BANK_DEBT). Bank debt includes term loans and revolving credit, whereas total debt captures all types of debt.[11] In the robustness section, we use two alternative measures of debt choice.

2.2.2. Variable of interest: Brand capital

Because we interpret brand capital as cumulative investment in building brand awareness, we rely on advertising expenditures to measure brand capital. Advertising expenditures in Compustat encompass the costs of advertising media (i.e., radio, television, and periodicals) and promotional expenses. According to Simon and Sullivan (1993), advertising influences firms' brand awareness through brand associations, perceived quality, and user experience. Therefore, using advertising expenditures to gauge brand capital is intuitive. This approach also allows us to draw inferences based on a reasonably large sample of firms over an extended period.[12]

Following contemporary studies (e.g., Belo et al., 2014; Belo et al., 2022; Hasan et al., 2022; Ismail et al., 2021; Vitorino, 2014), we construct brand capital based on advertising expenses using the perpetual inventory method:

$$B_{i,t} = \left(1 - \delta^B\right) B_{i,t-1} + A_{i,t} \tag{1}$$

To implement the law of motion in the above equation, we specify the initial stock as.

$B_0 = \frac{A_0}{g+\delta^B}$, where, B, A, δ^B, and g represent the brand capital, advertisement expenses, depreciation rate, and advertisement expenses growth rate, respectively. Following the literature, we use a 50% depreciation rate to estimate brand capital (Bagwell, 2007; Belo et al., 2014; Hasan et al., 2022; Ismail et al., 2021).[13]

For the main empirical analyses, we scaled brand capital by the firm's market value of equity (*BRAND/MVE*) and sales (*BRAND/SALE*). In the robustness check, we also use three alternative scalings of brand capital.

2.2.3. Control variables

Following previous studies (Boubaker et al., 2017; Boubakri & Saffar, 2019; Denis & Mihov, 2003; Lin et al., 2013), we control for various firm characteristics thought to affect debt choice: firm size (*SIZE*), market-to-book ratio (*MTB*), financial leverage (*LEV*), profitability (*ROA*), assets tangibility (*TANG*), distress risk (*ALTMAN*), credit ratings (*RATING*), and industry concentration (*IND_CON*). We also control for year and industry (two-digit SIC code) fixed effects. The variables are defined in Appendix A.

2.3. Baseline model

To test the relationship between brand capital and debt choice (*BANK_DEBT*), we estimate the following regression model:

$$\begin{aligned} BANK\_DEBT = {} & \alpha_0 + \beta_1 BRAND + \beta_2 SIZE + \beta_3 MTB + \beta_4 LEV + \beta_5 ROA \\ & + \beta_6 TANG + \beta_7 ALTMAN + \beta_8 RATING + \beta_9 IND\_CON \\ & + YEAR\ FE + INDUSTRY\ FE + \varepsilon \end{aligned} \tag{2}$$

where *BANK_DEBT*, the dependent variable, represents the proportion of bank debt to total debt (see Section 2.2.1). The main independent variable is BRAND (*BRAND/MVE* and *BRAND/SALE*) (see Section 2.2.2). We also include a set of controls (see Section 2.2.3) and cluster standard errors at the firm level.[14]

3. Results

3.1. Descriptive statistics

Table 1 reports the summary statistics of the variables. The mean (median) and standard deviation of *BANK_DEBT* are 0.418 (0.286) and 0.419, respectively. This suggests that, on average, bank debt constitutes 41.8% of the total debt, which concurs with earlier research (e.g., Boubaker et al., 2018). The descriptive statistics indicate that brand capital is nontrivial and amounts, on average, to 15.3% of the total market value of equity (*BRAND/MVE*) and 7.5% of total sales (*BRAND/SALE*), consistent with the results of recent studies (e.g., Hasan et al., 2022). The average sample firm is moderately large (*SIZE* = 5.761), well-leveraged (*LEV* = 0.353), has high growth opportunities (*MTB* = 2.177), and exhibits negative profitability (*ROA* = −0.031). Additionally, the sample firms exhibit low asset tangibility (*TANG* = 0.232) and industry concentration (*IND_CON* = 0.074). Overall, the reported summary statistics are in line with those previously reported in the literature (Boubaker et al., 2018; Ismail et al., 2021; Wu & Lai, 2020).

3.2. Correlation

Table 2 presents the correlations of variables used in the main regression model. We observe a significantly negative correlation of *BRAND/MVE* and *BRAND/SALE* with *BANK_DEBT* ($\rho = -0.04$; $p < 0.01$), providing preliminary support to our hypothesis that brand capital prompts firms to reduce reliance on bank debt. We also find that *BANK_DEBT* is significantly and negatively correlated with *SIZE*, *MTB*, and *RATING* ($p < 0.01$) and positively correlated with *LEV*, *ROA*, *ALTMAN*, and *IND_CON* ($p < 0.01$). The correlation coefficients between the

[9] We choose not to extend our data beyond the year 2019 to mitigate the impact of COVID-19 on economic downturn, corporate performance, and corporate debt (Ellul, Erel, & Rajan, 2020).

[10] Our inference remains unaffected when excluding utility firms (SIC: 4900–4999) from the analysis and when replacing the missing values of bank debt with 0. We also obtain similar results when restricting our analysis to the sub-sample of firms with a valid credit rating (untabulated).

[11] This includes bonds and notes (senior and subordinated), commercial papers, term loans, and revolving credits, and other types of debt.

[12] One may contend that brand capital can also be defined and measured from the perspective of consumer perception. While consumer perception is crucial, it is subjective and prone to volatility, influenced by transient trends, cultural shifts, and individual experiences. Additionally, there is a lack of readily available data on consumers' perception of brand capital for a reasonably large sample of firms over an extended period, potentially compromising the comprehensive understanding of a brand's true value. We emphasize that our brand capital measure aligns with the emerging finance and economics literature (Belo et al., 2014; Belo et al., 2022; Hasan et al., 2022).

[13] We also employ different depreciation rates, ranging from 30% to 70%, in the robustness tests.

[14] The inferences from our analyses remain robust when we correct standard errors by clustering at both the firm and year levels.

Table 1
Summary statistics.

	Mean	Std. dev.	P5	P25	Median	P75	P95
			Dependent variable				
BANK_DEBT	0.418	0.419	0.000	0.000	0.286	0.920	1.000
			Variable of interest				
BRAND/MVE	0.153	0.447	0.001	0.008	0.030	0.098	0.626
BRAND/SALE	0.075	0.148	0.002	0.010	0.029	0.076	0.278
			Control variables				
SIZE	5.761	2.705	1.208	3.757	5.913	7.650	10.174
MTB	2.177	3.098	0.476	0.853	1.305	2.192	6.191
LEV	0.353	0.526	0.004	0.097	0.239	0.419	0.925
ROA	−0.031	0.172	−0.211	−0.02	0.009	0.026	0.058
TANG	0.232	0.210	0.019	0.072	0.161	0.329	0.703
ALTMAN	0.653	0.476	0.000	0.000	1.000	1.000	1.000
RATING	0.312	0.463	0.000	0.000	0.000	1.000	1.000
IND_CON	0.074	0.077	0.022	0.033	0.044	0.079	0.237
			Variables used in additional analyses				
BRAND/TA	0.081	0.157	0.002	0.009	0.029	0.084	0.309
BRAND_LG	2.726	2.196	0.085	0.769	2.279	4.304	6.863
BRAND/TE	0.208	0.435	0.004	0.021	0.058	0.173	0.968
ADV/TA	0.037	0.065	0.001	0.004	0.014	0.040	0.146
INTAN/TA	0.218	0.219	0.000	0.025	0.150	0.360	0.661
INST_HOLDING	0.583	0.334	0.009	0.293	0.663	0.862	1.000
WW	−0.121	0.468	−0.427	−0.320	−0.236	−0.109	0.459
DIV	0.294	0.456	0.000	0.000	0.000	1.000	1.000
ANALYST	4.940	7.322	0.000	0.000	1.000	7.000	21.000
AUDIT SPECIALIZATION	0.205	0.404	0.000	0.000	0.000	0.000	1.000
OPACITY	0.209	0.218	0.036	0.081	0.137	0.245	0.671
CASH	0.163	0.176	0.005	0.032	0.098	0.230	0.565
DUALITY	0.581	0.493	0.000	0.000	1.000	1.000	1.000
BLOCK HOLDING	16.028	1.457	13.552	15.103	16.059	16.959	18.479
CEO AGE	4.011	0.129	3.784	3.932	4.025	4.094	4.220
PUBLIC DEBT	0.407	0.420	0.000	0.000	0.256	0.895	1.000
SECURED DEBT	0.512	0.437	0.000	0.002	0.534	0.998	1.000
UNSECURED DEBT	0.456	0.437	0.000	0.000	0.367	0.984	1.000

This table provides summary statistics for the sample, which covers 20,280 publicly-listed U.S. firm-years from 2001 to 2019. The continuous variables are winsorised at the 1st and 99th percentiles. Appendix A defines the variables.

