

The Impact of Enterprise Digital Transformation on Total Factor Productivity in the Manufacturing Industry-An Empirical Analysis Based on Chinese A-share Listed Enterprises

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Abstract:In the era of digital economy,digital transformation has become an important path for high-quality development of manufacturing enterprises.Based on the data of China's A-share manufacturing companies,this paper empirically examines the impact of digital transformation on the total factor productivity of manufacturing.Through a series of robust analysis,this paper finds digital transformation significantly improves the level of manufacturing TFP,and the effect of digital transformation on manufacturing TFP is affected by management structure,agency cost and financing constraints to varying degrees.Based on heterogeneity,it is found that the property of ownership,high-tech characteristics and regional distribution have a different impact on the efficiency improvement of enterprises in digital transformation.

Keywords:Digital Transformation;Total factor Productivity;Financing Constraints;Governance structure;Agency Costs

1. Introduction

Since reform and open up more than 40 years,the high-speed growth of Chinese's economy form "Chinese miracle".In recent years,the national economic development is stable,but the growth rate has slow down.As an important pillar of China's economic development,the manufacturing industry is a booster for the sustained and stable growth of the national economy.However,compared to developed countries,China's manufacturing industry is large but not strong,technical level isn't high,lack of independent research capabilities.Therefore,it's an urgent task to improve the total factor productivity of China's manufacturing industry and realize the upgrading and transformation of manufacturing industry.At present,the digital economy is gradually changing the pattern of economic development and market competition,so the digital transformation of the manufacturing industry is particularly important.According to the "Digital China Development Report 2022",the construction of digital China has entered a new stage of overall layout and comprehensive promotion.In 2022,the scale of China's digital economy will reach 50.2 trillion yuan,ranking second in the world in terms of total volume,with a year-on-year nominal growth of 10.3% and the proportion of GDP rising to 41.5%.

Digital transformation of enterprises is deep integrating and utilizing of the Internet,the Internet of Things,big data,cloud computing,artificial intelligence,their production and operation processes,thereby changing the management structure and internal operating mechanisms of enterprises[1].The optimization of management structure can drive the improvement of total factor productivity in the manufacturing industry,and improve the level of financing constraints and reduce agency costs during the transformation process.Therefore,we propose:if the digital transformation can enhance the total factor productivity of enterprises?What channels do digital transformation of enterprises lead to changes in total factor productivity?Therefore,this article studies the impact of digital transformation on the total factor productivity of the manufacturing industry,explores the mechanism of their action,And the differences in the nature of property rights,regional distribution,and high-tech characteristics of enterprises that this influence presents.

2. Theoretical analysis and research hypotheses

The factors affecting the development of enterprise total factor productivity can be divided into two levels: the internal level includes management structure, resource allocation, technology research and development, etc., and the external perspective includes spillover effect, competition, policy control etc.[2]. Enterprise digital transformation can optimize the technical level and enhance the operation efficiency of enterprises[3][4]. By reshaping the internal structure of enterprises, digital transformation can accelerate the response speed of enterprises and improve the flexibility of enterprises in market activities[5]. Enterprise transformation led by digital technology will produce technology spillover effect, promote the digital transformation of enterprises through the penetration of digital elements, and make digital technology become the fundamental driving force for market progress[6]. In short, digital transformation can drive the improvement of total factor productivity of enterprises. Accordingly, we propose:

H1: Digital transformation can promote total factor productivity of manufacturing.

The characteristic of modern enterprise system is the separation of management and ownership, which leads to the problem of agency cost, and the problem of power structure can't be ignored. Zhao Chenyu(2022) [7] proposed that digital transformation would gradually change the organizational form of enterprises and improve their production efficiency and management efficiency. In addition, the cross-space and partial limitation features of digital technology gradually transform the organizational structure into an unstructured form Liu Qi[8], which leads to a decline in the number of management levels, resulting in enterprises not being able to continue to implement the previous Taylor scientific management system, and therefore gradually delegating power[9]. Furthermore, the technical characteristics of digital transformation improve the transparency of market information, the access to market information and the information that investors pay attention to enterprises are more symmetrical, and the board of directors has a better understanding of operating efficiency, which reduces the supervision cost of enterprises to a certain extent[10]. But in this process, it is difficult to solve the problem of interest consistency, and the differentiation of power will inevitably increase the agency cost. In addition, digital transformation causes shareholders to begin to cede power[11], which limits the efficiency of decision-making and makes it difficult to guarantee the long-term interests of enterprises by making multiple decisions, thus hindering enterprise operations[12][13]. It can be seen that the promotion of digital transformation on the total factor productivity level of manufacturing industry will be affected by the agency cost and ownership structure of enterprises. Based on the above analysis, this paper proposes the following hypothesis:

