The value of corporate digital transformation: evidence from bond pricing

Kangqi Jiang
kangqijiang@126.com
Business School, Shantou University, Shantou 515063, China

Xin Xie
xiexin997722@163.com
School of Accounting, Guangzhou College of Commerce, Guangzhou, 511363, China

Yu Xiao
xiaoyu_9911@163.com
School of Economics, Jinan University, Guangzhou 510632, China

Badar Nadeem Ashraf
(Corresponding author)
Ashrafb4@lsbu.ac.uk
LSBU Business School, London South Bank University, London, UK

Acknowledgements: We thank the support provided by the STU Scientific Research Initiation Grant [Grant No. STF24004T] and the National Natural Science Foundation of China [Grant No. 72403150].

Abstract

This study explores the impact of corporate digital transformation on bond credit spreads. Analyzing bonds and medium-term notes issued by Chinese listed firms over the period 2008-2020 and measuring corporate digital transformation with textual analysis of the Management Discussion and Analysis part of annual reports, we find robust evidence that companies with higher digital transformation experience lower bond credit spreads. The main results hold through various robustness checks, including instrumental variables, propensity score matching, and placebo tests. We further observe that credit spread reduction is higher for firms that are smaller, non-state-owned, have lower credit ratings, and have less analyst coverage. As to the channels of influence, digital transformation reduces credit spreads by reducing the information asymmetry between firms and investors with enhanced information transformation mechanisms and lowering corporate default risk by strengthening operating efficiency. These findings contribute to understanding digital transformation's impact on a firm's creditworthiness and access to capital.

Keywords: Digital transformation; Credit spreads; Information asymmetry; Default risk

1. Introduction

The fourth industrial revolution is underway with the advent of technologies such as the Internet, mobile technologies, cloud computing, robotics, big data and advanced analytics, and artificial intelligence and machine learning. Beyond changing consumer behavior, these technologies are becoming an important driver of global economic growth (Parviainen et al., 2022). Together with emerging digital technology enterprises, this growth is mainly fueled by "industrial digitalization," where traditional industries adopt digital technologies to improve business processes and efficiency (Chen & Jiang, 2024). This transformation, manifested as enterprise digital transformation, involves optimizing production processes, business models, and organizational structures through technology (Gurbaxani & Dunkle, 2019; Verhoef et al., 2021; Jiang et al., 2022). The outbreak of the COVID-19 pandemic has further accelerated the Corporate digital transformation presents business opportunities and challenges (Chen & Jiang, 2024). Opportunities may include higher efficiency, enhanced innovation, expanded market reach, data-driven decision-making, and enterprise agility. Challenges may arise from capital investment expenditure, change management, integration difficulties, and cybersecurity risks. Recent literature explores the impact of digital transformation on various aspects of enterprise performance, including productivity (Babina et al., 2024; Brynjolfsson et al., 2019; Du & Jiang, 2022; Ding et al., 2024), cost behavior (Li et al., 2024; Du et al., 2024), and innovation capability (Mikalef et al., 2019; Wen et al., 2022; Niu et al., 2023; Gaglio et al., 2023; Wu & Li, 2024). Investors also value digitalization, which can affect firms' systematic risk and cost of equity capital (Jiang et al., 2024; Zhang et al., 2022). This paper extends this research by investigating whether corporate digital transformation affects bond credit spreads.

The evidence from the bond market is important for at least two reasons: First, the development of the bond market and the diversification of bond varieties have made debt financing an important source of capital for companies. Companies can issue bonds to adjust to their optimal capital structure, taking debt's tax benefits (Lu et al., 2010; Ghouma et al., 2018). Second, bonds are considered safer investments than stocks and often attract sophisticated institutional long-term investors (Jaskowski & Rettl, 2023). These investors often have access to superior tools to assess whether corporate risks have been incorporated appropriately into bond prices.

The data for this study comes from Chinese A-share listed companies. This choice is motivated by several factors. First, China boasts the world's largest digital market, with leading data resources and a rapidly growing digital economy valued at $7.1 trillion in 2021, second only to the US (CAICT, 2021). Furthermore, the Chinese government actively promotes digital transformation through various policies, creating an exogenous factor that strengthens our research design. Second, despite its rapid growth, China's bond market (the world's second largest) has experienced a high frequency of defaults in recent years (Lyu et al., 2022). This can be attributed to the market's relative youth, imperfect regulations, and unstandardized credit rating mechanisms (Livingston et al., 2018). Studying the bond market in this context allows us to explore how digitalization can impact a developing market. The Chinese case offers valuable insights that can be applied to similar developing economies seeking growth through digital transformation.

We utilize yields of bonds issued by Chinese A-share companies over the period 2008-2020 alongside Treasury bond yields to construct bond credit spread indicators. Textual analysis of the Management Discussion and Analysis part of annual reports is conducted to measure the extent of enterprise digital transformation. Our baseline results demonstrate a negative correlation between digitalization and bond credit spreads, suggesting that faster digital transformation leads to tighter credit spreads. We conducted various robustness tests to ensure the reliability of our findings, including changing fixed effects, clustering levels, variable definitions, and sample periods (excluding pre-2011 data to avoid financial crisis effects). Additionally, we employed instrumental variables (IV), difference-in-difference (DID), propensity score matching (PSM), and placebo tests to address potential endogeneity issues. Notably, the positive impact of digital transformation on credit spreads is amplified for non-state-owned enterprises (SOEs), smaller firms, lower credit ratings, and companies with higher information asymmetry. Finally, we explore the mechanisms through which digital transformation affects bond credit spreads, finding that it reduces information asymmetry and the probability of corporate default, ultimately leading to tighter credit spreads.

We offer three key contributions: Firstly, we examine the impact of digital transformation on bond pricing. Understanding how digitalization lowers debt financing costs through tighter credit spreads can incentivize companies to accelerate their digital transformation journeys. Secondly, we construct proxy variables for digital transformation using text analysis and machine learning, offering a methodology applicable to most listed firms. Thirdly, we shed light on the mechanisms by which digital transformation affects credit spreads, revealing it reduces information asymmetry and corporate default risk.

The following next discusses the existing literature on the economic effects of digital transformation and factors influencing bond credit spreads. We then establish a theoretical framework outlining the expected relationship between digitalization and bond credit spreads. Subsequently, the paper details our research methodology, data sources, and empirical results. Section 5 explores the mechanisms through which digital transformation impacts credit spreads, followed by concluding remarks and observations in Section 6.

2. Literature review and theoretical considerations

2.1. Enterprise digital transformation

Enterprise digital transformation is defined as the innovative use of digital technologies and devices to empower production processes or business models, enabling firms to adapt to the changing digital environment and consumer behavior (Gurbaxani & Dunkle, 2019; Verhoef et al., 2021; Jiang et al., 2022).

Given the global trend of digitalization, understanding the impact of enterprise digital transformation on economic efficiency is crucial. The recent literature has discussed the economic consequences of enterprises digital transformation mainly from the perspective of firm performance (Zeng et al., 2022; Zhai et al., 2022; Chen & Srinivasan, 2024; Malodia et al., 2023), productivity (Babina et al., 2024; Gaglio et al., 2023; Brynjolfsson et al., 2019; Du & Jiang, 2022; Ding et al., 2024), green governance (Bendig et al., 2023; Zhou et al., 2023; Zheng et al., 2024; Shao et al., 2024; Ding et al., 2024), cost behaviors (Li et al., 2024; Du et al., 2024), corporate compliance (Chen et al., 2024; Cheng et al., 2024), innovation capability (Mikalef et al., 2019; Wen et al., 2022; Niu et al., 2023; Gaglio et al., 2023; Wu & Li, 2024) and other factors (Fedyk et al., 2022; Jiang et al., 2022; Jiang et al., 2024; Chen & Jiang, 2024;

Zhang et al., 2024).

Regarding value creation, the existing literature generally suggests that digital transformation has a catalytic effect. For example, Chen & Srinivasan (2024) found that digitally transformed companies exhibit an 8%-24% higher Tobin's Q than their peers. Additionally, digital transformation can positively impact ROA and capital turnover. Mikalef et al. (2020) found that big data analytics capabilities can help companies gain a competitive advantage by improving their dynamic capabilities and operational capacity. Studies on SMEs also indicate that digital transformation can facilitate the creation of new distribution channels and innovative business models (Matarazzo et al., 2021).

Regarding productivity, the existing literature presents two main perspectives. One view suggests that digital transformation may not effectively drive productivity growth, as evidenced by studies like Babina et al. (2024). However, another view is positive, with empirical analyses by Brynjolfsson et al. (2019) and Du & Jiang (2022) demonstrating that firms can significantly improve productivity levels through digital transformation. In terms of innovation, most literature agrees that digital transformation can enhance firms' innovation performance (Blichfeldt & Faullant, 2021; Tan et al., 2022).