Table 2
Pairwise correlations.

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)
(I) *BANK_DEBT*	1.00										
(II) *BRAND/MVE*	−0.04*	1.00									
(III) *BRAND/SALE*	−0.04*	0.34*	1.00								
(IV) *SIZE*	−0.11*	−0.29*	0.01	1.00							
(V) *MTB*	−0.05*	−0.12*	0.07*	0.29*	1.00						
(VI) *LEV*	0.04*	0.10*	−0.05*	−0.18*	0.32*	1.00					
(VII) *ROA*	0.07*	0.10*	−0.26*	0.26*	−0.51*	−0.54*	1.00				
(VIII) *TANG*	0.02*	0.04*	−0.04*	−0.00	−0.07*	0.10*	0.07*	1.00			
(IX) *ALTMAN*	0.03*	−0.00	−0.05*	0.29*	0.29*	−0.18*	0.35*	−0.06*	1.00		
(X) *RATING*	−0.15*	0.14*	0.01	0.61*	−0.06*	0.17*	0.15*	0.13*	0.07*	1.00	
(XI) *IND_CON*	0.03*	0.08*	−0.00	−0.01	−0.09*	0.04*	0.01	0.19*	0.13*	0.11*	1.00

This table reports pairwise correlations between the key variables. Our dependent variable is *BANK_DEBT*, and the main independent variable is brand capital (*BRAND/MVE* and *BRAND/SALE*). Significance at the 1% level is denoted by *. Appendix A defines the variables.

covariates are relatively small, indicating that multicollinearity is not a major concern for our study. The variance inflation factors for our regressions (unreported) are <2.41, which is substantially lower than the cut-off value of 10 and further confirms that multicollinearity is not a concern for our analysis (Wooldridge, 2015).

3.3. Main results

Table 3 shows the baseline regression results for the impact of brand capital on debt choice. The variable of interest is either *BRAND/MVE* or *BRAND/SALE*, depending on the specification. The dependent variable is *BANK_DEBT*. In Columns (1) and (2), the regression estimates demonstrate that the coefficients of brand capital are negative and statistically significant ($p < 0.01$), confirming our prediction that firms with high brand capital reduce their reliance on bank debt. This finding is also economically meaningful. For example, the coefficient of *BRAND/MVE* (= −0.035; $p < 0.01$) in Column (1) indicates that a one-standard-deviation (= 0.447) increase in brand capital results in a 3.74% (5.47%) decrease in the ratio of bank debt relative to the mean (median) level of bank debt. Similarly, the coefficient of *BRAND/SALE* (= −0.112; $p < 0.01$) in Column (2) suggests that a one-standard-deviation increase in brand capital results in a 3.97% (5.80%)

Table 3
Baseline regression.

Variables	(1)	(2)	(3)	(4)
BRAND/MVE	**−0.035*** [0.010]**		**−0.034*** [0.010]**	
BRAND/SALE		**−0.112*** [0.035]**		**−0.115*** [0.036]**
SIZE	−0.034*** [0.003]	−0.032*** [0.003]	−0.035*** [0.003]	−0.033*** [0.003]
MTB	−0.008*** [0.002]	−0.007*** [0.002]	−0.008*** [0.002]	−0.007*** [0.002]
LEV	0.007 [0.016]	0.009 [0.017]	0.007 [0.017]	0.009 [0.018]
ROA	0.283*** [0.040]	0.264*** [0.043]	0.289*** [0.041]	0.271*** [0.044]
TANG	0.061 [0.038]	0.050 [0.039]	0.068* [0.039]	0.057 [0.040]
ALTMAN	0.052*** [0.013]	0.052*** [0.013]	0.054*** [0.013]	0.053*** [0.013]
RATING	−0.162*** [0.017]	−0.168*** [0.017]	−0.161*** [0.018]	−0.166*** [0.018]
IND_CON	0.088 [0.120]	0.083 [0.121]	0.113 [0.137]	0.103 [0.137]
Constant	0.321* [0.170]	0.318* [0.170]	0.639*** [0.022]	0.639*** [0.020]
Observations	20,280	20,199	20,280	20,199
Year FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Year×Industry FE	No	No	Yes	Yes
Adj. R^2	0.15	0.15	0.15	0.15

This table presents estimates from panel regressions explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on debt choice (*BANK_DEBT*). Standard errors reported in the brackets are heteroskedasticity-consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

decrease in the ratio of bank debt relative to the mean (median) level of bank debt. This economic significance is in line with prior literature (e.g., Boubaker et al., 2018).

In Columns (3) and (4), we estimate the regressions using Industry × Year fixed effects to capture time-varying industry effects (Chen, Maslar, & Serfling, 2020; Dhaliwal, Judd, Serfling, & Shaikh, 2016). We observe that the negative and significant link between brand capital and bank debt persists ($p < 0.01$). Regarding the control variables, we find that large firms and those with high growth opportunities and better S&P long-term debt ratings rely less on bank debt than do other firms. Taken together, the signs of the coefficients of the control variables are generally in line with those previously reported in the literature (Boubaker et al., 2018; Boubakri & Saffar, 2019; Lin et al., 2013; Rauh & Sufi, 2010).[15] Overall, the main regression reported in Table 3 supports our conjecture that firms with high brand capital reduce their reliance on bank debt.

3.4. Sensitivity analysis

3.4.1. Alternative regression models

We employ four alternative regression models to mitigate concerns that the coefficients estimated using the ordinary least squares model could be inconsistent. First, following Boubakri and Saffar (2019), we use the Tobit regression model to account for the presence of truncated variables (our bank debt variable ranging between 0 and 1). The results in Panel A of Table 4 show that the coefficients of *BRAND/MVE* and *BRAND/SALE* are negative and significant ($p < 0.01$), as shown in Columns (1) and (5), respectively. Second, we use Newey–West standard errors to mitigate concerns about serial correlation and heteroskedasticity in the error terms. Columns (2) and (6) reveal that our results remain qualitatively unchanged. Third, we use weighted least squares (WLS) models to mitigate the concern of a heterogeneous number of firms across different industries. As shown in Columns (3) and (7), our findings from the WLS regression results remain qualitatively the same. Finally, the coefficients of BRAND/MVE and BRAND/SALE remain significantly negative ($p < 0.01$) when we employ a Fama–MacBeth regression in Columns (4) and (8), respectively. Overall, we observe that the negative effect of brand capital on bank debt is not driven by any specific regression specifications.

3.4.2. Alternative measures of the variable of interest

As a robustness check, we use three additional alternative measures of brand capital: brand capital to total assets (*BRAND/TA*), the natural logarithm of brand capital (*BRAND_LG*), and brand capital to total employees (*BRAND/TE*). The results reported in Panel B (Table 4) show that the coefficients of the alternative measures of brand capital remain negative and significant (coefficients range from −0.027 to −0.073; $p <$ 0.05 or better; see Columns (1)–(3)).

As a further robustness check, we use bank debt as a proportion of total liabilities to measure bank debt and re-estimate the main regression. In Panel B (Table 4), Columns (4) and (5) show that the coefficients of *BRAND/MVE* (= −0.026; $p < 0.01$) and *BRAND/SALE* (= −0.049; $p <$ 0.01) corroborate our main results. Finally, to avoid interference from other kinds of debts, we scale bank debt by the sum of bank debt and bond debt. As shown in Table A.1 (online appendix), we obtain similar results ($p < 0.01$).

3.4.3. Alternative depreciation rates

Following the literature, our main analysis uses the 50% depreciation rate to estimate brand capital (Belo et al., 2014; Ismail et al., 2021). In this section, we use different depreciation rates, ranging from 30% to 70%, to mitigate the concern of a specific depreciation rate driving our results. Panel C (Table 4) shows that the coefficients of *BRAND/MVE* and *BRAND/SALE* remain qualitatively the same ($p < 0.01$) when different depreciation rates are applied to the estimation of brand capital. Therefore, we conclude that our main findings are unaffected when using different depreciation rates.

3.4.4. Lagged regression specification

Because brand capital develops over time and is generally slow-moving, we adopt a contemporaneous regression model for our main analysis. However, as a robustness test, we employ a lagged regression specification to alleviate the concern that brand capital in the current year could affect a firm's debt choice the next year. Table A.2 shows that none of our results are materially affected when this regression specification is employed.

3.4.5. Excluding the global financial crisis (GFC) period

To alleviate the concern about the impact of the GFC period on our documented findings, we re-estimate the main regression results after excluding this period (2007–2008). Table A.3 shows that our main findings remain unaffected after doing so.

