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Unravelling the credit risk puzzle of digital transformation in intelligent manufacturing enterprises: the moderating role of supply chain finance

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Abstract: *The influence of digital transformation (DT) on corporate credit risk is experimentally investigated in this article from 2015 to 2021 using a sample of listed Chinese intelligent manufacturing enterprises (IMEs). The results indicate a nonlinear relationship between credit risk and DT. Once DT reaches a certain point, credit risk decreases. Overcommitment to DT raises credit risk. Several robustness tests confirm that the conclusion is still valid. DT impacts credit risk through three different mechanisms, according to mechanism analysis: the finance effect, and the innovation effect. According to heterogeneity analysis, the nonlinear impact of DT on credit risk is more pronounced in IMEs with lower governance levels and higher productivity. This study enables us to understand DT 's economic consequences. This paper provides empirical insights for IMEs to develop DT and prevent credit risk rationally.*

Keywords: *Digital transformation; Credit risk; Intelligent manufacturing; Nonlinear relationship*

1. Introduction

DT and intelligent manufacturing are complementary, with intelligent manufacturing serving as the driving force behind global technological development[1] and serving at the forefront of this movement. DT in intelligent manufacturing refers to integrating digital technologies to improve efficiency, productivity, flexibility, and adaptability[2]. With digital technologies, conventional manufacturing companies are evolving into IMEs. Globally, intelligent manufacturing is going through a thorough transition from Industry 4.0 to Industry 5.0 due to DT [2]. However, the level of DT in Chinese manufacturing companies is far less advanced than in industrialized nations like the US and Europe. Selecting Chinese IMEs as the subject of DT research is particularly representative in this context.

Most current research on the relationship between enterprise risk and DT is positive. For example, it has been shown to lower the risk of corporate bankruptcy[3] and stock price crashes[4]. Global businesses are confronted with the difficulty of "squeezed transformation" as DT moves into the phase of "complete reinvention", with a limited time frame and challenging obstacles. This conundrum may set off the dark sides of DT, such as an increase in credit risk[5]. Overinvestment in DT can have negative managerial effects, such as exacerbating inter-organizational conflicts and resistance to change[6], increasing the cost of operating and maintaining digital assets exponentially[7], and ultimately creating a cost-benefit imbalance[8]. Regarding the financial implications, excessive investment in DT can widen the digital divide between supply chain companies, worsen information asymmetry inside and outside the company [9], and raise agency costs. Regarding the effects on innovation, excessive investment in DT might make a company's innovation activities more dependent on digital technologies [10], which stifles original thought and creativity. Additionally, an abundance of information might impair the effectiveness of information processing and perhaps lead managers and R&D staff to make incorrect market assessments [11], thus impeding innovation efficiency. The above effects produce results that negatively affect enterprises' profitability and cash flow stability, ultimately leading to an outbreak of credit risk. In light of this, is there a linear or nonlinear link between corporate credit risk and DT in IMEs? Does it have a good or bad impact? There is room for more investigation into the conflicting findings of the current study.

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The marginal contribution of this paper may be the following: First, it provides new evidence on the divergence of the relationship between DT and enterprise risk, especially credit risk. Regarding the impact of DT on enterprise risk, opinions differ on whether it is better or worse. In addition to enhancing our understanding of the economic ramifications of DT, this research offers fresh support for the digitization paradox by analyzing both positive and negative effects. Second, it develops the research notion of "DT - credit risk" by establishing the theoretical framework of "DT -financing effect/innovation effect - credit risk".

2. Theoretical analysis and research hypothesis

2.1. Financing effect

On the one hand, moderate DT links the production and operation divisions is by incorporating operational data from businesses into digital systems [12]. Creditors can more quickly and accurately comprehend an enterprise's internal operations with the aid of a digital system, which lowers information-transmission barriers and boosts efficiency [13], lessens the degree of information asymmetry between creditors and enterprises, and lowers information-obtaining costs [14], which reduces the cost of debt financing and credit risk for enterprises. On the other hand, excessive investments in DT by IMEs have the potential to widen the digital divide between them and supply chain upstream and downstream companies, which could make collaborative supply chain management more difficult [15]and increase the credit risk for IMEs. For instance, end-to-end system docking issues make it difficult for data elements to circulate and share, leading to the formation of data silos. The inability of IMEs to fully understand upstream and downstream operational data makes it more difficult for financial institutions to grant financing concessions for the entire supply chain. This is counterproductive to lowering the cost of debt financing and raises the credit risk across the board.