More relevant to this paper are the studies that explore the capital market reaction to corporate digital transformation, firm stock price crash risk (Jiang et al., 2022; Wu et al., 2022) and the cost of equity financing (Zhang et al., 2024). These studies suggest that digital transformation can mitigate information asymmetry and agency problems, leading to favorable capital market outcomes.

2.2. Bond Credit Spreads

Bond credit spreads represent the additional compensation demanded by bond investors to offset the perceived default risk of the issuer. From the firm's perspective, these spreads represent the cost of debt financing (Borisova et al., 2015). Generally, higher default risk is associated with higher credit spreads.

The determinants of bond credit spreads encompass three main aspects: the firm's external macroeconomic environment, the firm's own characteristics, and the degree of information asymmetry between the firm and investors.

Macroeconomic factors, such as financial crises, monetary policy shocks, and economic policy uncertainty, can significantly influence credit spreads (Ashraf & Shen, 2019; Caldara & Herbst, 2019; Kaviani et al., 2020; Cesa-Bianchi & Sokol, 2022). In general, favorable macroeconomic conditions are associated with lower credit spreads.

High-quality enterprises with strong profitability, sustainability, and stable cash flows, are generally favored by creditors (Gryglewicz, 2011; Kim et al., 2015; Wei et al., 2022; Okimoto & Takaoka, 2024; Caramichael & Rapp, 2024). These characteristics can help firms obtain lower credit spreads and reduce bond financing costs.

2.3. Theoretical considerations

Digital transformation can potentially reduce bond credit spreads through two primary channels: by mitigating information asymmetry between investors and firms, and by reducing the default risk of firms. Figure 1 depicts these two channels.

Regarding the first channel, information asymmetry between the external investors and the firm can lead to higher financing costs. Due to their limited access to internal information, external creditors remain unable to judge the true financial health of the firm and consequently demand a higher risk premium to finance the firm (Gao et al.,2020; Wang et al., 2021; Wei et al.,2022; Jaskowski & Rettl, 2023; Bartov et al., 2023). Studies by Lu et al. (2010) and Han & Zhou (2013) demonstrate that investors charge a significant risk premium for information uncertainty, even after controlling for other factors affecting credit spreads.

Digital transformation can minimize information asymmetry in several ways. First, digital technology facilitates more efficient information transmission and retrieval, reducing the cost of acquiring and analyzing data (Goldfarb & Tucker, 2019; Verhoef et al., 2021). Second, investors can more easily track a firm's financial performance and behavior using digital tools (Fedyk et al., 2022; Jiang et al., 2024). Finally, digital transformation can enhance the quality of corporate disclosure, providing investors with more accurate and timely information (Loebbecke & Picot, 2015; Babina et al., 2024). Companies can generate detailed reports that provide investors with a real-time view of their operations (Chen & Jiang, 2024). This can help deter opportunistic behaviors, reduce agency risk, and improve the reliability of financial reports (Bloom et al., 2014; Vial, 2019; Cheng et al., 2024; Chen et al., 2024). For example, Jiang et al. (2022) found that digital transformation can improve analyst coverage and disclosure quality in a sample of Chinese listed companies.

Smaller firms often experience higher information asymmetry due to limited resources and less analyst attention. Digital transformation, however, can be more accessible to smaller and mid-sized enterprises than larger organizations. By enabling greater flexibility, agility, and competitiveness, digital transformation can be particularly beneficial for smaller firms. Consequently, we expect smaller firms to experience a more significant reduction in bond credit spreads as a result of digital transformation.

For the second channel, digital transformation can improve a firm's profitability and financial position, thereby reducing the likelihood of default. By enhancing efficiency, innovation, and market competitiveness, digital transformation can increase a firm's revenue and reduce costs (Chen & Srinivasan, 2024). This improved financial performance can strengthen a firm's solvency and reduce the risk of default (Chen & Jiang, 2024; Babina et al., 2024).

Based on this discussion, we propose the following research hypotheses:

H1: Corporate digital transformation reduces bond credit spreads.

H2: Corporate digital transformation reduces bond credit spreads by alleviating information asymmetry.

H3: Corporate digital transformation reduces bond credit spreads by mitigating default risk.

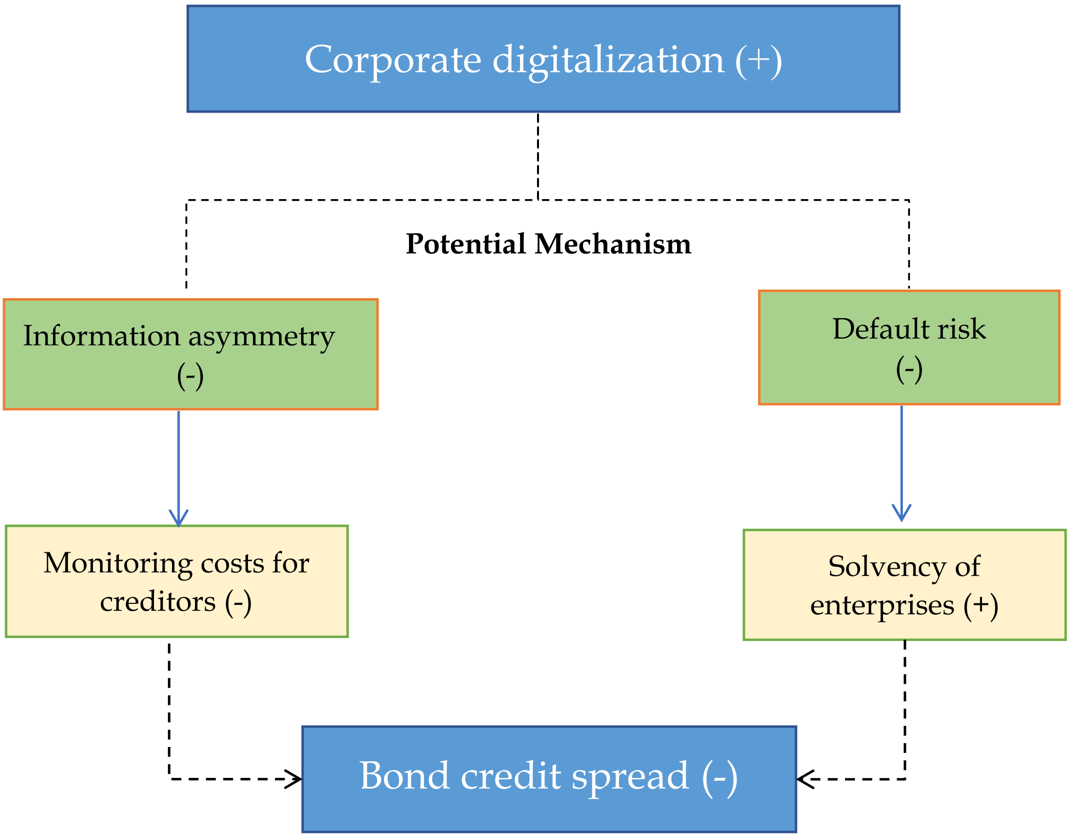

Figure 1. Logical framework (Source: Authors' own work)

3. Data and model setting

3.1. Data sources

This paper selects enterprise bonds, corporate bonds, and medium-term notes issued by Chinese listed companies in the bond market from 2008 to 2020 as the research object of this paper. Regarding the sources of data, we obtained data on company characteristics from the CSMAR database and Wind database and annual reports of listed companies used to construct corporate digital transformation indicators from the Shanghai Stock Exchange and Shenzhen Stock Exchange. To ensure the consistency and reliability of the research results, after getting the raw data, we excluded the financial industry enterprises with significantly different asset structures from other enterprises, excluded PT, ST, or *ST enterprises with abnormal financial conditions, and excluded the floating rate bond samples for which credit spreads could not be calculated. In addition, in order to mitigate the bias caused by extreme values on the research results, all continuous variables in this paper are winsorized at the upper and lower 1% levels. After the processing, we end up with a sample of 7250 bonds from 638 firms.

3.2. Model Setup

We set up the following model to examine the effect of corporate digital transformation on bank spreads.

$$CS_{ijt} = \beta_0 + \beta_1 Digital_{ijt} + \varphi CV + firm\,fixed + year\,fixed + \varepsilon_{ijt} \quad (1)$$

where CS is the credit spread of a bond i issued by firm j in year t. $Digital$ is a proxy variable indicating the degree of digital transformation of a firm j year t constructed using text analysis. CV are control variables that may affect the bond credit spreads, including firm-level and bond-level characteristics. We include firm-fixed effects and year-fixed effects to control for firm-level factors that do not vary over time and time effects common to all bonds. Finally, ε denotes the error term, and we cluster the standard errors to the firm level. We focus on the direction and significance of the β_1 coefficient. If β_1 is significantly negative, it confirms the theoretical hypothesis that firms' digital transformation can reduce bond credit spreads.