3.5. Endogeneity concerns

We employ a series of empirical strategies to alleviate endogeneity concerns arising from omitted variable bias and reverse causality issues.[16]

[15] To assess the effect of leverage on the main results, we run the regressions without leverage as a control variable. The untabulated findings reveal qualitatively similar results.

[16] One may contend that both brand capital and debt choice are potential decision factors for firms, implying a potential simultaneity problem. However, it is important to note that brand capital accumulates over time, whereas debt choice is a decision made in a specific year (t). As a result, we assert that these two variables do not constitute simultaneous decisions within the same time frame. Nevertheless, our analyses in section 3.5 effectively address any concerns regarding joint decision/ simultaneity.

Table 4
Sensitivity analysis.

Panel A: Alternative regression models

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tobit	Newey-West	WLS	Fama-MacBeth	Tobit	Newey-West	WLS	Fama-MacBeth
BRAND/MVE	**−0.050*****	**−0.035*****	**−0.031*****	**−0.040*****				
	[0.017]	**[0.007]**	**[0.011]**	**[0.009]**				
BRAND/SALE					**−0.200*****	**−0.112*****	**−0.092****	**−0.124*****
					[0.072]	**[0.022]**	**[0.041]**	**[0.017]**
SIZE	−0.055***	−0.034***	−0.036***	−0.036***	−0.052***	−0.032***	−0.034***	−0.033***
	[0.006]	[0.002]	[0.004]	[0.003]	[0.006]	[0.002]	[0.004]	[0.003]
MTB	−0.020***	−0.008***	−0.009***	−0.009***	−0.019***	−0.007***	−0.008***	−0.008***
	[0.004]	[0.001]	[0.002]	[0.001]	[0.005]	[0.001]	[0.002]	[0.001]
LEV	0.049	0.007	0.002	0.013	0.053*	0.009	0.005	0.021**
	[0.030]	[0.008]	[0.021]	[0.009]	[0.032]	[0.008]	[0.023]	[0.009]
ROA	0.484***	0.283***	0.261***	0.314***	0.450***	0.264***	0.244***	0.310***
	[0.080]	[0.026]	[0.047]	[0.025]	[0.086]	[0.027]	[0.052]	[0.029]
TANG	0.142**	0.061***	0.001	0.059***	0.122*	0.050***	−0.008	0.048***
	[0.065]	[0.018]	[0.046]	[0.013]	[0.066]	[0.018]	[0.046]	[0.015]
ALTMAN	0.072***	0.052***	0.066***	0.053***	0.071***	0.052***	0.066***	0.053***
	[0.023]	[0.007]	[0.015]	[0.010]	[0.023]	[0.007]	[0.015]	[0.011]
RATING	−0.224***	−0.162***	−0.136***	−0.164***	−0.233***	−0.168***	−0.141***	−0.170***
	[0.030]	[0.008]	[0.020]	[0.014]	[0.029]	[0.008]	[0.019]	[0.014]
IND_CON	0.040	0.088*	0.121	0.145***	0.029	0.083*	0.117	0.132**
	[0.213]	[0.049]	[0.124]	[0.049]	[0.213]	[0.049]	[0.124]	[0.048]
Constant	0.083	0.321***	0.340*	0.517***	0.087	0.318***	0.335*	0.515***
	[0.287]	[0.059]	[0.177]	[0.052]	[0.288]	[0.059]	[0.178]	[0.051]
Observations	20,280	20,280	20,280	20,199	20,199	20,199	20,199	20,199
Year FE	Yes	Yes	Yes	–	Yes	Yes	Yes	–
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj./ Pseudo R^2	0.07	–	0.14	0.16	0.07	–	0.14	0.16

Panel B: Alternative measures of key variables

Variables	(1)	(2)	(3)	(4)	(5)
	Alternative brand			Alternative bank debt (bank debt/total liabilities)	
BRAND/TA	**−0.073****				
	[0.036]				
BRAND_LG		**−0.027*****			
		[0.005]			
BRAND/TE			**−0.036*****		
			[0.014]		
BRAND/MVE				**−0.026*****	
				[0.006]	
BRAND/SALE					**−0.049*****
					[0.019]
SIZE	−0.033***	−0.017***	−0.033***	−0.020***	−0.018***
	[0.003]	[0.004]	[0.003]	[0.002]	[0.002]
MTB	−0.007***	−0.010***	−0.007***	−0.007***	−0.007***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]
LEV	0.006	0.014	0.009	0.095***	0.101***
	[0.016]	[0.016]	[0.018]	[0.014]	[0.015]
ROA	0.270***	0.258***	0.288***	0.256***	0.255***
	[0.041]	[0.040]	[0.044]	[0.027]	[0.029]
TANG	0.059	0.056	0.043	0.068***	0.063**
	[0.038]	[0.038]	[0.039]	[0.026]	[0.027]
ALTMAN	0.054***	0.046***	0.051***	0.010	0.010
	[0.013]	[0.013]	[0.013]	[0.008]	[0.008]
RATING	−0.167***	−0.144***	−0.167***	−0.026**	−0.031***
	[0.017]	[0.018]	[0.017]	[0.010]	[0.010]
IND_CON	0.082	0.086	0.093	0.168**	0.165**
	[0.120]	[0.121]	[0.121]	[0.081]	[0.081]

(*continued on next page*)

3.5.1. *Inclusion of additional controls*

For the main analysis, we use a common set of controls employed in earlier studies (Boubaker et al., 2018; Boubakri & Saffar, 2019; Lin et al., 2013). In this section, we include a few additional controls that may affect debt choice to alleviate the issue of omitted variable bias. For example, to ease the concern of omitted advertisement expense and other reported intangible items, we explicitly control for advertisement (*ADV/TA*) and intangibles (*INTAN/TA*) (Hasan et al., 2022). We control for institutional holdings as several studies show that ownership structure affects firms' financing decisions (e.g., Mehran, 1992). We include discretionary accruals (*OPACITY*) as past studies show that financial reporting quality affects firms' debt choice (Bharath et al., 2008). We also include cash holdings (*CASH*) as corporate liquidity has been shown to influence debt choice. Finally, we include CEO characteristics such as

Table 4 (*continued*)

Panel B: Alternative measures of key variables

Variables	(1)	(2)	(3)	(4)	(5)
	Alternative brand			Alternative bank debt (bank debt/total liabilities)	
Constant	0.312*	0.283*	0.317*	0.159	0.151
	[0.17]	[0.167]	[0.171]	[0.102]	[0.103]
Observations	20,280	20,280	19,856	20,280	20,199
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.15	0.15	0.15	0.15

Panel C: Alternative depreciation rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depreciation rate =	0.30	0.40	0.60	0.70	0.30	0.40	0.60	0.70
BRAND/MVE	**−0.022*****	**−0.029*****	**−0.050*****	**−0.060*****				
	[0.006]	**[0.008]**	**[0.013]**	**[0.016]**				
BRAND/SALE					**−0.084*****	**−0.120*****	**−0.192*****	**−0.238*****
					[0.022]	**[0.031]**	**[0.051]**	**[0.063]**
SIZE	−0.035***	−0.034***	−0.035***	−0.035***	−0.033***	−0.032***	−0.032***	−0.032***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
MTB	−0.009***	−0.009***	−0.008***	−0.008***	−0.008***	−0.008***	−0.007***	−0.007***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
LEV	0.010	0.011	0.007	0.008	0.013	0.013	0.008	0.009
	[0.018]	[0.017]	[0.016]	[0.016]	[0.019]	[0.018]	[0.017]	[0.017]
ROA	0.301***	0.295***	0.283***	0.283***	0.280***	0.270***	0.258***	0.257***
	[0.043]	[0.041]	[0.040]	[0.040]	[0.045]	[0.044]	[0.043]	[0.043]
TANG	0.070*	0.067*	0.062	0.059	0.057	0.053	0.049	0.046
	[0.039]	[0.039]	[0.038]	[0.038]	[0.040]	[0.039]	[0.039]	[0.039]
ALTMAN	0.052***	0.052***	0.052***	0.052***	0.051***	0.051***	0.051***	0.051***
	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]
RATING	−0.161***	−0.161***	−0.162***	−0.162***	−0.168***	−0.168***	−0.168***	−0.168***
	[0.018]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
IND_CON	0.079	0.090	0.086	0.087	0.074	0.084	0.079	0.080
	[0.121]	[0.120]	[0.120]	[0.120]	[0.121]	[0.120]	[0.121]	[0.120]
Constant	0.331*	0.320*	0.323*	0.323*	0.329*	0.321*	0.322*	0.322*
	[0.169]	[0.169]	[0.169]	[0.169]	[0.170]	[0.170]	[0.171]	[0.171]
Observations	19,633	19,977	20,274	20,264	19,555	19,898	20,193	20,183
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15

This table presents a sensitivity analysis of the estimates from panel regressions explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on debt choice (*BANK_DEBT*) using alternative regression models (Panel A), alternative measures of key variables such as brand capital scaled by total assets (*BRAND/TA*), the natural logarithm of brand capital (*BRAND_LG*), and brand capital to total employees (*BRAND/TE*) (Panel B), and various depreciation rates for brand capital estimation (Panel C). Standard errors reported in the brackets are heteroskedasticity-consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

CEO age (*CEO_AGE*), CEO gender (*CEO_FEMALE*), and CEO's cash and bonus compensation as a proportion of total compensation (*CEO_COM*) to alleviate the concern that CEO-level characteristics may affect debt choice. The results in Panel A (Table 5) confirm that the negative relationship between brand capital and bank debt remains robust to the inclusion of these additional controls, both separately and collectively.

