The Threshold Effect of Digital Transformation on Innovation Performance of Manufacturing

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Abstract. Studying the digital transformation of manufacturing has become one of the necessary conditions for the high-quality development of China's manufacturing industry. By selecting the data of manufacturing, listed companies in Shanghai and Shenzhen from 2007 to 2021, this paper empirical analyzes whether digital transformation promotes the innovation performance of manufacturing. it is found by analysis that digital transformation can significantly promote the innovation performance for manufacturing, but it is not linear. Then, the threshold effect test is used to determine the influence of digital transformation of manufacturing companies on the technological innovation performance, in order to have a clearer understanding of the role of digital transformation in promoting technological innovation.

Keywords: Innovation performance; digital transformation; manufacturing enterprises; Threshold effect

1 Introduction

Vial (2019)[1] proposed that enterprise digital transformation refers to the process of improving an entity by triggering significant changes in its attributes through the combination of information, computing, communication, connectivity and other factors. Qi Yudong (2020)[2] believe that scale effect is an important driving force for enterprise digitalization. In the same degree of digitalization, the larger the size, the better the enterprise performance.

For the digital transformation of enterprises, the main research methods are case analysis, quantitative analysis and text mining, and evaluation index system and other tools will be used. The research on manufacturing digital transformation is not mature enough, also there is still space for innovation. The influence of the development of digital economic base on the innovation performance of manufacturing enterprises may not be a simple linear effect. This research uses the threshold effect model to empirically analyze the threshold effect of digital transformation on technological innovation performance of manufacturing enterprises.

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2 Theoretical foundation and research assumption

2.1 Manufacturing digital transformation and innovation performance

Elia (2018) [3], said the company digital transformation of the operation mode of innovation, so it will affect on innovation performance. He, F. & Liu, H. (2019) [4] said the digital opportunity can move the firm's innovation performance increase. Digital technology can not only increase innovation performance, but also collect massive data information, which can help companies innovate business models. As most critical production factor for the digital transformation of manufacturing industry, data has a deeper and wider integration ability than traditional production factors such as labor, capital and technology, and can promote the integration between industries. The digital transformation of manufacturing industry has further blurred the industrial boundaries through data, accelerated industrial integration, and promoted technology integration, product integration, and market integration, which can further improve the innovation performance of manufacturing industry. Through above logical analysis, digital transformation can become a new driving force to promote the improvement of manufacturing innovation performance by reducing the cost of manufacturing innovation, optimizing the structure and organization of the industry, and accelerating the innovation integration of the industry. Based above, this paper proposes the following hypothesis:

Hypothesis 1: Digital transformation plays a positive role in improving the innovation performance of manufacturing enterprises.

2.2 Nonlinear effect of digital transformation on manufacturing innovation performance

Innovation spillover effect of network technology has nonlinear characteristic of "marginal effect" change. Based on the digital technology-led digital transformation of manufacturing industry, in the early stage of digital transformation, due to imperfect information infrastructure construction and low utilization rate of digital technology, the digital transformation level of manufacturing industry is low, and the promotion effect of manufacturing innovation performance is not high. However, with the improvement of information technology infrastructure and the increasing level of digital transformation, the marginal cost of information acquisition, processing and analysis of manufacturing enterprises decreases, and the obtained innovation performance shows a marginal increasing trend, indicating that digital transformation has a non-linear effect on the manufacturing innovation performance. Based on this, this paper proposes the following hypothesis:

Hypothesis 2: The impact of digital transformation on manufacturing innovation performance has a nonlinear effect.

3 Study design

3.1 Model setting

3.1.1Benchmark model setting.