3.3. Bond Credit Spreads

Bond credit spreads refer to the risk premium over the risk-free rate. Following Lyu et al. (2022), we measured bond credit spread as the difference between the yield to maturity of corporate bonds and the yield to maturity of Treasury bonds of the same maturity. The data on Treasury yields are obtained from the China Bond Information Network. For corporate bonds with maturities not matching those of Treasury bonds, we used linear interpolation to estimate the corresponding Treasury bond yields.

For the robustness test, we also calculated the bond credit spreads in two alternative ways: the difference between the yield to maturity of corporate bonds and the one-year fixed deposit rate and the difference between the yield to maturity of corporate bonds and the five-year fixed deposit rate.

3.4. Enterprise digital transformation

Following Chen & Srinivasan (2024), we use textual analysis to construct digital transformation variable. We use keywords about digital transformation in firms' annual reports to measure the degree of digital transformation. However, distinct from the existing literature, this paper uses the deep learning RoBERTa-wwm-ext model to construct a digital keyword lexicon. We started by first obtaining and collating all listed companies' annual reports from 2007-2020 from the websites of Shanghai Stock Exchange and Shenzhen Stock Exchange, and then retained the management business discussion and analysis (MD&A) chapters in the annual reports. Subsequently, we establish the base phrases of enterprise digital transformation keywords by collecting and reading the digital transformation-related policy documents issued by the Chinese government in recent years.

Next, this article uses the deep learning RoBERTa-wwm-ext model to sort out keywords in MD&A that have the same meaning as the basic phrases and expand the digital keyword phrases to form a digital transformation lexicon. Common deep learning models primarily include the Word2vec model (Mikolov, 2013), BERT model (Devlin, 2018), and RoBERTa-wwm-ext model (Cui et al., 2019). The Word2vec model can only present static word vectors that are the same across different contexts, thus it struggles with addressing polysemy. In contrast, the BERT model utilizes a multi-layer attention mechanism to compute word vectors, allowing the same word to have different vectors in various contexts, successfully solving the issue of polysemy (Chen et al., 2023). However, the BERT model is a pre-training model designed for English text and cannot be directly applied to Chinese text. We selected the RoBERTa-wwm-ext model proposed by Cui et al. (2019) as the text pre-training model. This model is suitable for Chinese text and improves upon the BERT model in three aspects: pre-training tasks, training data, and training strategies. We retained extended word groups with a cosine similarity exceeding 0.8 with basic word groups and eliminated words that are irrelevant to the digital transformation of enterprises. Finally, we calculated the frequency of digital keywords in MD&A parts based on the extended digital lexicon. We took its natural logarithm to proxy the degree of digital transformation of enterprises in our analysis.

In the robustness test, to address the concern that although enterprises disclose digital keywords in their annual reports but do not carry out actual digital transformation, we use the ratio of the increase in digital intangible assets to intangible assets and the ratio of the increase in digital intangible assets to total assets as alternative proxies of digital transformation (Chen et al., 2023).

3.5. Control Variables

Control variables include firm-level and bond-level characteristics. Firm-level control variables include the number of employees ($Size$), leverage (Lev), return on net assets (ROA), duality (Dua), and the percentage of shares held by the largest shareholder (Shl) (Borisova et al., 2015; Lyu et al., 2022). Larger firms tend to have lower credit spreads due to reduced default risk, while higher leverage can increase financial risk and widen credit spreads. Higher ROA indicates stronger profitability and is associated with lower credit spreads. Duality and the largest shareholder's shareholding ratio reflect corporate governance quality (Bhagat & Bolton, 2019; Shu & Chiang, 2020), with better corporate governance reducing information opacity and credit spreads.

Bond-level control variables include bond issue size (BS), residual maturity (RM), credit rating (Credit), and whether the bond is guaranteed (Guarantee) (Lyu et al., 2022). Existing research suggests that bond liquidity, proxied by bond issuance size and remaining maturity, has a negative impact on credit spreads (Chen et al., 2007). Ederington et al. (1987) found that credit ratings explain cross-sectional differences in credit spreads, controlling for firm and issuance characteristics. Finally, we control whether the bond is guaranteed, as guarantees can mitigate information asymmetry and agency problems.

Table 1 provides descriptive statistics for all variables used in the benchmark regressions, and Table A1 presents variable definitions.

Table 1

Descriptive statistics

Variable	Observation	Mean	S.D.	Min	P25	P50	P75	Max
CS	7,250	2.18	2.12	-4.83	1.18	1.84	2.81	16.32
$Digital$	7,250	1.96	1.37	0	1.10	1.95	2.89	5.29
$Size$	7,250	9.21	1.54	5.58	8.23	9.06	10.13	13.07
Lev	7,250	0.60	0.15	0.20	0.50	0.62	0.72	0.88
ROA	7,250	0.07	0.08	-0.41	0.04	0.07	0.11	0.26
Dua	7,250	0.85	0.35	0	1	1	1	1
Shl	7,250	38.87	16.82	8.21	25.78	37.70	50.70	82.50

BS	7,250	2.31	0.89	0	1.61	2.30	3	4.70
RM	7,250	0.75	0.86	-2.34	0.36	0.93	1.36	2.25
$Credit$	7,250	3.08	0.90	1	2	3	4	4
$Guarantee$	7,250	0.27	0.44	0	0	0	1	1

Source: Authors' own work

4. Empirical findings

4.1. Baseline regression results

We estimated Equation (1) to examine the relationship between corporate digital transformation and bond credit spreads. Table 2 presents the regression results. In Column (1), we included only firm- and year-fixed effects. The coefficient for enterprise digital transformation (β_1) is -0.11, statistically significant at the 5% level, indicating a significant negative correlation between the two variables.

We added firm-level and bond-level control variables in Column (2). The results remained consistent, with the β_1 coefficient remaining significantly negative at -0.09. This suggests that a one-unit increase in corporate digital transformation is associated with a 0.09 reduction in corporate bond credit spreads, equivalent to 4% of the average bond credit spread over the sample period.

These findings provide empirical support for our theoretical hypothesis that digital transformation has a significant negative impact on bond credit spreads, confirming research hypothesis H1.

Table 2

Baseline regression

	(1) CS	(2) CS
$Digital$	-0.11**	-0.09**
	(-2.47)	(-2.27)
$Size$		-0.29
		(-1.65)
Lev		2.20***
		(3.17)
ROA		-0.62
		(-1.04)
Dua		-0.02

		(-0.12)
Shl		-0.02***
		(-3.04)
BS		0.01
		(0.17)
RM		-0.11**
		(-2.09)
$Credit$		-0.12
		(-1.02)
$Guarantee$		-0.14
		(-1.15)
$Constant$	2.39***	5.15***
	(28.38)	(3.26)
Observations	7,249	7,249
R^2	0.45	0.45
Firm FE	Y	Y
Year FE	Y	Y
Firm Cluster	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. (Source: Authors' own work)

4.2. Robustness tests

4.2.1. Changing fixed effects or clustering levels

To assess the robustness of our baseline regression results, we conducted several sensitivity analyses. First, we added bond fixed effects, city fixed effects, and industry fixed effects to the benchmark regression model to control for time-invariant factors that may influence bond credit spreads. As shown in Columns (1), (2), and (3) of Table 3, the coefficient for digital transformation (β_1) remained statistically significant at the 5% level, and the magnitude of the coefficients was consistent with the baseline regression. This suggests that time-invariant factors have a minimal impact on our findings.

Second, we addressed potential within-group correlation and heteroskedasticity issues in the error terms by adjusting the level of clustering standard errors in the baseline regression model. We clustered standard errors at the firm and year level (Column 4), industry level (Column 5), industry and year level (Column 6), and bond level (Column 7). In all cases, the statistical significance of the β_1 coefficient remained at the 5% level, indicating that these issues do not materially affect our conclusions.