3.5.2. *The ITCV analysis*

Although our regression model includes a set of controls commonly used in the literature, our results could be biased by the omission of factors affecting both brand capital and debt choice. To mitigate this issue, we use the ITCV technique (Chapman et al., 2019; Frank, 2000). This procedure estimates the degree of correlation between an omitted variable and the most impactful control variable required to nullify our findings. It is well-suited for our analysis as the confounding variable remains unidentified and is possibly unobservable.

Panel B of Table 5 presents the results. The ITCVs ($BRAND/MVE_{ITCV} = -0.0113$, $BRAND/SALE_{ITCV} = -0.0089$) are calculated as the lowest products of partial correlation between bank debt and other explanatory variables. The tabulated results suggest that the correlations between brand capital and bank debt with the unobserved confounding variable need to be 0.106 and 0.094 for *BRAND/MVE* and *BRAND/SALE*, respectively, to invalidate our main results.

Given that we do not know the confounding variable, we calculate the raw and partial impact of each explanatory variable and compare it with the minimum values of the correlations. Table 5 shows that none of the individual impact factors of the regressors is greater than the minimum values of the correlations. For example, the partial impact factor of *SIZE* (the highest impact variable) and *MTB* (the second-highest impact variable) for *BRAND/MVE* is 0.028 and 0.005, respectively, indicating that an unobservable confounding variable needs to be at least 3.79 and 21.2 times greater than the impact of *SIZE* and *MTB* to overturn our findings. Thus, it is reasonable to conclude that our regression results are unlikely to be influenced by unobservable confounding variables.

3.5.3. *Tests for omitted variable bias using Oster (2019)*

We employ bound estimates of Oster (2019) to further alleviate concerns about omitted variable bias. This method uses information on movements in coefficients and R-squared estimates to assess how strong the effect of unobservable factors would have to be to invalidate the conclusions of our study. A non-zero bounded set from Oster's (2019) estimate indicates that the effect of the main explanatory variable (i.e.,

Table 5
Endogeneity tests: Omitted variable bias.

Panel A: Use of additional controls								
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BRAND/MVE	**−0.030***** **[0.010]**	**−0.031***** **[0.010]**	**−0.045***** **[0.014]**	**−0.035***** **[0.010]**	**−0.031***** **[0.010]**	**−0.054***** **[0.020]**	**−0.052**** **[0.014]**	
BRAND/SALE								**−0.288***** **[0.099]**
ADV/TA	−0.107 [0.094]						0.478* [0.245]	0.769** [0.338]
INTAN/TA		0.206*** [0.031]					0.187*** [0.065]	0.202*** [0.065]
INST_HOLDING			0.033 [0.028]				−0.058 [0.046]	−0.041 [0.044]
OPACITY				−0.084*** [0.025]			0.121 [0.077]	0.130* [0.076]
CASH					−0.523*** [0.033]		−0.640*** [0.082]	−0.622*** [0.082]
CEO_AGE						0.065 [0.060]	0.113* [0.066]	0.115* [0.066]
CEO_FEMALE						0.045 [0.043]	0.048 [0.047]	0.045 [0.047]
CEO_COM						0.027 [0.029]	0.017 [0.033]	0.021 [0.033]
Constant	0.325* [0.170]	0.253 [0.166]	0.399** [0.170]	0.612*** [0.106]	0.420*** [0.153]	0.133 [0.301]	0.306 [0.286]	0.258 [0.282]
Observations	20,280	19,875	13,876	18,757	20,280	7805	6243	6243
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.15	0.19	0.15	0.18	0.24	0.31	0.31

Panel B: The impact threshold for a confounding variable (ITCV) analysis				
	(1)	(2)	(3)	(4)
	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)
	BRAND = *BRAND/MVE*		*BRAND* = *BRAND/SALE*	
SIZE	0.058	0.028	0.025	−0.001
MTB	0.011	0.005	−0.030	−0.003
LEV	−0.007	0.002	−0.011	−0.002
ROA	−0.004	0.001	−0.030	−0.022
TANG	0.001	0.001	−0.001	−0.001
ALTMAN	−0.001	−0.001	−0.001	−0.002
RATING	0.005	−0.020	0.017	−0.001
IND_CON	0.002	0.002	−0.001	0.000
Benchmark				
ITCV	−0.0113		−0.0089	
The needed correlations between brand and bank debt with the unobserved confounding variable to invalidate the finding	0.106		0.094	

Panel A of this table presents the estimates from panel regressions explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on debt choice (*BANK_DEBT*) using additional controls, including advertisement expenses scaled by total assets (*ADV/TA*), intangibles scaled by total assets (*INTAN/TA*), institutional holdings (*INST_HOLDING*), discretionary accruals (*OPACITY*), cash holdings scaled by total assets (*CASH*), CEO age (*CEO_AGE*), CEO gender (*CEO_FEMALE*), and CEO's cash and bonus compensation as a proportion of total compensation (*CEO_COM*). Panel B presents the results of the ITCV analysis used to examine the effect of brand capital on debt choice. Standard errors reported in the brackets are heteroskedasticity-consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

BRAND/MVE or *BRAND/SALE*) on our dependent variable (i.e., *BANK_DEBT*) is robust. Table 6 presents the parameters and bound estimates obtained based on Oster (2019). We observe that the identified bounds for our estimates do not contain '0.' Therefore, we conclude that our regression estimations are not prone to omitted variable bias.

3.5.4. Instrumental variable approach

In this section, we conduct an instrumental variable estimation using heteroskedasticity-based instruments, a novel identification technique developed by Lewbel (2012). This technique does not rely on external instruments. Instead, it creates instruments based on the heterogeneity in the error term of the first-stage regression model, making it particularly useful when external instruments are weak or unavailable. Recent corporate finance studies have successfully used this method to alleviate endogeneity issues (Chen et al., 2021; Hasan et al., 2022).

The two-stage regression results obtained using heteroskedasticity-based instruments are shown in Columns (1) and (2) of Table 7. The relationship between brand capital and bank debt remains significantly negative (*BRAND/MVE* $= -0.029$; $p < 0.01$ and *BRAND/SALE* $= -0.087$; $p < 0.05$). Furthermore, our analysis is not subject to under-identification, weak instrument, or over-identification concerns. Thus, the negative link between brand capital and bank debt is robust and unlikely to be due to endogeneity problems.

3.5.5. Two-step system GMM

To enhance the robustness of our analysis against endogeneity, we use a two-step system GMM approach. While both the GMM (Holtz-Eakin, Newey, & Rosen, 1988) and two-step system GMM (Roodman,

Table 6
Tests for omitted variable bias using Oster (2019).

Variable of Interest	(1) Controlled		(2) Uncontrolled		(3) Parameters: $\delta = 1$; $R_{MAX} = \min(1.3\tilde{R}, 1)$
	Beta	R^2	Beta	R^2	Identified Set
BRAND/MVE	−0.035	0.150	0.003	0.001	−0.047, −0.035
BRAND/SALE	−0.112	0.150	−0.240	0.007	−0.072, −0.112

This table presents the results from the omitted variable bias test developed by Oster (2019). Our dependent variable is *BANK_DEBT*, and the main independent variable is brand capital (*BRAND/MVE* and *BRAND/SALE*). Columns (1) and (2) report beta and R2 from controlled and uncontrolled OLS regressions, respectively. Column (3) shows the identified set obtained using the parameters. Following prior studies (e.g., Gao & Huang, 2020; Oster, 2019), we set $\delta = 1$ and $R_{max} = \min(1.3\tilde{R}, 1)$. Appendix A defines the variables.

2009) construct estimators based on assumptions of specific moments rather than the whole distribution of random variables, the latter provides errors in two-step estimation, thus reducing severe downward bias for standard errors. Prior studies suggest that the two-step system GMM can tackle concerns arising from simultaneity, reverse causality, and unobserved heterogeneity (Kang, Kim, & Lu, 2018; Kryzanowski & Mohebshahedin, 2016).