2.2. Innovation effect

On the one hand, the DT of IMEs will promote the improvement of innovation efficiency to a moderate degree. From an R&D perspective, the industrial Internet platform allows customers to engage in R&D design actively, resulting in an accurate docking of supply and demand [16]. Additionally, by reducing the physical distance between enterprise R&D and consumers, businesses can better understand customer preferences and unique needs and reduce the risk that their innovative products will not be well received by the market [17], boosting innovation efficiency. Firms with high innovation efficiency can develop new products and services more efficiently, enabling them to better adapt to changes in market demand and maintain a competitive advantage in the market, thereby enhancing corporate reputation [18]. Reputable firms can attract investors, suppliers, and customers, which enhances business stability and thus reduces corporate credit risk [19].On the other hand, IMEs' excessive and disorderly investment in DT can depress innovation efficiency. According to path theory, over-investment in digital technology may lead to innovation path dependence in firms, inhibiting innovative thinking and activities. Firms tend to show inherent inertia in technology application and innovation activities when they overly depend on existing digital technologies [20]. This inertia makes enterprises tend to follow the already successful technological routes and neglect to explore new innovative ideas and technologies, which limits their sensitivity to changes in the external environment and inhibits the diversity and flexibility of their innovative thinking.

H1: Digital transformation affects credit risk through innovation efficiency and debt financing costs.

3. Research methodology

3.1. Data and sample

The list of IMEs is derived from the 2015-2021 Intelligent Manufacturing Demonstration Project List issued by the Ministry of Industry and Information Technology of the People's Republic of China. In this study, the sample selection was carried out as follows: (1) The list was matched with Chinese A-share listed companies, excluding non-listed companies and those listed after December 31, 2015, as the sample needs data to calculate the default distance (DD); (2) The samples were limited to the manufacturing industry; (3) To eliminate the influence of outliers, all continuous variables were

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winsorized at the 1st and 99th percentiles; (4) To reduce multicollinearity, mean centering was applied to the variables involved in interaction terms. Ultimately, the final sample consisted of 260 IM listed companies.

3.2. Variable construction

3.2.1. Dependent variable

The dependent variable in this article is corporate credit risk. We measure an enterprise's credit risk using the default distance (DD) determined by the KMV model. The credit risk decreases with increasing DD .

3.2.2. Independent variable

The independent variable in this study is DT ($lnDT$). Drawing on the measurement methodology and DT dictionary from Wu et al.[21] and Xiao et al.[22], we utilized text analysis to conduct a frequency count of "DT" related terms in the annual reports of listed companies. The degree of DT was measured by taking the logarithm of the total term frequency plus one. The specific definitions and measurement methods for these variables can be found in Table 1.

Table 1: Variable definitions.

Variable type	Variable name	Codes	Proxy measures
Dependent Variable	Credit Risk	DD	Using the KMV model to calculate the distance to default.
Independent Variable	Digital Transformation	$lnDT$	Calculate the total word frequency using text mining, add 1 to the obtained result, and then take the logarithm.
Control variables	Growth Capability	$Growth$	Operating revenue growth rate
	Board Size	$lnBoard$	Natural logarithm of the board size
	Board Independence	Inr	Percentage of Independent Directors in the Board
	Profitability	Roa	Net Profit / Total Assets Ratio
	Liquidity Level	Liq	Current Assets / Total Assets
	Industry	$Industry$	Industry dummy variable
	Year	$Year$	Year dummy variable