Table 3

Change fixed effects or clustering levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CS	CS	CS	CS	CS	CS	CS
$Digital$	-0.11***	-0.09**	-0.09**	-0.09**	-0.09**	-0.09**	-0.09***
	(-2.84)	(-2.23)	(-2.25)	(-2.28)	(-2.29)	(-2.21)	(-2.67)
$Constant$	5.50***	5.16***	5.16***	5.15***	5.16***	5.16***	5.15***
	(4.68)	(3.23)	(3.25)	(3.28)	(3.17)	(3.21)	(4.56)
Observations	6,853	7,247	7,247	7,249	7,247	7,247	7,249
R^2	0.55	0.44	0.45	0.45	0.45	0.45	0.45
Controls	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Bond FE	Y	N	N	N	N	N	N
City FE	N	Y	N	N	N	N	N
Indu FE	N	N	Y	N	N	N	N
Firm Cluster	Y	Y	Y	Y	N	N	N
Year Cluster	N	N	N	Y	N	Y	N
Indu Cluster	N	N	N	N	Y	Y	N
Bond Cluster	N	N	N	N	N	N	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are the same as in the baseline regression, i.e., $Size, Lev, ROA, Dua, Shl, BS, RM, Credit$, and $Guarantee$. (Source: Authors' own work)

4.2.2. Changing the explanatory and explained variables

We conducted robustness tests using alternative measures to address the potential endogeneity concerns of measurement errors regarding our dependent and explanatory variables.

First, we replaced the raw word frequency of digital keywords with Digital_rank for the main explanatory variable of digital transformation. Digital_rank is a categorical variable that assigns a rank (3, 2, 1, or 0) based on the raw word frequency, providing a more nuanced measure of digital activity (Chen & Srinivasan, 2024; Chen et al., 2023). Further, we also replaced the explanatory variable with the ratio of the increase in digital intangible assets to intangible assets (Digital_asset) and the ratio of the increase in digital intangible assets to total assets (Digital_asset1). These measures provide more direct indicators of a firm's investment in digital transformation. As shown in Columns (1), (2), and (3) of Table 4, the negative impact of digital transformation on bond credit spreads remained significant after using these alternative measures.

Second, we employed alternative measures for the dependent variable: the difference between bond yields and one-year fixed deposit rates (CS1) and the difference between bond yields and five-year fixed deposit rates (CS5). Additionally, we replaced the dependent varible with the mean of corporate bond credit spreads (CS_mean) for each year and used firm-level means for bond-related control variables. As shown in Columns (4), (5), and (6) of Table 4, these changes did not materially affect our findings, and in some cases, the effect of digital transformation on credit spreads became even more significant.

4.2.3. Excluding the impact of the financial crisis

To mitigate the potential impact of macro shocks caused by the financial crisis, we excluded the years affected by this event. Given the lagged effects of the 2008 financial crisis, we removed observations prior to 2011. As shown in Column (7) of Table 4, the negative relationship between digital transformation and bond credit spreads remained significant after excluding these years, confirming the robustness of our findings.

Table 4

Changing explanatory variables, explanatory variables, and excluding special samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CS	CS	CS	$CS1$	$CS5$	CS_mean	CS
$Digital\_rank$	-0.07**						
	(-2.06)						
$Digital\_asset$		-0.01*					
		(-1.92)					
$Digital\_asset1$			-1.39*				
			(-1.71)				
$Digital$				-0.09**	-0.09**	-0.11**	-0.10**
				(-2.29)	(-2.26)	(-2.54)	(-2.39)
$Constant$	5.08***	4.39**	4.23**	6.24***	3.33**	6.67***	5.31***
	(3.23)	(2.15)	(2.10)	(3.94)	(2.06)	(4.63)	(3.12)
Observations	7,249	5,513	5,513	7,249	7,249	3,505	7,084
R^2	0.45	0.45	0.45	0.47	0.46	0.55	0.45
Controls	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y

Year FE	Y	Y	Y	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y	Y	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are the same as in the baseline regression, i.e., $Size, Lev, ROA, Dua, Shl, BS, RM, Credit$, and $Guarantee$. The controls in Column (6) do not contain bond-level control variables. (Source: Authors' own work)

4.3. Endogeneity test

To further mitigate the concerns of omitted variable bias and reverse causality, we conduct the following tests, including instrumental variable analysis, using National Big Data Comprehensive Pilot Zone policy as an exogenous shock to enterprise digital transformation, a matched sample of digital transformed and non-transformed firms, and placebo test.

4.3.1. Instrument variables

For an instrumental variable (IV) analysis, the IV must satisfy two conditions: correlation and exogeneity. Correlation means the IV must be correlated with the endogenous variable (digital transformation), while exogeneity means the IV must not be directly correlated with the dependent variable (bond credit spreads).

Following Du & Jiang, (2022), we selected the mean value of digital transformation of other firms in the same industry (mean_digital) as an IV for digital transformation. This IV is relevant due to the cohort effect, where firms' investment decisions are influenced by peers in the same industry. Moreover, competitive pressure can motivate firms to accelerate digital transformation in response to the rapid digitalization of other firms. The exogeneity condition is also satisfied as it is unlikely that the digital transformation level of other firms directly affects a specific firm's bond credit spreads.

Table 5 presents the IV estimation results. Column (1) shows the first-stage regression, confirming the significant positive correlation between a firm's digital transformation and the mean digital transformation of other firms in the same industry. The KPF and CDF values were 62.03 and 473.33, respectively, both greater than 16, indicating that the instrument is not weak. Column (2) shows the second-stage regression, where the coefficient for digital transformation (β_1) remained significantly negative at the 5% level. The absolute value of β_1 was larger than in the baseline regression, consistent with the IV method specification. These results suggest that our findings are robust to endogeneity concerns.

4.3.2. National Big Data Comprehensive Pilot Zone

To further address endogeneity concerns, we employed the National Big Data Comprehensive Pilot Zone policy as an exogenous shock to digital transformation. This policy aims to promote digital resource openness, develop digital industries, and provide integrated planning for digital infrastructure construction and financial support (Lyu et al., 2024; Shen & Wang, 2024). We hypothesized that this policy could promote digital transformation by improving regional digital infrastructure and reducing transformation costs and risks.

China launched the first Big Data Comprehensive Pilot Zone in Guizhou province in September 2015, followed by a second batch of pilot regions including Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing, and Guangdong in 2016. Based on the timing and locations of these pilot zones, we developed the following model.

$$CS_{ijt} = \alpha_{0+}\alpha_1 Bigdata_{jt} + \gamma CV + firm\ fixed + year\ fixed + \varepsilon_{ijt} \qquad (2)$$

where CS_{ijt} and control variables are defined in the same way as in model (1), $Bigdata_{jt}$ reflects the policy effect of the National Big Data Comprehensive Pilot Zone, which is equal to 1 if firm's region is included in the pilot in that year, and 0 otherwise.

Our primary coefficient of interest is α_1, which reflects the change in credit spreads for firms affected by the policy relative to unaffected firms. We controlled for firm- and year-fixed effects and clustered standard errors at the firm level. Column (3) of Table 5 presents the estimation results. A significantly negative α_1 indicates that credit spreads for policy-affected firms were significantly lower after the policy implementation compared to unaffected firms.

To validate our policy shock, we conducted a parallel trend test. Figure 2 shows the results, indicating no significant difference in credit spreads between the treatment and control groups in the years preceding the policy implementation. However, starting in the third year after the policy, the treatment group experienced a significant decrease in credit spreads compared to the control group, with the effect further amplifying in the fourth year. These findings suggest that the policy shock was valid and had a causal impact on credit spreads.

Table 5

Endogeneity test: IV method, DID method, PSM method

	(1)	(2)	(3)	(4)
	IV-first	IV-second	DID	PSM
	$Digital$	CS	CS	CS
$mean\_digital$	0.51***			
	(7.88)			
$Digital$		-0.36**		-0.14**
		(-2.34)		(-2.42)
$Bigdata$			-0.24*	
			(-1.80)	
$Constant$	1.00		4.97***	8.98***
	(1.17)		(3.21)	(3.71)
Observations	7,164	7,164	7,321	7,140
R^2			0.45	0.48
KPF	62.03			
CDF	473.33			
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm-fixed effects (Firm FE) and year-fixed effects (Year FE) in all columns. Controls denote control variables, which are the same as in the baseline regression, i.e., $Size, Lev, ROA, Dua, Shl, BS, RM, Credit$, and $Guarantee$. (Source: Authors' own work