Using the two-step system GMM, we observe that the coefficients of brand capital remain negative and significant (coefficient of *BRAND/MVE* $= -0.017$, $p < 0.01$ and coefficient of *BRAND/SALE* $= -0.062$, $p < 0.05$; see Columns (3) and (4) of Table 7). We observe the expected statistical significance and insignificance from the autocorrelation tests of the first (i.e., AR(1)) and second (i.e., AR(2)) differences. Moreover, the Hansen J-statistic validates our estimates. Overall, the two-step system GMM regression confirms that our main result is not driven by endogeneity.

3.5.6. Entropy balancing estimates

We also employ entropy balancing estimates to mitigate endogeneity concerns (Hainmueller, 2012). This technique reweights observations to achieve covariate balance for the first three moments, thereby ensuring that the treated and control groups are similar in terms of the mean, standard deviation, and skewness. Recent studies have used this technique to address endogeneity problems (e.g., Arifin, Hasan, & Kabir, 2020; Jiang, John, Li, & Qian, 2018). For our estimation, we divide the sample into a treatment group (firms with more than the sample median brand capital) and a control group (firms with less than the sample median brand capital).

Table A.4 reports the covariate balance between the treatment and control groups. We find an improvement in the covariate distributions after reweighting, indicating similar characteristics for both the treatment and control groups. The entropy regression analysis is presented in Table 8. As shown in Columns (1) and (2), the coefficients of *BRAND/MVE* and *BRAND/SALE* are negative and significant ($p < 0.05$), confirming that endogeneity is not likely the driver of our key findings.

3.5.7. Propensity score matching (PSM)

To comprehensively address endogeneity issues, we employ propensity score matching (PSM) as an alternative method to mitigate self-selection biases. PSM involves matching sample firms with control firms possessing similar characteristics, determined by a function of covariates. We select optimal matching using the single nearest-neighbor matching technique within the PSM procedure, with a caliper of 0.01. Our choice of this procedure aligns with prior literature (e.g., Austin, 2011) as a means to control variations in characteristics between firms with high and low brand capital.

In our approach, we first divide our sample into two groups according to the median level of brand capital, designating the group with higher brand capital as the treated group and the one with lower brand

Table 7
Heteroskedasticity-based instrumental variable regression and the two-step system GMM regression.

Variables	(1)	(2)	(3)	(4)
	Lewbel (2012)		System GMM	
BRAND/MVE	**−0.029*****		**−0.017*****	
	[0.011]		**[0.004]**	
BRAND/SALE		**−0.087****		**−0.062****
		[0.040]		**[0.026]**
BANK_DEBT(Lagged)			0.661***	0.682***
			[0.015]	[0.015]
SIZE	−0.034***	−0.032***	−0.015***	−0.013***
	[0.003]	[0.003]	[0.002]	[0.002]
MTB	−0.008***	−0.007***	−0.003**	−0.004***
	[0.002]	[0.002]	[0.001]	[0.001]
LEV	0.007	0.009	0.001	0.010
	[0.016]	[0.017]	[0.007]	[0.007]
ROA	0.283***	0.273***	0.126***	0.090***
	[0.040]	[0.043]	[0.023]	[0.019]
TANG	0.061	0.052	0.041**	0.017
	[0.038]	[0.039]	[0.017]	[0.017]
ALTMAN	0.052***	0.052***	0.011*	0.020***
	[0.013]	[0.013]	[0.006]	[0.007]
RATING	−0.163***	−0.168***	−0.058***	−0.060***
	[0.017]	[0.017]	[0.007]	[0.008]
IND_CON	0.089	0.085	−0.067	−0.312**
	[0.120]	[0.120]	[0.113]	[0.122]
Constant	−1.709***	−1.617**	−1.709***	−1.617**
	[0.634]	[0.636]	[0.634]	[0.636]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	20,280	20,199	16,441	16,399
Adj. R^2	0.13	0.13	–	–
Under-identification test:				
Kleibergen-Paap rk LM statistic	280.53	337.32		
p-value	0.00	0.00		
Weak identification test:				
Cragg-Donald Wald F statistic	839.99	739.74		
Stock-Yogo (2005) critical value	157.79	157.79		
Hansen J statistic (*p*-value)	0.12	0.53	0.11	0.32
Arellano-Bond test for AR(1)			−15.36***	−15.26***
p-value			0.00	0.00
Arellano-Bond test for AR(2)			0.62	0.73
p-value			0.53	0.47

Columns (1) and (2) present the two-stage regression results obtained using heteroskedasticity-based instruments (Lewbel, 2012). Columns (3) and (4) report the regression results obtained using the two-step system GMM. Our dependent variable is *BANK_DEBT*, and the main independent variable is brand capital (*BRAND/MVE* and *BRAND/SALE*). Standard errors reported in the brackets are heteroskedasticity consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

capital as the control group. Then, we model the propensity of a higher level of brand capital based on firm-specific determinants. We include the same set of controls as utilized in our baseline regression, fostering a potentially balanced distribution of treated and control firms in the matched sample. In general, if, after conditioning on the propensity score, no systematic differences are evident in baseline covariates between treated and untreated subjects, this indicates the correct specification of the propensity score model. Table A.5, Panel A presents results demonstrating no significant differences between treated and control groups, except for *IND_COM*, which is significant at the 10% level, providing reasonable support for our estimation.

Panel B of Table A.5 presents regression results for the PSM approach. Columns (1) and (2) reveal consistently negative and

Table 8
Entropy balancing estimates.

Variables	(1)	(2)
	BANK_DEBT	*BANK_DEBT*
BRAND_MVE	**−0.025**** **[0.011]**	
BRAND/SALE		**−0.084**** **[0.011]**
Constant	0.446*** [0.138]	0.501*** [0.104]
Other controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	20,280	20,199
Adj. R^2	0.16	0.16

This table reports the entropy balancing method regression results. Our dependent variable is *BANK_DEBT*, and the main independent variable is brand capital (*BRAND/MVE* and *BRAND/SALE*). Standard errors reported in the brackets are heteroskedasticity consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

significant coefficients on both *BRAND/MVE* (= −0.060; $p < 0.01$) and *BRAND/SALE* (= −0.089; $p < 0.10$), aligning with our baseline regression results.

3.5.8. Difference-in-differences (DiD) test

As a final strategy to mitigate endogeneity issues, we introduce an exogenous shock to brand capital and estimate the effects of this shock on bank debt. Consistent with Cheng, Guo, Weng, and Wu (2021), we exploit abnormal growth in brand capital as a proxy for economic shocks. Specifically, we follow a two-step procedure. First, we measure the industry–year-level mean brand capital growth rate. Next, we apply the quantile ranking procedure using the mean brand capital growth rates, wherein the top quartile of the sample is considered to have experienced a positive economic shock. Research has revealed considerable firm-level heterogeneity in such economic shocks, both within and across industries. To alleviate the concern of multiple shocks within a short time period, we eliminate mild shocks arising from lower brand capital growth rates over four consecutive years within the same industry.

Then, using PSM, we match firms that experience such shocks with those that do not experience such shocks within a ± 4-year window. For PSM, we employ a logit regression that regresses *SHOCK* (i.e., a variable with a score of 1 for firms that have undergone shocks to brand capital, and 0 otherwise) on controls in Eq. (1). To obtain a better match, we restrict the upper limit for caliper distance to 0.01. After merging the matched and full samples, we retain the observations within the ±4-year window of the event year. Finally, we employ the following DiD regression:

$$\begin{aligned} BANK\_DEBT = &\alpha_0 + \beta_1 SHOCK \times POST + \beta_2 SHOCK + \beta_3 POST + \beta_4 SIZE \\ &+ \beta_5 MTB + \beta_6 LEV + \beta_7 ROA + \beta_8 TANG + \beta_9 DISTRESS \\ &+ \beta_{10} RATING + \beta_9 IND.CON + YEAR\ FE + INDUSTRY\ FE + \varepsilon \end{aligned} \tag{3}$$

where *BANK_DEBT* represents the ratio of bank debt to total debt, and *POST* represents years following shocks to brand capital within the ±4-year window. β_1 captures the average treatment effect. We include all of the controls used in Eq. (2).

Panel A (Table 9) exhibits the PSM diagnostic test results. In terms of firm characteristics, there are no significant differences between the PSM control and treated firms. The DiD regression results in Panel B (Table 9) show that the coefficient of *SHOCK* × *POST* is negative and significant ($p < 0.05$ or better), implying that firms that experienced a brand capital shock reduce their reliance on bank debt to a greater extent than firms that do not experience such a shock. This finding

Table 9
Difference-in-differences (DiD) test.

Panel A: PSM analysis

Variable	Treated	Control	*t*-value	$p > \|t\|$
SIZE	5.674	5.628	0.30	0.768
MTB	2.350	2.200	0.77	0.444
LEV	0.373	0.341	0.92	0.357
ROA	−0.042	−0.037	−0.45	0.651
TANG	0.184	0.196	1.08	0.280
ALTMAN	0.676	0.642	1.23	0.221
RATING	0.285	0.292	−0.27	0.790
IND_CON	0.057	0.056	0.12	0.907

Panel B: Difference-in-differences analysis.