3.3. Model specification

To test the main hypothesis of this paper, we constructed the following regression model:

$$DD_{i,t} = \gamma_0 + \gamma_1 lnDT_{i,t} + \gamma_n \sum Controls + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{1}$$

$$DD_{i,t} = \alpha_0 + \alpha_1 lnDT_{i,t} + \alpha_2 lnDT^2{}_{i,t} + \alpha_n \sum Controls + \sum Industry + \sum Year + \varepsilon_{i,t} \tag{2}$$

In this model, $DD_{i,t}$ represents the default distance and serves as a proxy for corporate credit risk. $lnDT_{i,t}$ indicates the firm's DT degree. $lnDT^2_{i,t}$ is the square of $lnDT_{i,t}$, indicating a nonlinear effect. $\sum Controls$ represents the control variables. $\sum Industry$ and $\sum Year$ denote industry-fixed effects and year-fixed effects, respectively. $\varepsilon_{i,t}$ denotes the error term. The standard errors in each regression are clustered at the firm level. If γ_1 is not significant, α_1 is significantly greater than 0 and α_2 is significantly less than 0. An inverted U-shaped relationship exists between $lnDT$ and DD, supporting the Hypothesis 1. Meanwhile, following Lind and Mehlum [23], a U-test is employed further to validate the inverted U-shaped relationship between $lnDT$ and DD .

4. Empirical results and analyses

4.1. Baseline results

Table 2 displays the regression results for equations (1) and (2) in Columns (1) through (4). In this

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instance, control variables are included in Columns (2) and (4) but not in Columns (1) and (3). γ_1 is -0.003 and 0.008, and Columns (1) – (2) demonstrate that this is not significant. α_1 is 0.227, and α_2 is -0.029, as indicated by Column (3), and both are significant at the 5% level. α_1 is 0.243, and α_2 is -0.029, both significant at the 5% level, as indicated by Column (4). The first hypothesis is true.

Table 2: Regression analysis.

Variables	(1)	(2)	(3)	(4)
	DD	*DD*	*DD*	*DD*
lnDT	-0.003 (-0.09)	0.008 (0.26)	0.227** (2.09)	0.243** (2.35)
lnDT^2			-0.029** (-2.19)	-0.029** (-2.32)
Constant	2.671*** (21.47)	1.717*** (3.42)	2.239*** (9.73)	1.236** (2.26)
Controls	NO	YES	NO	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1,820	1,820	1,820	1,820
Adj.R^2	0.352	0.361	0.354	0.363

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively (This also applies to the tables below).

The U-test result for equations (2) is shown in Table 3. Column (1)'s t-value is 2.09, indicating significance at the 5% level. The Fieller test interval is [2.7707611,6.5526498], and the Extreme Point is 4.147078. Both of these values fall into the interval [0,7.524561] of $lnDT$. The slope at the minimum value is 0.2431244, which is significantly positive at the 1% level, and the slope at the maximum value is -0.1980066, which is significantly negative at the 5% level. The above results further verify that hypotheses 1 is valid.

Table 3: U-test analysis.

	(1)
Slope at the lower bound	0.2431244*** (2.349873)
Slope at the upper bound	-0.1980066** (-2.092308)
Extreme point	4.147078
T-value	2.09**
Fieller test (95% confidence interval)	[2.7707611, 6.5526498]
Interval of $lnDT$	[0, 7.524561]

4.2. Robustness tests

(1) Instrumental variable method

This study used two-stage least squares regressions with explanatory factors that lag one period as instrumental variables to reduce endogeneity issues brought on by missing variables. $IV\_L.lnDT$ and $IV\_L.lnDT^2$ are the instrumental variables for $lnDT$ and $lnDT^2$, respectively. The first stage regression findings, which are displayed in Table 4's Column (1), reveal that the instrumental variables meet the correlation criteria. The coefficients of $IV\_L.lnDT$ and $IV\_L.lnDT^2$ are both substantially positive at the 1% level, at 0.822 and 0.0435, respectively. Additionally, the null hypothesis of weak instrumental variables is rejected since the Cragg-Donald's Wald F-statistic (731.675) is higher at the 10% level than the critical threshold (7.03). In line with the findings of the benchmark regression, the second stage regression's coefficient of $lnDT$ is 0.498, and the regression result of $lnDT^2$ is -0.0582, both of which are statistically significantly positive at the 1% level.