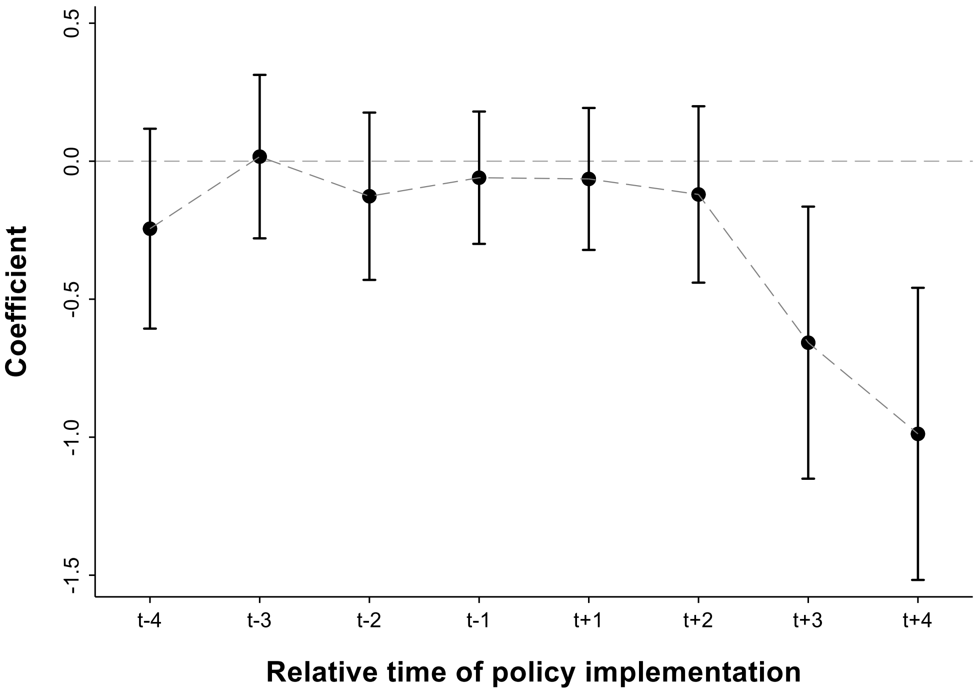

Figure 2. Parallel trend test

Note: Figure 2 depicts the dynamic treatment effects for the years before and after the National Big Data Comprehensive Pilot Zone policy took effect. The horizontal axis is the time relative to the year of policy implementation. The solid line indicates the 90% confidence interval. **(**Source: Authors' own work)

4.3.3. PSM

To address potential selection bias, we employed propensity score matching (PSM) to ensure that the treatment and control groups have similar characteristics. We defined firms with digital transformation levels above the 75th percentile as the treatment group. This threshold allowed for a larger control group, enabling more precise matching.

We used logit regression to estimate propensity scores, incorporating the same covariates as in the baseline regression. The kernel matching method was then used to select the most appropriate control groups for the treatment group. Appendix Table A2 presents the PSM balance test results, showing that the differences in covariates between the treatment and control groups were significantly reduced after matching, with all deviations within 5%. Post-matching t-tests also confirmed the absence of systematic differences between the two groups. Figure 3 visually illustrates the reduction in statistical differences in covariates before and after PSM.

We conducted a weighted regression using the matched sample. As shown in Column (4) of Table 5, the negative relationship between digital transformation and bond credit spreads remained significant, confirming our previous findings.

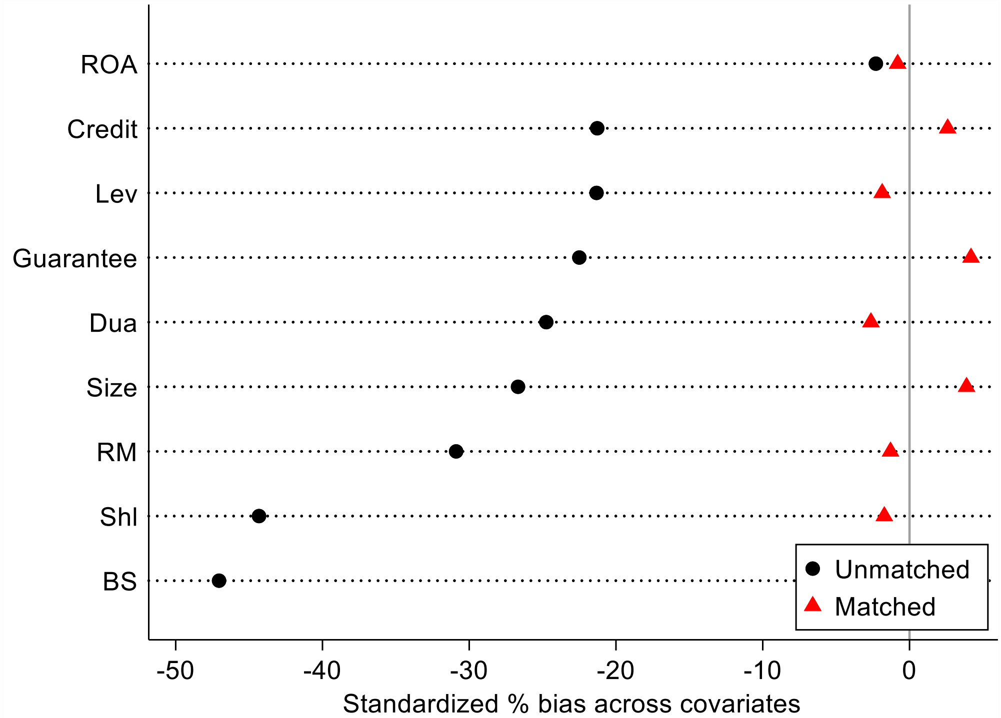

Figure 3. PSM for covariates (Source: Authors' own work)

4.3.4. Placebo test

To further address potential endogeneity concerns, we conducted a placebo test. We randomly assigned digital transformation values while keeping other factors constant and performed 1000 random matches. Figure 4 shows the probability density plots of the estimated coefficients and p-values for these 1000 regressions.

The results indicate that the probability density plot of the estimated coefficients after random assignment is approximately normally distributed with values close to 0. Additionally, the vast majority of the coefficients were insignificant. These findings suggest that our results are unlikely to be driven by unobservable factors.

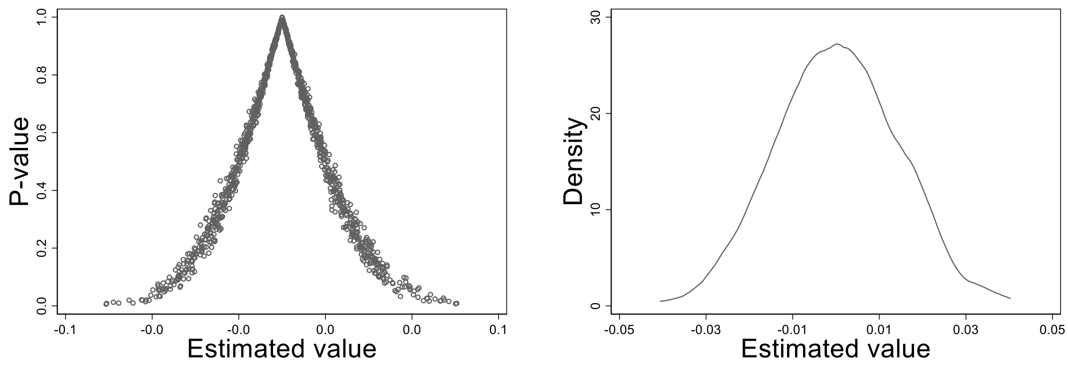

Figure 4. Placebo test

Note: Figure 4 depicts the probability density plots of the coefficients and p-values for 1000 regressions performed after random assignment of $Digital$. (Source: Authors' own work)

4. Cross-sectional analysis

To examine the heterogeneity of the impact of digital transformation on bond credit spreads, we analyzed firms with different characteristics.

First, we focused on state-owned enterprises (SOEs) and non-SOEs. Columns (1) and (2) of Table 6 present the regression results, indicating a positive but insignificant effect of digital transformation on credit spreads for SOEs. However, the effect was significantly negative for non-SOEs. Several factors may contribute to this heterogeneity. SOEs often receive more government, public, and media attention, and may have more stringent information disclosure systems. Conversely, non-SOEs may benefit more from digital transformation due to less developed disclosure systems and greater reliance on information channels. Additionally, SOEs may have more stable capital sources and market advantages, leading to lower default risk. Non-SOEs, facing more competitive pressure and uncertainty, may benefit more from the default risk mitigation channels provided by digital transformation.

Second, we analyzed the impact of firm size. Larger firms may receive more public attention, while smaller firms may have higher information-gathering costs. Thus, digital transformation can be particularly beneficial for smaller firms in reducing information costs. Moreover, smaller firms may achieve better growth through digital transformation than larger ones. Columns (3) and (4) of Table 6 show that digital transformation significantly reduces bond credit spreads for smaller firms but not for larger firms. These findings suggest that the impact of digital transformation on credit spreads is more pronounced for smaller firms.