Variables	(1)	(2)
SHOCK×POST	**−0.054***** **[0.021]**	**−0.051**** **[0.020]**
SHOCK	0.069*** [0.027]	0.075*** [0.026]
POST	0.091*** [0.015]	0.017 [0.019]
Constant	0.579*** [0.198]	0.190*** [0.180]
Observations	6218	6218
Other controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	No	Yes
Adj. R^2	0.635	0.193

Panel A reports the PSM diagnostic test results that compare firm characteristics between treatment and control firms, wherein treatment firms experienced shocks to brand capital and control firms did not experience such shocks within a ± 4–year window. Panel B reports the DiD estimations. *SHOCK* takes a value of 1 for firms that experienced industry-level brand capital shocks, and 0 otherwise. *POST* is equal to 1 for years following shocks to brand capital within the ±4–year window. Standard errors reported in the brackets are heteroskedasticity-consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

alleviates endogeneity concerns and supports the causal interpretation of our result.

To further strengthen our findings from the DiD analysis, we perform a placebo test, wherein we replace the actual treatment firms (i.e., *SHOCK*) with random samples (*SHOCK_RANDOM*). We then re-estimate our DiD analysis using these randomly treated firms. We find that the coefficient of the interaction term (i.e., *SHOCK_RANDOM* × *POST*) is statistically insignificant, reinforcing the validity of our findings (see Table A.6).

4. Cross-sectional analysis and additional tests

4.1. Cross-sectional analysis

Thus far, we have presented evidence of a significantly negative relationship between brand capital and debt choice. In this section, we perform cross-sectional analyses to understand how the documented relationship depends on the levels of information asymmetry, corporate governance, and financial conditions. This analysis not only sheds light on the mechanisms through which brand capital affects debt choice but also supports identification, as the relationship is unlikely to exist if our brand capital merely reflects unobserved economic forces (Boubakri & Saffar, 2019).

4.1.1. The role of information asymmetry

Studies show that information asymmetry plays a key role in explaining debt choice (Bharath et al., 2008; Li et al., 2019). Banks are in a position to provide loans to financially opaque firms because they have easy access to non-public information and can closely monitor borrowers (Berlin & Loeys, 1988; Li et al., 2019). However, we contend that firms with higher brand capital have less information asymmetry, making it easier for them to raise funds from the public debt market. Therefore, we expect the negative relationship between brand capital and bank debt to be more salient in the presence of high (vs. low) information asymmetry.

To assess this prediction, we use four information asymmetry measures: credit rating (*RATING*), analyst following (*ANALYST*), auditor industry specialization (*AUDIT_SPECIALIZATION*), and discretionary accruals (*LOW_OPACITY*). These variables have been widely used to capture information asymmetry (Chen et al., 2021; Lu, Chen, & Liao, 2010; Roulstone, 2003). We begin with *RATING*, a variable that takes a value of 1 if a firm has an S&P long-term debt rating, and 0 otherwise. Our second measure of information asymmetry is *ANALYST*, which takes a value of 1 if the firm's analyst following is greater than the sample median, and 0 otherwise. As the third measure of information asymmetry, we use *AUDIT_SPECIALIZATION*, which takes a value of 1 if the firm's auditor has a market share of >30% (in terms of audit fee revenue) in the client's industry (two-digit SIC code), and 0 otherwise. Finally, we use *LOW_OPACITY*, which takes a value of 1 if the absolute value of discretionary accruals for the firm is lower than the sample median, and 0 otherwise. By construction, firms with a credit rating, a large analyst following, an industry specialist auditor, and low opacity are associated with low information asymmetry.

To empirically test the moderating role of information asymmetry, we modify the baseline regression (Eq. (2)), interact *BRAND/MVE* with these information asymmetry proxies, and re-estimate the regression. Panel A (Table 10) shows significantly positive coefficients of *BRAND/MVE* × *RATING* (= 0.052; $p < 0.01$), *BRAND/MVE* × *ANALYST* (= 0.060; $p < 0.05$), and *BRAND/MVE* × *AUDIT_SPECIALIZATION* (= 0.041; $p < 0.05$) and a significantly negative coefficient of *BRAND/MVE* × *LOW_OPACITY* (= −0.027; $p < 0.01$). Overall, Panel B shows that the negative link between brand capital and bank debt attenuates when information asymmetry is low. This finding supports the information asymmetry-based argument used in our study.

4.1.2. The role of corporate governance

We explore whether corporate governance affects the link between brand capital and bank debt. The literature suggests that corporate governance mechanisms mitigate the agency problems caused by the separation of ownership and control. Therefore, effective corporate governance can substitute for the necessary bank monitoring; this increases the attractiveness of borrowing from the public debt market (Boubaker et al., 2018; Liao, 2015). We contend that companies with high brand capital are in the limelight and closely followed by analysts, investors, consumers, and other key stakeholders, which, in turn, reduces managerial abilities and opportunities for self-serving behaviours. Therefore, we expect the negative relationship between brand capital and bank debt to be more (less) evident for firms with weak (strong) governance mechanisms.

To examine the above conjecture, we use four proxies for corporate governance: institutional holdings (*INST_HOLDING)*, blockholder ownership (*BLOCK_HOLDING*), net corporate governance score (*CG_SCORE*) obtained from the Morgan Stanley Capital International (MSCI), and CEO age (*CEO_OLD*) (Andreou, Louca, & Petrou, 2017; Hasan et al., 2022; Liao, 2015). We begin with *INST_HOLDING*, a dummy variable that takes a value of 1 if the institutional shareholdings of a firm are higher than the sample median, and 0 otherwise. We then use *BLOCK_HOLDING,* which takes a value of 1 if the blockholder ownership is greater than the sample median, and 0 otherwise. We use *CG_SCORE* as our third governance proxy, which takes a value of 1 if the net corporate governance score is higher than the sample median, and 0 otherwise. Finally, we use *CEO_OLD*, which takes a value of 1 if the CEO's age is higher than the sample median and 0 otherwise.[17] By construction, firms with higher institutional holdings, block holdings, governance scores, and older CEOs are associated with strong corporate governance.

To analyze the moderating role of corporate governance, we modify the baseline regression (Eq. (2)), interact *BRAND/MVE* with the governance proxies, and re-estimate the regression. Panel B (Table 10) reveals that the coefficients of *BRAND/MVE* × *INST_HOLDING* (= 0.070; $p < 0.10$), *BRAND/MVE* × *BLOCK_HOLDING* (= 0.109; $p < 0.01$), *BRAND/MVE* × *CG_SCORE* (= 0.186; $p < 0.05$), and *BRAND/MVE* × *CEO_AGE* (= 0.082; $p < 0.01$) are positive and statistically significant. Overall, the results in Panel B show that the negative effect of brand capital on bank debt is more (less) salient for firms with weak (strong) corporate governance. These findings also support our corporate governance-based explanation for the negative association between brand capital and bank debt.

4.1.3. The role of financial conditions

The financial position of a firm is a critical factor in determining debt choice (Denis & Mihov, 2003; Lin et al., 2013). The literature suggests that firms facing high ex-ante financial distress risk prefer to borrow privately, as private debt is easier to renegotiate than public debt in the case of a covenant violation (Denis & Mihov, 2003). Because brand capital improves firms' financial performance and reduces the possibility of financial distress (Larkin, 2013; Pillai, 2012; Rego et al., 2009), we anticipate the negative effect of brand capital on bank debt to be more (less) evident when firms have weaker (stronger) financial conditions.

We use the Altman (*1968*) Z-score (ALTMAN), WW index (WW) (Whited & Wu, *2006*), dividends payer dummy (DIV), and firm size (SIZE) to capture firms' financial conditions. ALTMAN is a dummy variable that takes a value of 1 if the Z-score is less than the sample median, and 0 otherwise; WW is a dummy variable that equals to1 if the WW index is more than the sample median, and 0 otherwise; and SIZE_D equals to 1 if SIZE is less than the sample median, and 0 otherwise. DIV equals 1 for firms without dividends payout, and 0 otherwise. By construction, higher values of these measures corresponded to weaker financial conditions.

Panel C (Table 10) reveals that the interactive coefficients are all negative and statistically significant at the conventional level. These results collectively suggest that the negative effect of brand capital on bank debt is exacerbated for firms with weaker financial conditions. This finding supports our financial condition-based argument for a negative association between brand capital and bank debt.

4.2. Additional analyses

In this section, we conduct additional analyses to provide further insights into the relationship between brand capital and other dimensions of debt choice.