(2) Further tests of the inverted U-shaped relationship

By taking into account the cubic of the explanatory factors, the existence of an inverted U-shaped link between DT and default distance is further confirmed, in line with the findings of Haans et al.[24]. The model may be S- or N-shaped if the explanatory variables' cubic is significant. Column (2) of Table

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4 displays the regression findings. The coefficient of $lnDT$ is 0.281, indicating a significant positive at the 5% level; the coefficient of $lnDT^2$ is -0.031, indicating a significant negative at the 1% level; and the coefficient of $lnDT^3$ is -0.006, indicating no significant change. Further test results show that the relationship between DT and default distance is inverted U-shaped rather than S- or N-shaped, supporting the original hypothesis.

(3) Alternative dependent variable

In order to confirm the robustness of the findings, we regress the credit rating ($Creditrating$) in place of the firm default distance in this study referring to Wang and Yang[25]、Yao and Xiaowei[26]. The credit risk decreases as the level rises. The credit ratings of IMEs are assigned in accordance with the People's Bank of China's "Credit Rating Elements, Symbols and Meanings" for the classification and requirements of corporate credit ratings. Based on the quantitative techniques presented in the relevant literature[25,26], IMEs' credit ratings are assigned sequentially. Regression results are displayed in Table 4's Column (3), where the coefficient of $lnDT$ is 1.575, which is significantly positive at the 1% level, and the coefficient of $lnDT^2$ is -0.160, which is significantly negative at the 5% level, supporting the original hypothesis.

Table 4: Endogeneity tests.

Variables	(1) IV-2SLS		(2)	(3)
	First stage $lnDT$	Second stage DD	DD	$Creditrating$
$IV\_L.lnDT$	0.822*** (0.0204)			
$IV\_L.lnDT^2$	0.0435*** (0.0155)			
$lnDT$		0.498*** (0.177)	0.281** (2.45)	1.575*** (2.79)
$lnDT^2$		-0.0582*** (0.0200)	-0.031** (-2.41)	-0.160** (-2.29)
$lnDT^3$			-0.006 (-0.96)	
Constant			1.100* (1.83)	-4.999** (-2.26)
Controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Cragg-Donald Wald F statistic	731.675			
Stock-Yogo weak ID test critical values: 10% maximal IV size	7.03			
Kleibergen-Paap rk LM statistic	21.02***			
Observations	1560	1560	1820	1820
$Adj.R^2$	0.739	0.020	0.363	0.166

4.3. Mechanism analysis

4.3.1. Financing effect

Based on the mechanism of action described in the previous section, the cost of debt financing is chosen as a proxy variable for the financing effect in this paper. Referring to the study of Kong [27], it is measured using the total amount of firms' interest expenses plus fee expenses and other finance costs as a percentage of total liabilities at the end of the period. The regression results are shown in Column (1) in Table 5, with coefficients of -0.004 for $lnDT$ and 0.001 for $lnDT^2$, both significant at the 5% level. According to the findings above, a considerable U-shaped link exists between the cost of debt financing and DT. Specifically, as the degree of DT increases, debt financing will first fall before increasing.

4.3.2. Innovation effect

Based on the abovementioned mechanism, this paper utilizes the DEA model to measure innovation efficiency. From the input side, human, financial and material resources are indispensable to carry out innovation activities; from the output side, scientific research results are the most direct outputs, and

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economic performance is the commercialization of innovation activities. This article refers to existing research [28] and choose the total R&D expenses, the number of R&D employees, and the net fixed assets of businesses as the input side indicators. The quantity of patent applications and income generated by the business are chosen as output metrics. The regression findings are displayed in Table 5's Column (2). The coefficients of $lnDT$ and $lnDT^2$ are 0.107 and -0.011, respectively, and are significant at the 1% and 5% levels. According to the above findings, there is an inverse U-shaped relationship between innovation efficiency and DT.