Table 6

Cross-sectional analysis: ownership and size

	(1)	(2)	(3)	(4)
	SOEs	non-SOEs	Small	Big
	CS	CS	CS	CS
$Digital$	0.01	-0.19**	-0.14**	-0.04
	(0.22)	(-2.48)	(-2.39)	(-0.58)
$Constant$	3.88*	9.94***	8.84***	0.52
	(1.81)	(4.09)	(3.84)	(0.25)
Observations	4,612	2,635	3,637	3,587
R^2	0.40	0.44	0.47	0.39
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are the same as in the baseline regression, i.e., $Size, Lev, ROA, Dua, Shl, BS, RM, Credit$, and $Guarantee$;SOEs denote state-owned enterprises, non-SOEs denote non-SOEs, Small denotes enterprises with total assets below the median, and Big denotes enterprises with total assets above the median. **(**Source: Authors' own work)

Third, we analyzed the impact of digital transformation on firms with different credit ratings and levels of analyst attention.

Credit ratings signal the likelihood of a firm repaying its debt, influencing investor demand for bonds. Firms with lower credit ratings are associated with higher risk premiums. We hypothesized that the information effect of digital transformation would be more significant for these firms. Columns (1) and (2) of Table 7 confirm this expectation, showing a more pronounced impact of digital transformation on credit spreads for firms with lower credit ratings.

Analyst attention can also impact information opacity. Firms with less analyst attention may have higher information opacity, making the information effect of digital transformation more pronounced. As shown in Columns (3) and (4) of Table 7, digital transformation has a more significant impact on reducing credit spreads for firms with low analyst attention.

Table 7

Cross-sectional analysis: information asymmetry

	(1)	(2)	(3)	(4)
	High rating	Low rating	More Analysts	Less Analysts
	CS	CS	CS	CS
$Digital$	-0.05	-0.14**	0.02	-0.12*
	(-1.25)	(-2.04)	(0.34)	(-1.87)
$Constant$	3.64*	7.78***	2.96*	6.91***
	(1.87)	(3.02)	(1.91)	(2.85)
Observations	4,860	2,373	3,427	3,727
R^2	0.45	0.46	0.45	0.46
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively. The t-statistics for firm-level clustering are in parentheses. We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are the same as in the baseline regression, i.e., $Size, Lev, ROA, Dua, Shl, BS, RM, Credit$, and $Guarantee$; High rating means the bond credit rating is above the median; Low rating means bond credit rating is below the median, More Analysts means corporate analyst attention is above the median; Less Analysts means corporate analyst attention is below the median. (Source: Authors' own work)

5. Influence channels

This section explores the two potential channels, information asymmetry and default risk, through which digital transformation can influence bond credit spreads.

5.1. Information asymmetry channel

Information asymmetry plays a crucial role in determining bond credit spreads. In the bond market, companies possess superior knowledge of their own operating conditions and cash flows compared to investors. This asymmetry can lead to higher investment risks for investors, as they may face difficulties in obtaining accurate information about the firm's financial status. To compensate for these information risks, investors often demand a higher risk premium, resulting in wider bond credit spreads.

Digital transformation can mitigate information asymmetry by reducing the cost of information storage and transmission. By leveraging digital technology, companies can more easily access and analyze their internal operating conditions, improving the accuracy and transparency of their financial reporting. This reduction in information asymmetry can lead to lower credit spreads, as investors face reduced uncertainty about the firm's financial health.

Following Ren et al. (2023), we use analyst attention (Analyse) and report attention (Report) as proxies for information asymmetry. Higher analyst and report attention indicate lower information opacity. We replaced the explanatory variables in model (1) with Analyse and Report. Due to the change in explanatory variables, our control variables differ from the baseline regression, and we excluded bond-level variables. To examine the impact of digital transformation on information asymmetry and default risk in the full sample, we expanded the sample to include all listed firms in China from 2007 to 2020. The control variables used in the mechanism test are detailed in Appendix Table A1.

Columns (1) and (2) of Table 8 present the regression results for the information channel. Digital transformation has significantly increased the attention of analysts and research reports for listed companies, indicating a reduction in information opacity. These findings support research hypothesis H2.

Table 8

Information channels

	(1)	(2)
	Analyst	*Report*
Digital	0.06***	0.07***
	(4.59)	(4.58)
Constant	1.08***	1.40***
	(2.98)	(3.14)
Observations	12,053	12,053
R^2	0.66	0.66
Controls	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
Firm Cluster	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively; The t-statistics for firm-level clustering are in parentheses; We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are different from the baseline regression because the dependent variables are different, i.e., $Size, Lev, Tang, Growth, Dividend, Shl, SOE, TAT$. variables are defined in detail in Appendix Table A1. **(**Source: Authors' own work)

5.2. Default risk channel

Credit risk models suggest that a firm's financial distress is closely linked to its operating conditions. Firms with strong operating conditions tend to have more stable cash flows and solvency, reducing the probability of default. Consequently, these firms can often obtain lower credit spreads due to the reduced risk premium demanded by investors.

Existing literature generally highlights the positive economic consequences of digital transformation, such as increased value creation through optimized production processes and business models. Moreover, digital transformation can help firms adapt to changing consumer behavior and gain a competitive advantage in the marketplace. These improvements in productivity, value creation, and competitive performance can enhance a firm's profitability and reduce the likelihood of default.

In this paper, we use $Zscore$ to proxy for a firm's financial distress. There are three common forms of $Zscore$ models in the existing literature as follows (Meles et al.,2021), and the larger the value of $Zscore$, the smaller the probability of default of the firm. Also, this paper uses the $Oscore$ model to portray the default risk of a firm (Ohlson, 1980), and the larger the value of the $Oscore$, the less risky the firm is. The variables used in Equation (3)-Equation (6) are defined in Appendix Table A1. In this paper, we will replace the explanatory variables with $Zscore1, Zscore2, Zscore3$ and $Oscore$ to validate our default risk channel. We use the full sample from 2007-2020 as above, and our control variables are changed since the explanatory variables are unrelated to bonds. The regression results in Table 9 show that the effects of digital transformation on $Zscore$ are all significantly positive at the 1% statistical level, while the effects on $Oscore$ are significantly positive at the 5% statistical level, suggesting that the digital transformation of firms significantly improves financial conditions and plays a key role in reducing credit spreads. Based on the aforementioned empirical results, we can infer that research hypothesis ***H3*** holds.

$$Zscore1 = 0.999 \times V_1 + 0.6 \times V_2 + 3.3 \times V_3 + 1.4 \times V_4 + 1.2 \times V_5 \tag{3}$$
$$Zscore2 = 0.998 \times V_1 + 0.42 \times V_2 + 3.107 \times V_3 + 0.847 \times V_4 + 0.717 \times V_5 \tag{4}$$
$$Zscore3 = 3.25 + 1.05 \times V_2 + 6.72 \times V_3 + 3.26 \times V_4 + 6.56 \times V_5 \tag{5}$$
$$\begin{aligned} Oscore = {} & -1.32 - 0.407 \times Asset + 6.03 \times Lev - 1.43 \times V_5 + 0.0757 \times V_6 - 2.37 \times ROA \\ & - 1.83 \times V_7 + 0.285 \times V_8 - 1.72 \times V_9 - 0.521 \times V_{10} \end{aligned} \tag{6}$$

Table 9

Default risk channels

	(1)	(2)	(3)	(4)
	Zscore1	*Zscore2*	*Zscore3*	*Oscore*

Digital	0.09***	0.06***	0.16***	-0.02**
	(2.59)	(2.96)	(3.10)	(-2.42)
Constant	7.01***	4.73***	16.09***	-11.81***
	(7.01)	(7.96)	(10.44)	(-41.23)
Observations	12,053	12,053	12,053	12,053
R^2	0.73	0.76	0.79	0.89
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Cluster	Y	Y	Y	Y

Note: ***, **, and * are significant levels of 1%, 5%, and 10%, respectively; The t-statistics for firm-level clustering are in parentheses; We include firm fixed effects (Firm FE) and year fixed effects (Year FE) in all columns. Controls denote control variables, which are different from the baseline regression because the dependent variables are different, i.e., $Size, Lev, Tang, Growth, Dividend, Shl, SOE, TAT$. variables are defined in detail in Appendix Table A1. **(**Source: Authors' own work)

6. Conclusion

As the digital revolution sweeps across the globe, companies are increasingly embracing digital transformation. This paper explores the advantages of digital transformation in the capital market, specifically focusing on its impact on bond credit spreads. We leverage advanced machine learning and text analysis techniques to construct robust proxies for corporate digital transformation from the Management Discussion and Analysis parts of annual reports. Our findings reveal a significant negative association between digital transformation and bond credit spreads, even after controlling for other relevant factors influencing credit spreads.

To ensure the robustness of our results, we conducted a series of tests. These include incorporating different fixed effect structures, varying the clustering levels for standard errors, employing alternative measures for both independent and dependent variables, and excluding data from potentially confounding years. Additionally, we addressed potential endogeneity concerns by utilizing instrumental variables (IV) methods, exploiting the National Big Data Comprehensive Pilot Zone as an exogenous shock, applying propensity score matching (PSM), and conducting placebo tests. Notably, none of these tests altered our core conclusion: digital transformation leads to tighter credit spreads.