In order to test the improvement effect of digital transformation on manufacturing innovation performance, this paper sets the following benchmark model:

$$rdsale_{i,\ t} = \beta_0 + \beta_1 dig_{i,t} + \beta_2 cotrols_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{1}$$

$$patent_{i,\ t} = \beta_0 + \beta_1 dig_{i,t} + \beta_2 cotrols_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{2}$$

In model (1), the explained variable rdsale is the level of innovation input of manufacturing enterprises, the core explanatory variable dig is the degree of digital transformation of manufacturing enterprises, and controls represent other control variables that affect innovation performance of manufacturing at the firm level. In order to avoid estimation errors caused by missing variables and reverse causality problems, in this paper, province fixed effect μ and time fixed effect γ are added to the model to improve the robustness of the regression results. $\varepsilon_{i,t}$ represents the random error term. β0 represents the intercept term, β2 is the directional correlation coefficient of the control variable, β1 represents the correlation coefficient of the digital transformation of the manufacturing industry, and the size and positive and negative of the coefficient indicate its influence of the innovation performance of manufacturing enterprises.

3.1.2 Threshold effect model.

Based on the above research, the paper further discusses whether the relationship between digital transformation and innovation performance is non-linear, that is, whether the impact of digital transformation on innovation performance is affected by the value of third-party variables.

The threshold panel model proposed by Hansen can automatically identify threshold values through data, so as to overcome the limitation of subjective artificial division of structural points. This paper uses the threshold panel model to find the threshold value of digital transformation, and uses the threshold regression method to verify whether there is threshold effect in the relationship between digital transformation and manufacturing performance. The following regression with threshold values is constructed:

$$rdsale_{i,t} = \alpha_0 + \alpha_1 dig.I(dig \le \mu_1) + \alpha_2 dig.I(\mu_2 \ge dig > \mu_1) + \alpha_3 dig.I(\mu_3 \ge dig > \mu_2) + \alpha_4 dig.I(dig > \mu_3) + \sum\alpha_i controls_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$patent_{i,t} = \alpha_0 + \alpha_1 rdsale.I(dig \le \mu_1) + \alpha_2 rdsale.I(\mu_2 \ge dig > \mu_1) + \alpha_3 rdsale.I(\mu_3 \ge dig > \mu_2) + \alpha_4 rdsale.I(dig > \mu_3) + \sum\alpha_i controls_{i,t} + \varepsilon_{i,t} \tag{4}$$

Model (3) is a multi-threshold effect model about the influence of digital transformation on innovation performance of manufacturing, dig is threshold variable, I(.) Is a characteristic function, taking the value 1 when conditions are met, and 0 otherwise. μ_1, μ_2, μ_3 are the threshold variables, and the meanings of other variables are the same as in model (1). α_1, α_2, α_3, α_4 are the correlation coefficients of digital transformation on manufacturing innovation performance under different threshold intervals, and $\sum\alpha_i$ are the correlation coefficients of control variables.

3.2 Variable specification and data sources

3.2.1 Explained variables

The manufacturing innovation performance can be measured from two dimensions of R&D input and innovation output respectively. Research and development investment intensity (rdsale) is measured, which is the ratio of the enterprise's research and development investment to its total revenue in the current year. Innovation output refers to the total number of patent applications obtained by an enterprise. According to the classification of the National Bureau of Statistics of China, patents applied in China include invention, utility model and design. In this paper, all patents applied by an enterprise in the current year (patent1) are used as the proxy variable of enterprise innovation performance.

3.2.2 Explanatory variables

Degree of digital transformation of manufacturing enterprises (dig). This paper collects and organizes annual reports of listed manufacturing enterprises on Shanghai Stock Exchange and Shenzhen Stock Exchange through Python crawler, and extracts all the text, and uses this as the subsequent feature word screening. Then the word frequency of digital technology direction is classified and aggregated to form the final word frequency, so as to build the index system of enterprise digital transformation. Since this kind of data has a typical feature,"right-bias", this paper deals with it logarithmically, so as to obtain the overall index describing the digital transformation of enterprises.

3.2.3 Control variables.

In order to more accurately and comprehensively analyze the impact of digital transformation on manufacturing innovation performance and mitigate impact of missing variables on empirical results, this paper controls enterprise-level variables by referring to relevant studies. The control variables at the firm level include: Firm scale (lna) is measured by the total assets of the firm plus a logarithm; Business age (age) is measured using the year of observation (the current statistical deadline) minus the IPO year; Growth Opportunity (tobinq) is measured using market capitalization/total assets. Financial leverage ratio (lev) is measured using total liabilities/total assets; The cash flow position (cf) is calculated as net cash flows from operating activities/total assets at beginning of the period; Dual roles (dz) Whether the chairman and the general manager are the same person; zero indicates no; 1 indicates yes; Proportion of top 10 shareholders (bs10); Whether the equity nature (gx) is a state-owned enterprise, 1 is a state-owned enterprise; audit Opinion Type (audit) 1 is the standard unqualified opinion audit type.