H2: Digital transformation for manufacturing total factor productivity is negatively moderated by management structure;

H3: Digital transformation on manufacturing industry total factor productivity is negatively regulated by agency costs;

To improve total factor productivity, enterprises need to invest related resource factors, which requires a large amount of capital, which will crowd out the cash flow of enterprises, and may increase the level of financing constraints. However, in the long run, the technical benefits brought by digital transformation make the cash flow operation of enterprises more accurate, which is conducive to the optimal allocation of funds and the improvement of the use efficiency[14]. Digital transformation can standardize the transaction process and provide an unstructured description of external financing demand information, thus helping to reduce the level of financing constraints[15]. More importantly, the promotion process of enterprise digital transformation is conducive to enhancing the innovation ability of enterprises and improving the technical level of enterprises, that is, enterprises with strong financing ability have stronger technology research and development ability[16][17]. In the process of digital transformation, especially in the early stage of infrastructure construction, enterprises will achieve greater technological innovation results after their R&D financing needs are met, and the degree of digital transformation is higher, which is more

conductive to promoting the improvement of enterprises' total factor productivity[18][19].Based on the above analysis,this paper proposes:

H4:Digital transformation on manufacturing industry total factor productivity is positively moderating by financing constraints.

3. Empirical analysis

3.1 Description and Definition of Variables

3.1.1 Sample selection and data sources

The data samples in this paper are selected from A-share listed enterprises,in order to ensure the operational continuity characteristics of the enterprises in the data,the data with missing values of the relevant indexes are excluded,and the unbalanced panel data are converted into balanced panel data;since the financial characteristics of the listed companies in the financial industry are too different from other types of enterprises,they are also excluded from the sample data of this paper;and the ST,ST*,PT,PT* types of enterprises are excluded.The final screening of the resulting data is 7678 observations,and the research interval is 2011-2021.All the data in this paper are from the Cathay Pacific database (CSMAR).

3.1.2 Variable selection and descriptions

Table 1.research variables descriptions

	Variable	Variable meaning	Variable declaration
Explained Variables	TFP_LP	Total factor productivity	LP_method
	TFP_OLS	Total factor productivity	OLS_method
Explanatory Variables	DCG	Degree of digital transformation	textual analysis
	asset	total assets	Ln(total assets)
	pe	PE ratio	Total market capitalization/total net profit
	growth	Growth capacity	Market capitalization/total assets
Control Variables	assetdebt	Gearing Ratio	Total Liabilities/Total Assets
	lev	Level of financial leverage	EBITDA/ (EBITDA - total capitalization × debt ratio × interest rate)
	independent	Percentage of independent	directors Ratio of independent directors to the number of board of directors
	boc	Size of Supervisory Board	Number of Supervisory Board members
	managefinc	Ratio of managerial control	Ratio of managerial control
	cashflow	Cash flow level	Net cash flow from operating activities/total assets at the beginning of the period
	left	Degree of separation of two positions	Proportion of control of listed company owned by actual controller - Proportion of ownership of listed company owned by actual controller
	dual	Separation of two positions	1 if the chairman serves as ceo,0 otherwise
Moderating variable	SA	Financing constraint	-0.737*firm size + 0.043*firm size2 -0.040*firm age
	turo	Agency cost	Total asset turnover ratio

The methods of OP,OLS and LP are commonly used to estimate the total factor productivity.The Olley-Pakes method can provide a consistent estimate of the production function of the enterprise layer,but one of the assumptions is that the proxy variable (investment) and the total output are always monotonically maintained.This means that samples with zero investment cannot be estimated,resulting in many firm samples being discarded in the estimation process.Levinsohn and

Petrin(2003)[20] studied a new estimation method to solve this problem. This method does not use the amount of investment as the proxy variable, but uses the intermediate input index which is easier to obtain data. In addition, several methods are provided to test the agreement degree of proxy variables, which can greatly expand the selection range of proxy variables. LP method can flexibly select proxy variables according to the characteristics of available data, so this paper adopts LP method to estimate the total factor level:

$$\ln y_{it} = \alpha + \alpha_1 \ln k_{it} + \alpha_2 \ln l_{it} + \alpha_3 \ln m_{it} + \varepsilon_{it} \quad (1)$$

The company TFP can be obtained according to Equation 1 after subjecting it to LP method estimation by proxying the following equation:

$$TFP_{it} = \exp(\ln y_{it} - \alpha \ln k_{it} - \beta \ln l_{it} - \gamma \ln m_{it}) \quad (2)$$

where y is firm output, K is capital inputs, L is labor inputs, M is intermediate inputs, and α 、 β 、 γ are the correlation coefficients of the respective input types.