Furthermore, our research demonstrates that the impact of digitalization on credit spreads varies across firms with different characteristics. The positive effect is strengthened for non-state-owned enterprises (SOEs), smaller firms, companies with lower analyst attention, and those with lower credit ratings. These findings suggest that digital transformation can be a particularly powerful tool for firms that may traditionally face challenges in the bond market.

We further explore the channels through which digital transformation reduces bond credit spreads. Our analysis highlights two key aspects: information transparency and default risk. Digital technologies lower the cost of information access and improve the quality of information disclosure for investors. Additionally, digital transformation improves business processes, ultimately reducing the risk of default.

Our findings have important implications for both enterprises and governments: Digital transformation, in addition to improvements in productivity and innovation performance, benefits firms in reducing financing costs, especially bond interest rates. This implies firms can reap broader benefits from developing a robust digitalization strategy and better addressing the challenges and uncertainties associated with digital transformation. Governments can play a supporting role by creating a conducive digital environment, facilitating the development of digital infrastructure, ensuring accessibility of digital resources, investing in digital talent training, and providing targeted financial incentives. Such measures can help alleviate the associated costs and risks, and a heterogenous policy approach can be beneficial to address the varying needs of different companies. Increased policy support and guidance to non-state enterprises facing high competition and smaller firms with higher information transfer costs could be beneficial.

While our deep learning methods for compiling keywords related to digital transformation are robust, there is a possibility of incompleteness in our keyword dictionary. Additionally, while text analysis is widely used to capture a company's operations, text frequency alone may not fully represent a company's economic investment in digital transformation. Structured indicators of digital transformation should be further explored. In future research, we aim to focus on specific innovative behaviors within digital transformation, such as digital innovation, and to investigate the role of digitalization in driving product innovation.

Reference

Ashraf, B.N., Shen, Y. (2019). Economic policy uncertainty and banks' loan pricing. *Journal of Financial Stability,* 44, 100695

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, 103745.

Bartov, E., Faurel, L., & Mohanram, P. (2023). The role of social media in the corporate bond market: Evidence from twitter. *Management Science*, 69(9), 5638-5667.

Bendig, D., Schulz, C., Theis, L., & Raff, S. (2023). Digital orientation and environmental performance in times of technological change. *Technological Forecasting and Social Change*, 188, 122272.

Bhagat, S., & Bolton, B. (2019). Corporate governance and firm performance: The sequel. *Journal of Corporate Finance*, 58, 142-168.

Blichfeldt, H., & Faullant, R. (2021). Performance effects of digital technology adoption and product & service innovation–A process-industry perspective. *Technovation*, 102275.

Bloom, N., Garicano, L., Sadun, R., & Van Reenen, J. (2014). The Distinct Effects of Information Technology and Communication Technology on Firm Organization. *Management Science*, 60(12), 2859-2885.

Borisova, G., Fotak, V., Holland, K., & Megginson, W. L. (2015). Government ownership and the cost of debt: Evidence from government investments in publicly traded firms. *Journal of Financial Economics*, 118(1), 168-191.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). 1. Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics (pp. 23-60). University of Chicago Press.

Caldara, D., & Herbst, E. (2019). Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs. *American Economic Journal: Macroeconomics*, 11(1), 157-192.

Caramichael, J., & Rapp, A. C. (2024). The green corporate bond issuance premium. *Journal of Banking & Finance*, 162, 107126.

Cesa-Bianchi, A., & Sokol, A. (2022). Financial shocks, credit spreads, and the international credit channel. *Journal of International Economics*, 135, 103543.

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *The Journal of Finance*, 62(1), 119-149.

Chen, M., Zhao, K., & Jin, W. (2024). Corporate digital transformation and tax avoidance: evidence from China. *Pacific-Basin Finance Journal*, 85, 102400.

Chen, W., & Srinivasan, S. (2024). Going digital: Implications for firm value and performance. *Review of Accounting Studies*, 29(2), 1619-1665.

Chen, Y., Fan, Z., Gu, X., & Zhou, L.-A. (2020). Arrival of Young Talent: The Send-Down Movement and Rural Education in China. *American Economic Review*, 110(11), 3393-3430.

Chen, Z., & Jiang, K. (2024). Digitalization and corporate investment efficiency: Evidence from China. *Journal of International Financial Markets, Institutions and Money*, 91, 101915.

Chen, Z., Xiao, Y., & Jiang, K. (2023). The impact of tax reform on firms' digitalization in China. *Technological Forecasting and Social Change*, 187, 122196.

Cheng, W., Li, C., & Zhao, T. (2024). The stages of enterprise digital transformation and its impact on internal control: Evidence from China. *International Review of Financial Analysis*, 92, 103079.

Cui, Y., Che, W., Liu, T., Qin, B., & Yang, Z. (2021). Pre-training with whole word masking for chinese bert. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29, 3504-3514.

Devlin, J. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Ding, X., Sheng, Z., Appolloni, A., Shahzad, M., & Han, S. (2024). Digital transformation, ESG practice, and total factor productivity. *Business Strategy and the Environment*.

Du, X., & Jiang, K. (2022). Promoting enterprise productivity: The role of digital transformation. *Borsa Istanbul Review*, 22(6), 1165-1181.

Du, X., Jiang, K., & Zheng, X. (2024). Reducing asymmetric cost behaviors: Evidence from digital innovation. *Humanities and Social Sciences Communications*, 11(1), 1-18.

Ederington, L.H., Yawitz, J.B. and Roberts, B.E. (1987), The Informational Content of Bond Ratings. *Journal of Financial Research*, 10: 211-226.

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process?. *Review of Accounting Studies*, 27(3), 938-985.

Gaglio, C., Kraemer-Mbula, E., & Lorenz, E. (2023). The effects of digital transformation on innovation and productivity: Firm-level evidence of South African manufacturing micro and small enterprises. *Technological Forecasting and Social Change*, 182, 121785.

Gao, H., Wang, J., Wang, Y., Wu, C., & Dong, X. (2020). Media Coverage and the Cost of Debt. *Journal of Financial and Quantitative Analysis*, 55(2), 429-471.

Ghouma, H., Ben-Nasr, H., & Yan, R. (2018). Corporate governance and cost of debt financing: Empirical evidence from Canada. *The Quarterly Review of Economics and Finance*, 67, 138-148.

Goldfarb, A., & Tucker, C. (2019). Digital Economics. *Journal of Economic Literature*, 57(1), 3-43.

Gryglewicz, S. (2011). A theory of corporate financial decisions with liquidity and solvency concerns. *Journal of Financial Economics*, 99(2), 365-384.

Gurbaxani, V., & Dunkle, D. (2019). Gearing up for successful digital transformation. *MIS Quarterly Executive*, 18(3), 6.

Han, S., & Zhou, X. (2013). Informed Bond Trading, Corporate Yield Spreads, and Corporate Default Prediction. *Management Science*, 60(3), 675-694.

Jaskowski, M., & Rettl, D. A. (2023). Information acquisition costs and credit spreads. *Journal of Banking & Finance*, 149, 106775.

Jiang, K., Du, X., & Chen, Z. (2022). Firms' digitalization and stock price crash risk. *International Review of Financial Analysis*, 82, 102196.

Jiang, K., Zhou, M., & Chen, Z. (2024). Digitalization and firms' systematic risk in China. *International Journal of Finance & Economics*.

Kaviani, M. S., Kryzanowski, L., Maleki, H., & Savor, P. (2020). Policy uncertainty and corporate credit spreads. *Journal of Financial Economics*, 138(3), 838-865.

Kim, J.-B., Song, B. Y., & Zhang, Y. (2015). Earnings performance of major customers and bank loan contracting with suppliers. *Journal of Banking & Finance*, 59, 384-398.

Livingston, M., Poon, W. P. H., & Zhou, L. (2018). Are Chinese credit ratings relevant? A study of the Chinese bond market and credit rating industry. *Journal of Banking & Finance*, 87, 216-232.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems*, 24(3), 149-157.

Lu, C. W., Chen, T. K., & Liao, H. H. (2010). Information uncertainty, information asymmetry and corporate bond yield spreads. *Journal of Banking & Finance*, 34(9), 2265-2279.

Lyu, H., Wang, W., Xu, S., & Zhou, J. (2022). Individual investment bankers' reputation concerns and bond yield spreads: Evidence from China. *Journal of Banking & Finance*, 140, 106508.