Table 5: Mechanism analysis.

Variables	(1) *DFC*	(2) *IE*
lnDT	-0.004** (-2.57)	0.107*** (2.67)
$lnDT^2$	0.001** (2.53)	-0.011** (-2.28)
Constant	0.054*** (4.88)	-0.196 (-1.00)
Controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Observations	1820	1,820
$Adj.R^2$	0.346	0.282

4.4. Heterogeneity analysis

4.4.1. Governance levels

Research has demonstrated that the level of corporate governance strengthens the non-linear relationship between business idiosyncratic risk and DT [29]. Thus, the degree of corporate governance may affect how the digital revolution affects credit risk in IMEs. In this paper, we build comprehensive indicators as proxy variables of governance ability from supervision, incentives, and decision-making through principal component analysis, drawing on the research of Zhou et al. [30]. The industry median is used to categorize the samples. Groups above the median are classified as Low, and groups below the median are classified as High. The regression results are presented in Table 6, columns (1) and (2), where the coefficients for firms with low governance are 0.403, significant at the 1% level, and -0.045, significant at the 5% level. The coefficients of $lnDT$ and $lnDT^2$ are insignificant for firms with a high level of governance. These results suggest that implementing DT has a more substantial impact on credit risk for firms with lower levels of governance than those with high levels of governance.

Table 6: Heterogeneity analysis.

Variables	Governance level		Production efficiency	
	(1) Low	(2) High	(3) High	(4) Low
	DD	*DD*	*DD*	*DD*
lnDT	0.403*** (2.94)	-0.039 (-0.24)	0.324*** (2.88)	0.091 (0.54)
$lnDT^2$	-0.045** (-2.33)	-0.002 (-0.11)	-0.036*** (-2.63)	-0.018 (-0.88)
	YES	YES	YES	YES
	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Constant	1.579** (2.49)	1.085 (1.12)	1.812*** (2.80)	1.377* (1.74)
Observations	910	909	909	910
$Adj.R^2$	0.377	0.365	0.371	0.354

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4.4.2. Production efficiency

DT has been demonstrated to increase productivity in businesses [31]. In addition, unpredictability in productivity can cause asset value swings, which impact a company's credit risk [32]. Thus, depending on the company's production efficiency, the effect of DT on credit risk in IMEs may differ. The DEA model is used in this paper to calculate production efficiency. Regarding the research of Y. Li [33], net fixed assets, goodwill, intangible assets, operating costs, and selling expenses are the variables on the input side, while operating income is the variable on the output side. The sample is categorized according to the industry median; the groups above and below are labelled High and Low, respectively. Table 6's columns (3) and (4) display the regression results. For high-productivity enterprises, the coefficients on $lnDT$ are 0.324, significant at the 1% level, and on $lnDT^2$, they are -0.036, significant at the 1% level. When it comes to businesses with low productivity, the coefficients of $lnDT$ and $lnDT^2$ are not significant. These findings imply that more productive enterprises than less productive firms are more affected by adopting DT about credit risk.

5. Conclusion

This study uses a sample of listed Chinese IMEs from 2015 to 2021 to empirically investigate the effects of DT on corporate credit risk. The results indicate that credit risk and DT in IMEs have a nonlinear relationship. When DT is achieved to a certain extent, credit risk is decreased. Credit risk rises with overinvestment in DT. The finding remains valid after conducting several robustness tests. Furthermore, the U-test shows that, at this stage, Chinese IMEs' level of DT is still on the left side of the inflection point and that credit risk is still reduced by growing investment in DT. Mechanism analysis demonstrates how DT's finance, and innovation effects impact credit risk. According to heterogeneity analysis, the nonlinear impact of DT on credit risk is more pronounced in IMEs with high productivity and low governance. According to the results of threshold regression, the impact of DT on credit risk about enterprise size has two thresholds.

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