4.2.1. Brand capital and public debt

Our earlier analyses focus on bank debt. Because firms with higher brand capital exhibit lower reliance on bank debt, we intuitively argue that they raise external financing from public debt. We directly test this prediction and measure public debt as the sum of commercial paper, senior, and subordinated bonds and notes, scaling this by total debt (Chen et al., 2021; Lin et al., 2013). We regress the public debt measure on our brand capital constructs (*BRAND/MVE* and *BRAND/SALE*) along with the baseline controls and present the findings in Columns (1) and (2) of Table 11. The coefficients of brand capital are positive and

[17] Andreou et al. (2017) show that, compared with older CEOs, younger CEOs are associated with increases in agency problems, bad news stockpiling, and stock price crash risk.

Table 10
Cross-sectional analysis.

Variables	(1)	(2)	(3)	(4)
	Panel A: The effect of information asymmetry			
BRAND/MVE	−0.049***	−0.042***	−0.042***	−0.043***
	[0.011]	[0.010]	[0.013]	[0.011]
RATING	0.171***			
	[0.018]			
BRAND/MVE×RATING	**0.052*** **			
	[0.017]			
ANALYST		0.008		
		[0.014]		
BRAND/MVE×ANALYST		**0.060** **		
		[0.024]		
AUDIT_SPECIALIZATION			0.020	
			[0.015]	
BRAND/MVE×AUDIT_SPECIALIZATION			**0.041** **	
			[0.021]	
LOW_OPACITY				−0.001
				[0.007]
BRAND/MVE×LOW_OPACITY				**0.024* **
				[0.014]
Constant	0.324*	0.334**	0.347***	0.582***
	[0.170]	[0.170]	[0.170]	[0.108]
Observations	20,280	20,280	18,298	18,757
Other controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.15	0.16	0.15
	Panel B: The effect of corporate governance			
BRAND/MVE	−0.052***	−0.082***	−0.040	−0.079***
	[0.014]	[0.019]	[0.041]	[0.021]
INST_HOLDING	−0.028*			
	[0.015]			
BRAND/MVE×INST_HOLDING	**0.070* **			
	[0.038]			
BLOCK_HOLDING		−0.025		
		[0.018]		
BRAND/MVE×BLOCK_HOLDING		**0.109*** **		
		[0.034]		
CG_SCORE			−0.008	
			[0.022]	
BRAND_MVE×CG_SCORE			**0.186** **	
			[0.078]	
CEO_OLD				0.007
				[0.014]
BRAND_MVE×CEO_OLD				**0.082*** **
				[0.032]
Constant	0.375**	0.339**	0.607***	0.429***
	[0.169]	[0.164]	[0.195]	[0.166]
Observations	13,876	11,559	8133	7868
Other controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.19	0.21	0.23	0.24
	Panel C: The effect of financial conditions			
BRAND/MVE	0.008	0.008	0.021	0.076
	[0.013]	[0.013]	[0.034]	[0.053]
ALTMAN	−0.013			
	[0.013]			
BRAND/MVE×ALTMAN	**−0.056** **			
	[0.029]			
WW		−0.010		
		[0.014]		
BRAND/MVE×WW		**−0.062*** **		
		[0.016]		
DIV			0.045***	
			[0.016]	
BRAND/MVE×DIV			**−0.059* **	
			[0.034]	
SIZE_D				0.119***
				[0.015]
BRAND_MVE×SIZE_D				**−0.092* **
				[0.053]

(*continued on next page*)

Table 10 (*continued*)

Variables	(1)	(2)	(3)	(4)
Constant	0.343**	0.340**	0.278	0.087
	[0.168]	[0.166]	[0.170]	[0.164]
Observations	20,280	18,305	20,280	20,280
Other controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.14	0.15	0.15	0.14

This table presents the cross-sectional analysis of the estimates from panel regressions explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on debt choice (*BANK_DEBT*). We examine the moderating role of information asymmetry (Panel A), corporate governance (Panel B), and financial conditions (Panel C) in explaining the relationship between brand capital and debt choice. Standard errors reported in the brackets are heteroskedasticity consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

Table 11
Additional analysis: Brand capital and other dimensions of debt.

Dep. Var. =	(1)	(2)	(3)	(4)	(5)	(6)
	Use of public debt		Secured and unsecured debt			
	Public debt	Public debt	Secured debt	Unsecured debt	Secured debt	Unsecured debt
BRAND/MVE	**0.024****		**−0.041*****	**0.045*****		
	[0.010]		**[0.010]**	**[0.010]**		
BRAND/SALE		**0.095*****			**−0.103*****	**0.111*****
		[0.035]			**[0.036]**	**[0.035]**
SIZE	0.041***	0.040***	−0.062***	0.066***	−0.060***	0.064***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
MTB	−0.004**	−0.006**	−0.004*	0.003	−0.002	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
LEV	0.094***	0.100***	−0.035**	0.037**	−0.044***	0.046***
	[0.015]	[0.016]	[0.016]	[0.016]	[0.017]	[0.017]
ROA	−0.282***	−0.258***	0.332***	−0.376***	0.297***	−0.337***
	[0.040]	[0.043]	[0.042]	[0.042]	[0.044]	[0.044]
TANG	−0.132***	−0.126***	0.145***	−0.140***	0.142***	−0.136***
	[0.035]	[0.035]	[0.037]	[0.036]	[0.037]	[0.036]
ALTMAN	−0.068***	−0.067***	0.008	−0.017	0.007	−0.016
	[0.013]	[0.013]	[0.013]	[0.012]	[0.013]	[0.012]
RATING	0.245***	0.247***	−0.130***	0.131***	−0.134***	0.135***
	[0.018]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
IND_CON	0.042	0.042	−0.002	0.084	0.004	0.078
	[0.112]	[0.112]	[0.117]	[0.115]	[0.117]	[0.115]
Constant	0.251	0.253	0.735***	−0.124	0.723***	−0.109
	[0.168]	[0.169]	[0.092]	[0.091]	[0.091]	[0.090]
Observations	20,280	20,199	20,280	20,280	20,199	20,199
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.22	0.22	0.22	0.23	0.22	0.23

This table presents the panel regression results explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on other dimensions of debt. Columns (1) and (2) report the regression results for the effect of brand capital on the use of public debt. Columns (3)–(6) report the results for the effect of brand capital on the use of secured and unsecured debt. Standard errors reported in the brackets are heteroskedasticity consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

significant ($p < 0.05$ or better), implying that brand-intensive firms rely more on the public debt market than do firms with less brand capital. This finding further supports our main results, suggesting that firms with high brand capital rely less (more) on private (public) debt.

4.2.2. Brand capital and debt security

We next examine whether brand capital is related to the use of secured and unsecured debt. Given the informational, monitoring, and risk-mitigating roles of brand capital, we expect firms with high brand capital to obtain and use more (less) unsecured (secured) loans. We scale both secured and unsecured loans by total debt and re-estimate Eq. (2) separately, using both secured and unsecured debt measures as dependent variables. The regression results in Columns (3) and (5) of Table 11 show that the coefficients of brand capital are negative and significant ($p < 0.01$) for secured loans. In contrast, the results in Columns (4) and (6) show that the coefficients of brand capital are positive and statistically significant ($p < 0.01$) for unsecured loans. Overall, we find that brand capital-intensive firms use less (more) secured (unsecured) debt.

4.2.3. Brand capital and different types of debt instruments

Our analyses show that firms with brand capital rely less (more) on bank debt (public debt). In this section, we explore whether these findings are driven by specific debt instruments. We decompose bank debt into term loans and revolving credit. Whereas term loans are generally employed to finance long-term investments, revolving credits are employed for short-term liquidity management. The results reported in Column (1) of Table 12 show that *BRAND/MVE* has a negative effect on term loans ($p < 0.01$). This implies that the negative link between brand capital and bank loans is mainly determined by the term loans component.

To further explore whether the positive link between brand capital and public debt is explained by any specific debt instruments, we decompose public debt into commercial paper, senior bonds and notes, and subordinated bonds and notes. The results in Columns (3)–(4) illustrate that *BRAND/MVE* has positive and significant ($p < 0.01$) effects on commercial paper and senior bonds and notes.

Table 12
Additional analysis: Brand capital and different types of debt instruments.