Lyu, Y., Xiao, X., & Zhang, J. (2024). Does the digital economy enhance green total factor productivity in China? The evidence from a national big data comprehensive pilot zone. *Structural Change and Economic Dynamics*, 69, 183-196.

Malodia, S., Mishra, M., Fait, M., Papa, A., & Dezi, L. (2023). To digit or to head? Designing digital transformation journey of SMEs among digital self-efficacy and professional leadership. *Journal of Business Research*, 157, 113547.

Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research*, 123, 642-656.

Meles, A., Salerno, D., Sampagnaro, G., & Fu, M. (2021). The going-public decision and firm risk. *Journal of Financial Stability*, 54, 100882

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment. *British Journal of Management*, 30(2), 272-298.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, 57(2), 103169.

Mikolov, T. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Niu, Y., Wen, W., Wang, S., & Li, S. (2023). Breaking barriers to innovation: The power of digital transformation. *Finance Research Letters*, 51, 103457.

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109–131.

Okimoto, T., & Takaoka, S. (2024). Sustainability and credit spreads in Japan. *International Review of Financial Analysis*, 91, 103052.

Parviainen, P., Tihinen, M., Kääriäinen, J., & Teppola, S. (2022). Tackling the digitalization challenge: how to benefit from digitalization in practice. *International Journal of Information Systems and Project Management*, 5(1), 63-77.

Ren, Y. S., Boubaker, S., Liu, P. Z., & Weber, O. (2023). How does carbon regulatory policy affect debt financing costs? Empirical evidence from China. *The Quarterly Review of Economics and Finance*, 90, 77-90.

Shao, Y., Xu, K., & Shan, Y. G. (2024). Leveraging corporate digitalization for green technology innovation: The mediating role of resource endowments. *Technovation*, 133, 102999.

Shen, X., & Wang, Z. (2024). Can digital industrialization promote energy conservation development in China? Empirical evidence based on national big data comprehensive pilot zone policy. *Journal of Environmental Management*, 368, 122125.

Shu, P.-G., & Chiang, S.-J. (2020). The impact of corporate governance on corporate social performance: Cases from listed firms in Taiwan. *Pacific-Basin Finance Journal*, 61, 101332.

Tan, T., Chan, K. C., & Hsu, Y. T. (2022). The forecasting power of digital transformation on future corporate innovation: Evidence from digital transformation certification. Available at SSRN 4068403.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28(2), 118-144.

Wang, K. T., Wu, Y., & Ho, K.-Y. (2021). Internal control reporting and cost of bond financing: Evidence from China. *International Review of Economics & Finance*, 76, 1323-1346.

Wei, X., Ruan, Q., Lv, D., & Wu, Y. (2022). Transportation infrastructure and bond issuance credit spread: Evidence from the Chinese high-speed rail construction. *International Review of Economics & Finance*, 82, 30-47.

Wen, H., Zhong, Q., & Lee, C.-C. (2022). Digitalization, competition strategy and corporate innovation: Evidence from Chinese manufacturing listed companies. *International Review of Financial Analysis*, 82, 102166.

Wu, K., Fu, Y., & Kong, D. (2022). Does the digital transformation of enterprises affect stock price crash risk? *Finance Research Letters*, 48, 102888.

Wu, Y., & Li, Z. (2024). Digital transformation, entrepreneurship, and disruptive innovation: evidence of corporate digitalization in China from 2010 to 2021. *Humanities and Social Sciences Communications*, 11(1), 1-11.

Zeng, H., Ran, H., Zhou, Q., Jin, Y., & Cheng, X. (2022). The financial effect of firm digitalization: Evidence from China. *Technological Forecasting and Social Change*, 183, 121951.

Zhai, H., Yang, M., & Chan, K. C. (2022). Does digital transformation enhance a firm's performance? Evidence from China. *Technology in Society*, 68, 101841.

Zhang, C., & Wang, Y. (2024). Is enterprise digital transformation beneficial to shareholders? Insights from the cost of equity capital. *International Review of Financial Analysis*, 92, 103104.

Zhang, Z., Lu, Y., & Wang, H. (2024). The impact of management power on digital transformation. *Asia Pacific Journal of Management*, 1-25.

Zheng, D., Song, H., Zhao, C., Liu, Y., & Zhao, W. (2024). Is it possible for semiconductor companies to reduce carbon emissions through digital transformation? Evidence from China. *International Journal of Production Economics*, 272, 109246.

Zhou, M., Jiang, K., & Zhang, J. (2023). Environmental benefits of enterprise digitalization in

China. *Resources, Conservation and Recycling*, 197, 107082.

Appendix A

Table A1

Definition of variables

Panel A: Variables in the baseline regression	
CS	The difference between bond yields and Treasury yields of the same maturity.
$Digital$	The natural logarithm of digitized keyword word frequency plus one in corporate annual reports
$Size$	The natural logarithm of the number of employees in the company
Lev	The ratio of total liabilities to total assets of the enterprise
ROA	The ratio of net profit to total assets of the enterprise
Dua	Dummy variable, if the general manager and the chairman of the board are the same person, the value is 0, otherwise it is 1
Shl	The shareholding ratio of the first largest shareholder of the enterprise
BS	The natural logarithm of total bond issuance
RM	The natural logarithm of the remaining maturity of the bond
$Credit$	Bond credit ratings, AAA takes the value of 6, AA+ takes the value of 5, AA takes the value of 4, AA- takes the value of 3, A+ takes the value of 2, A takes the value of 1
$Guarantee$	The dummy variable equals 1 if the bond is guaranteed, and 0 otherwise.
Panel B: Variables in Robustness Tests	
$Digital\_rank$	If the frequency of digitized words in the annual report is at the top, it takes the value of 3; at the middle, it takes the value of 2; at the bottom, it takes the value of 1; and if not, it takes the value of 0.
$Digital\_asset$	The ratio of the increase in digital intangible assets to intangible assets of the enterprise
$Digital\_asset1$	The ratio of the increase in digital intangible assets to the total assets of the enterprise
$CS1$	The difference between bond yields and one-year fixed deposit rates
$CS5$	The difference between bond yields and five-year fixed deposit rates
CS_mean	Mean value of credit spreads for bonds issued by firms
Panel C: Variables in the endogeneity test	
$Mean\_digital$	The average value of digital transformation of other companies in the three-tier industry in which the company is located
$Bigdata$	The policy variable equals 1 if the company's region is included in the pilot area, 0 otherwise.
Panel D: Variables in the mechanism test	
$Analyst$	The natural logarithm of analyst attention plus one
$Report$	The natural logarithm of attention by the study plus one
$Z-score$	Reflects the company's financial distress and is calculated as Z = 1.2$X1$ + 1.4$X2$ + 0.6$X3$ + 0.999$X4$ + 3.3$X5$. where $X1$ = working capital/total assets. $X2$ = retained earnings/total assets; $X3$ = EBIT/total assets; $X4$ = market value of equity/book value of total liabilities; and $X5$ = operating income/total assets;
$Asset$	Logarithm of total corporate assets
Lev	The ratio of total liabilities to total assets of the enterprise
$Tang$	The ratio of enterprise tangible assets to total assets

$Growth$	Growth rate of corporate net profit
$Dividend$	Corporate pre-tax cash dividends per share
Shl	The shareholding ratio of the first largest shareholder of the enterprise
SOE	The dummy variable equals 1 if the enterprise is state-owned, 0 otherwise.

Source: Authors' own work

Table A2

Balance test

Variable	Matched	Treated	Control	Bias	T-statistics	P-value
$Size$	U	8.94	9.33	-26.70%	-10.15	0.00
	M	8.95	8.90	3.90%	1.45	0.15
Lev	U	0.58	0.61	-21.30%	-8.44	0.00
	M	0.58	0.58	-1.90%	-0.62	0.53
ROA	U	0.07	0.07	-2.30%	-0.93	0.35
	M	0.07	0.07	-0.80%	-0.28	0.78
Dua	U	0.80	0.88	-24.70%	-10.28	0.00
	M	0.80	0.80	-2.60%	-0.82	0.41
Shl	U	33.95	41.18	-44.30%	-17.49	0.00
	M	33.97	34.25	-1.70%	-0.62	0.54
BS	U	2.03	2.43	-47.00%	-18.45	0.00
	M	2.03	2.04	-0.70%	-0.24	0.81
RM	U	0.57	0.83	-30.90%	-12.30	0.00
	M	0.57	0.58	-1.30%	-0.43	0.67
$Credit$	U	2.95	3.14	-21.30%	-8.49	0.00
	M	2.95	2.93	2.60%	0.89	0.38
$Guarantee$	U	0.20	0.30	-22.50%	-8.76	0.00
	M	0.20	0.19	4.20%	1.56	0.12

Source: Authors' own work