3.3 Data source

This study is selected from the CSMAR data of Shanghai and Shenzhen listed manufacturing in China from 2007 to 2021, and digital transformation data is from the word frequency statistics related to digital transformation of the annual report data of listed enterprises.

4 Analysis of empirical results

In the table 1, this paper mainly verifies the positive promotion effect of digital transformation on manufacturing innovation input based on panel fixed effect model. The digital transformation coefficients on R&D intensity (rdsale), patent application (patent1) and patent authorization (patent2) are positive and significant at the level of 1%. The coefficients of invention patent application and invention patent authorization are significantly positive at the level of 5%, making clear that whether from perspective of innovation performance input or innovation output, Digital transformation may significantly improve the manufacturing innovation performance. It further verifies the incentive influence of digital transformation on the manufacturing innovation performance.

Table 1. Regression results of digital transformation on innovation performance

	rdsale	Patent1	Patent2	Invention1	Invention2
dig	0.519^{***}	0.140^{***}	0.118^{***}	0.084^{**}	0.071^{**}
	(6.50)	(4.20)	(2.91)	(2.35)	(2.27)
Control variables					
Year-fixed	Yes	Yes	Yes	Yes	Yes
Province-fixed	Yes	Yes	Yes	Yes	Yes
N	10778	10778	10778	10778	10778
adj. R^2	0.281	0.045	0.049	0.035	0.055

t statistics in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.1 Threshold regression analysis

4.1.1Threshold effect test

According to the model setting, we first determine whether there is a threshold effect and number of thresholds. The F-value, p-value and critical value of the tri-threshold effect are calculated after 300 repeated sampling using the Bootstrap method.

Table 2. Threshold effect test results

Threshold	Bootstrap	Fstat	Prob	Criteria		
				10%	5%	1%
Single	300	35.25	0.000	9.017	11.104	16.851
Double	300	4.53	0.433	9.718	12.082	18.569
Triple	300	4.13	0.610	11.093	13.930	17.750

The threshold effect test results in table 2 show that, first of all, in the case of no threshold value, the F statistic is 35.25 and P value is 0.000, they can prove that the hypothesis is rejected at the significance level of 1%, that is, the threshold effect value exists, and the single threshold of the threshold variable dig is significant at the level of 1%. The value of F statistic is 4.53, the P value is 0.433, they can indicate that the hypothesis cannot be rejected even at the significance level of 10%. The double threshold and triple threshold are not significant, and the threshold existence test stops at this time, indicating that the number of effective thresholds is 1, that is, there is a single threshold effect between digital transformation and R&D intensity. Therefore, the model is modified as a single threshold regression model:

$$rdsale_{i,t} = \alpha_0 + \alpha_1 dig.I(dig \leq \mu_1) + \alpha_2 dig.I(dig > \mu_1) + \sum \alpha_i controls_{i,t} + \varepsilon_{i,t} \tag{5}$$

4.1.2 Threshold value estimation

The single threshold value of dig for digital transformation in table 3 is further obtained as 2.8332, and the 95% confidence interval is [0.490-0.596]. According to the result of regression, when the degree of digital transformation is lower than 2.8332, its impact on the innovation intensity of manufacturing enterprises (rdsale) is significantly positive, with a coefficient of 0.543. When the degree of digital transformation is higher than 2.8332, the influence of digital transformation (dig) on the innovation intensity of manufacturing (rdsale) is also significantly positive. The coefficient is 0.502, which indicates that when digital transformation reaches a certain level, its marginal utility on enterprise innovation intensity tends to weaken.