Dep. Var. =	(1)	(2)	(3)	(4)	(5)
	Bank debt types		Public debt types		
	Term loan	Revolving credit	Commercial paper	Senior bonds and notes	Subordinated bonds and notes
BRAND/MVE	**−0.034******	**0.002**	**0.001******	**0.028******	**−0.006**
	[0.008]	**[0.008]**	**[0.000]**	**[0.010]**	**[0.004]**
SIZE	−0.020***	−0.012***	0.002***	0.037***	−0.000
	[0.003]	[0.002]	[0.000]	[0.003]	[0.002]
MTB	−0.000	−0.008***	−0.000***	−0.001	−0.003***
	[0.002]	[0.001]	[0.000]	[0.002]	[0.001]
LEV	0.017	−0.006	0.001***	0.063***	0.030***
	[0.013]	[0.008]	[0.000]	[0.015]	[0.006]
ROA	0.207***	0.076***	−0.006***	−0.326***	0.049***
	[0.033]	[0.024]	[0.002]	[0.040]	[0.014]
TANG	0.136***	−0.062**	−0.000	−0.074**	−0.056***
	[0.035]	[0.026]	[0.002]	[0.035]	[0.014]
ALTMAN	−0.024**	0.080***	0.000	−0.039***	−0.030***
	[0.012]	[0.010]	[0.000]	[0.012]	[0.006]
RATING	−0.012	−0.156***	0.005***	0.195***	0.044***
	[0.014]	[0.012]	[0.001]	[0.019]	[0.009]
IND_CON	−0.146*	0.236**	0.004	0.086	−0.046
	[0.085]	[0.110]	[0.009]	[0.121]	[0.045]
Constant	0.136**	0.168	−0.009*	0.144	0.111***
	[0.069]	[0.129]	[0.005]	[0.174]	[0.039]
Observations	20,280	20,280	20,280	20,280	20,280
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.07	0.12	0.14	0.18	0.06

This table presents the panel regression results explaining the effect of brand capital (*BRAND/MVE* and *BRAND/SALE*) on different types of debt instruments. Columns (1) and (2) examine how brand capital affects different types of bank debt instruments. Columns (3)–(6) examine how brand capital affects different types of public debt instruments. Standard errors reported in the brackets are heteroskedasticity consistent and clustered at the firm level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. Appendix A defines the variables.

5. Conclusion

Using a large sample of publicly listed U.S. firms over the 2001–2019 period, we examine how brand capital affects firms' debt choice, whether through bank borrowing or public debt issuance. Grounded in theoretical frameworks of information asymmetry, governance mechanisms, and financial conditions, we anticipate an inverse relationship between brand capital and reliance on bank debt. Our empirical findings align with these expectations, revealing that firms with higher levels of brand capital demonstrate a reduced reliance on bank debt compared with their counterparts with lower brand capital. Our results remain robust to a wide array of robustness tests. To mitigate potential endogeneity concerns, we implement a comprehensive set of tests, including the impact threshold for confounding variable specifications, Oster (2019) bound estimates, a heteroskedasticity-based instrumental variable approach, a two-step GMM method, an entropy balancing method regression, PSM, and a DiD regression approach. Notably, the impact of brand capital on firms' debt choice emerges unscathed through all these tests.

Further insights emerge from our cross-sectional analyses, revealing that the negative association between brand capital and bank debt is more pronounced in firms characterized by high information asymmetry, weak corporate governance mechanisms, and poor financial conditions. Additional analyses shed light on the preference of brand capital-intensive firms for public debt, coupled with a nuanced use of secured and unsecured debt.

The findings from our study carry significant policy and practical implications for various stakeholders, including policymakers, regulators, financial intermediaries, and corporate decision-makers. The refined implications are fourfold. First, regulatory bodies overseeing financial reporting standards could consider incorporating guidelines emphasising the relevance of brand capital. Encouraging transparent reporting on brand values and their influence on financial performance may contribute to a more informed assessment of firms, especially in the context of public debt markets. Second, recognising the role of brand capital in reducing informational disadvantages, policymakers might explore measures to facilitate easier access to public debt markets. Policies fostering transparency and fair practices could enhance the appeal of public debt financing for brand capital-intensive firms.

Third, financial institutions and credit rating agencies may need to update their risk assessment models to incorporate the role of brand capital. If brand capital reduces default risk and improves credit ratings, financial institutions should consider these factors in their lending decisions, potentially leading to more favourable terms for firms with strong brand capital. Fourth, corporate decision-makers should integrate an understanding of brand capital into their financing decisions. Understanding that strong brand capital can enhance access to public debt markets and reduce dependence on bank debt allows for more informed and strategic financial planning. Importantly, firms with high brand capital should strategically leverage this asset during negotiations with lenders. The enhanced access to public debt markets may position these firms more favourably, potentially resulting in more advantageous terms in debt agreements, such as lower interest rates or more flexible repayment schedules.

We acknowledge the potential limitations of our study and offer possible extensions based on our findings. For example, our study employs an advertising expenditures-based measure to proxy for brand capital, a measure that might not fully capture the diverse spectrum of brand-building activities. It is possible that different industries employ diverse strategies for enhancing brand capital, which goes beyond traditional advertising. Therefore, future research may employ alternative measures such as the customer perception perspective, to further investigate the research question. Moreover, we acknowledge the limitations of our DiD test, recognising that using the stock of advertising expenses as a proxy for exogenous shocks may pose methodological challenges. Furthermore, our study primarily focuses on U.S. public firms, potentially limiting the generalisability of findings. Future studies may use cross-country analyses to examine whether different institutional settings, market conditions, and disclosure requirements across regions and sectors affect how brand capital influences debt choice in various contexts. Finally, future research may also explore whether a reduction in the cost of financing public debt for companies with higher brand capital corresponds to a similar reduction in the cost of funding for banks.

Data availability

No

Appendix A

Variable	Definitions and measurements
Dependent variable	
BANK_DEBT	Total bank debt over total debt. See Section 2.2.1 for details.
Variables of interest	
BRAND/MVE	Total brand capital over the firm's market capitalization (PRCC_F × CSHO). See Section 2.2.2 for details.
BRAND/SALE	Total brand capital over total sales (SALE). See Section 2.2.2 for details.
Control variables	
SIZE	The natural logarithm of market capitalization (PRCC_F × CSHO).
MTB	The ratio of the market value of assets ((PRCC_F × CSHO) + (DLTT + DLC)) to the book value of assets (AT).
LEV	The ratio of the sum of short-term and long-term debt (DLC + DLTT) to total assets (AT).
ROA	Return of assets, measured as the pre-tax income before extraordinary items (PI – XI) over average assets (AT).
TANG	Asset tangibility, measured as net property, plant, and equipment (PPENT) scaled by total assets (AT).
ALTMAN	Altman (1968)'s *Z*-score, measured as 1.2 × (WCAP/AT) + 1.4 × (RE/AT) + 3.3 × (EBIT/AT) + 0.6 × (PRCC_F × CSHO)/ LT) + 0.999 × (SALE/TA), where WCAP = working capital, RE = retained earnings, EBIT = earnings before interest and taxes, AT = total assets, PRCC_F × CSHO = market value of equity, LT = total liabilities, SALE = sales.
RATING	An indicator variable that equals 1 for firms with a long-term debt rating (S&P), and 0 otherwise.
IND_CON	Industry concentration, as proxied by the Herfindahl–Hirschman Index.
Variables used in additional analyses	
BRAND/TA	Total brand capital over book value of total assets (AT).
BRAND_LG	Natural logarithm of 1 plus brand capital.
BRAND_TE	Total brand capital scaled by total employees (EMP).
ADV/TA	Total advertisement expenses (XAD) over total assets (AT).
INTAN/TA	The ratio of total intangible assets (INTAN) to total assets (AT).
INST_HOLDING	The proportion of shares owned by institutional investors.
OPACITY	The absolute value of discretionary accruals, estimated using the modified Jones model (Dechow, Sloan, & Sweeney, 1995).
LOW_OPACITY	An indicator variable that takes a value of 1 if the absolute value of discretionary accruals is lower than the sample median, and 0 otherwise.
CASH	Cash and equivalents (CHE) over total assets (AT).
ANALYST	Analysts following, measured as the natural logarithm of the number of analysts that follow a firm in each year.
AUDIT_SPECIALIZATION	A dummy variable that takes a value of 1 if a firm's financial statements are audited by an auditor with a market share of >30% (with respect to audit fee revenue) in the client's industry (two-digit SIC code) in a year, and 0 otherwise.
BLOCK_HOLDING	This variable takes a value of 1 if the natural logarithm of the average total ownership by institutional block holders is greater than the sample median, and 0 otherwise.
CG_SCORE	The net corporate governance score obtained from the MSCI. We use a dummy variable that takes a value of 1 if the score is higher than the sample median, and 0 otherwise.
CEO_OLD	This variable takes a value of 1 if the CEO's age is above the sample median, and 0 otherwise.
WW	Financial constraint measure. It is estimated based on Whited and Wu (2006).
DIV	A dummy variable that takes a value of 1 if a firm does not pay a dividend in a given year, and 0 otherwise.
SIZE_D	A dummy variable that takes a value of 1 if *SIZE is less than the sample median, and 0 otherwise.*
PUBLIC DEBT	The ratio of public debt to total debt.
SECURED DEBT	The ratio of secured debt to total debt.
UNSECURED DEBT	The ratio of unsecured debt to total debt.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2024.103160.

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