Table 3. Threshold value estimation results

Threshold	Value	Confidence Interval
Single	2.8332	[0.490-0.596]

4.2 Regression results of threshold effect

From the threshold effect regression in table 4, results prove when the degree of digital transformation is lower than 1.6094, the influence coefficient of R&D intensity on the innovation output of manufacturing industry is 0.067, which is established at the significance level of 1%. When digital transformation degree is higher than 1.6094 and lower than 2.8904, the R&D coefficient intensity on the innovation output of manufacturing industry is 0.089. When the degree of digital transformation is greater than 2.8904, the influence coefficient of R&D intensity on the innovation output of manufacturing enterprises is 0.059. The implication is that the promotion of digital transformation has an inverted U-shaped relationship on the output of innovation performance.

Table 4. Regression results of threshold effect

	rdsale	patent
dig(dig<=2.8332)	0.543***	
	(0.027)	
dig(dig>2.8332)	0.502***	
	(0.034)	
rdsale(dig<=1.6094)		0.067***
		(0.014)
rdsale(1.6094<dig<=2.8904)		0.089***
		(0.017)
rdsale(dig>2.8904)		0.059*
		(0.023)
_cons	4.281***	0.723***
	(0.147)	(0.213)
N	10240	6510
adj. R^2	-0.058	-0.106

Standard errors in parentheses $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Furthermore, in table 5, digital transformation (dig) is taken as the threshold variable to study the impact of the threshold variable on innovation output (patent1) through innovation intensity (rdsale).

There are two threshold values in table 6, one of which is 1.6094 and the other is 2.8904. In the case that there are two threshold values for the null hypothesis, the value of F statistic is 3.03 and the P value is 0.827.

Table 5. Threshold effect test

Threshold	Boot-strap	Fstat	Prob	criteria		
				10%	5%	1%
Single	300	12.52	0.033	9.00	11.56	14.81
Double	300	11.60	0.037	8.90	10.91	15.77
Triple	300	3.03	0.827	11.88	15.84	23.15

Table 6. Threshold value estimation

Threshold	Value	Confidence Interval
Single	1.6094	[0.040-0.094]
Double	2.8904	[0.056-0.121]

To test whether the two groups of samples divided by the threshold value and their estimated parameters are significantly different, and construct LM statistics at the same time, which is determined by drawing the threshold value likelihood ratio function graph. In the figure, since the LR reference value at a given 5% level is 7.35, and the LR statistic of the estimated threshold value is below 7.35, indicating that the estimated threshold value is the same as the actual threshold value, the null hypothesis of double threshold is accepted, that is, digital transformation has a nonlinear impact of threshold on the innovation performance of manufacturing enterprises.

4.3 Robustness analysis

According to the practice of Zhang Yongshen et al. (2021) [5], the digitization level of an enterprise is measured by the proportion of the part related to digital transformation in the details of intangible assets disclosed in the notes to the financial reports of listed companies at the end of the year to the total intangible assets.

The following table 7 reports the regression results of the proxy variable of digital transformation (dig_intan) on innovation performance. Column (3) shows the regression results of digital transformation on the total number of patent applications under control of two-way fixed effects of time and province. Column (4) indicates the regression results of digital transformation on invention patent applications when controlling two-way fixed effects of time and province. The results of columns (1) and (2) show that the coefficient of digital transformation policy variable is significantly positive at the level of 1%, and the results of Column (3) show that it is significant at the level of 10%. The results of Column (4) show that the coefficient of digital transformation variable is significantly positive at the level of 5%, which further verifies that digital transformation may promote the innovation degree of manufacturing enterprises.

Table 7. Regression results

	rdsale	rdsale	Patent1	Invention1
dig_intan	2.688^{***}	2.475^{***}	0.595^{*}	0.372^{**}
	(4.73)	(4.54)	(1.94)	(2.13)
Control variables	No	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Province fixed	Yes	Yes	Yes	Yes
Observations	10716	10716	10716	10716
adj. R^2	0.149	0.261	0.037	0.029

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusions

Based on the in-depth analysis of the impact of digital transformation on the technological innovation of manufacturing enterprises, this paper verifies the nonlinear effect of digital transformation on the technological innovation performance of manufacturing according to the theory of digital technology and technological innovation. The conclusions have the following policy implications for promoting digital economy's development, stimulating technological innovation of manufacturing enterprises, and realizing innovation-driven high-quality development.

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