3.2 empirical model

This paper constructs the following benchmark model for hypothesis testing:

$$TFP_LP_{it} = \alpha + \beta_1 DCG_{it} + \beta_2 Control_{it} + \sum individual + \sum year + \varepsilon_{it} \quad (3)$$

In Eq.3, TFP_LP_{it} is the total factor productivity level of enterprise i in year t , DCG_{it} is the degree of digital transformation of enterprise i in year t , $Control_{it}$ is the control variable selected in this paper, $\sum individual$ indicates fixed individual effect, $\sum year$ indicates fixed time effect, and ε_{it} is the random error term.

In order to further study the impact mechanism of digital transformation on the total factor productivity level of the manufacturing industry, this paper sets up models 4-7 to test hypotheses 2-4.

$$TFP_LP_{it} = \alpha + \beta_1 DCG_{it} + \beta_2 left_{it} + \beta_3 DCG \times left_{it} + \beta_4 Control_{it} + \sum individual + \varepsilon_{it} \quad (4)$$

$$TFP_LP_{it} = \alpha + \beta_1 DCG_{it} + \beta_2 left_{it} + \beta_3 DCG \times dual_{it} + \beta_4 Control_{it} + \sum individual + \varepsilon_{it} \quad (5)$$

$$TFP_LP_{it} = \alpha + \beta_1 DCG_{it} + \beta_2 SA_{it} + \beta_3 DCG \times SA_{it} + \beta_4 Control_{it} + \sum individual + \varepsilon_{it} \quad (6)$$

$$TFP_LP_{it} = \alpha + \beta_1 DCG_{it} + \beta_2 Turo_{it} + \beta_3 DCG \times Turo_{it} + \beta_4 Control_{it} + \sum individual + \varepsilon_{it} \quad (7)$$

where $LEFT$, SA and $Turo$ denote the degree of separation of the two jobs, financing constraints and firm agency costs, respectively.

3. Analysis of empirical results

3.2.1 Descriptive statistics

Table 2 Descriptive statistics and analysis of variables

Panal A: Descriptive statistics						
VarName	Obs	Mean	SD	Min	Median	Max
TFP_ols	7678	10.876	1.154	8.067	10.746	14.518
TFP_LP	7678	8.830	0.963	6.381	8.731	11.917
DCG	7678	1.362	1.394	0.000	1.099	4.990
asset	7678	22.287	1.215	19.541	22.135	27.547
roa	7678	0.064	0.047	0.000	0.055	0.379
growth	7678	0.309	10.006	-1.672	0.083	865.908
assetdebt	7678	0.366	0.178	0.008	0.355	0.933
lev	7678	1.307	1.524	-2.129	1.048	79.087
independent	7678	37.386	5.575	18.180	33.330	66.670
managefinc	7678	0.657	0.475	0.000	1.000	1.000
left	7678	5.710	8.147	-22.424	0.007	47.849
dual	7247	0.286	0.452	0.000	0.000	1.000
SA	7678	-3.796	0.245	-5.318	-3.796	-2.762
turo	7678	0.678	0.365	0.046	0.605	4.798
Panal B: univariate difference test						
Implementation digital		Digital transformation not		difference test		

	transformation		implemented		
	Mean	Median	Mean	Median	Wilxon Z
TFP_LP	8.857	8.768	8.783	8.680	-3.876***
SA	-3.825	-3.833	-3.745	-3.741	14.636***
Turo	5.524	0	0.716	0.623	2.707***
left	0.656	0.593	6.031	0.268	5.619***
dual	0.297	0	0.267	0	-2.615***

Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

Table 2 lists the descriptive statistical results and univariate analysis results of the main variables in this paper. Panel A shows that the mean value of TFP_LP is 8.830, the standard deviation is 0.963, and the minimum and maximum values are 6.381 and 11.917, respectively, indicating that there are great differences in TFP among different enterprises. The mean value of DCG is 1.362, the standard deviation is 1.394, and the maximum value is 0 and 4.990 respectively, indicating that there are obvious differences in the degree of digital transformation among different enterprises. We divided the enterprises with a digital transformation degree of 0 into those that have not implemented digital transformation. The results of Panel B show that there are obvious differences in the results of total factor productivity among different groups. The mean and median of total factor level in the group implementing digital transformation have increased significantly, indicating that the total factor productivity of enterprises has increased. According to the results of Wilcoxon Z, all test values are significant, indicating that compared with enterprises that have not implemented digital transformation, enterprises that have implemented digital transformation have stronger self-generating ability, lower financing constraints and agency costs, smaller separation degree of two rights, and higher integration degree of two roles, which preliminarily proves that the hypothesis in this paper is valid.

3.2.2 Empirical Result Analysis

This article first conducts a multicollinearity test. Generally speaking, when the VIF value is less than 4, it can be considered that there is no multicollinearity problem. The results of this test are all less than 4, and the multicollinearity test is passed. Afterwards, a Hausman test was conducted, and the chi square value was 116.89, which was significant at the level of P value 0.01. The original hypothesis was rejected and a fixed effects model was used.

3.2.3 Baseline regression

Table 3 Baseline regression

VARIABLES	(1)TFP_LP	(2)TFP_LP	(3)TFP_LP	(4)TFP_LP
DCG	1.21*** (0.00425)	0.0605** (0.00263)	0.0929*** (0.00258)	0.0934*** (0.00258)
asset		0.617*** (0.00538)	0.584*** (0.00560)	0.583*** (0.00559)
roa		2.968*** (0.0771)	3.254*** (0.0772)	3.233*** (0.0776)
growth			-0.000350 (0.000251)	-0.000346 (0.000250)
assetdebt			0.537*** (0.0311)	0.547*** (0.0312)
lev				-0.00385** (0.00175)
independent				-0.000188 (0.000734)
managefinc				0.0352*** (0.00633)
Constant	8.665*** (0.00706)	-5.121*** (0.119)	-4.602*** (0.120)	-4.590*** (0.123)

id	yes	yes	yes	yes
Observations	7,678	7,678	7,678	7,678
R-squared	0.106	0.712	0.724	0.726

Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

Table 3 reports the test results of the impact of digital transformation on the total factor level of manufacturing enterprises. Column (1) shows the regression results with only core explanatory variables, and it can be found that the total index of digital transformation has a significant positive impact on total factor productivity of enterprises. Columns (2)-(3) are stepwise regression results, with the coefficient of DCG being significant at least at the 5% level. Column (4) is the regression result after adding control variables. It can be found that the digital transformation coefficient is 0.0934, which significantly improves the total factor productivity level of enterprises at a 1% confidence level, confirming hypothesis 1 in this article. From the perspective of control variables, enterprises with large scale, high management shareholding ratio, high return on total assets, and high asset liability ratio perform relatively well in total factor productivity.

3.2.4 Moderating effect analysis

Table 4 shows the test of the adjustment effect of management structure. This paper adopts the combination analysis of cross-multiplication terms and grouping regression. Column (1) is the result of verifying hypothesis 2, where the coefficient of the cross-multiplication term (DCG*left) of digital transformation and job separation is -0.000619, which is significant at the P-value of 5%, indicating that the job separation has a negative regulatory effect on the digital transformation and industrial structure upgrading of the manufacturing industry. In different two-weight separation groups, the DCG coefficient of the group with higher two-weight separation is 0.00141 higher than that of the group with lower two-job separation, indicating that the digital transformation of the group with higher separation has a higher impact on total factor productivity. In order to further prove the influence of management structure, the cross-fertilization coefficient of the whole sample regression is -0.0138, which is significant at the P-value of 0.01; the coefficient of dual variable is also acceptable at the P-value of 0.102; the DCG coefficient of the dual-occupation group is significant at the 0.1 level, which is -0.00945. However, the DCG coefficient in the non-dual-job group is significantly 0.0199 at the level of 0.01, indicating that the DCG coefficient will be higher when the power of the management structure is more decentralized. Hypothesis 2 in this paper is verified.

Table 4 Moderating effects of governance structures

VARIABLES	Overall	High segregation	Low segregation	Overall	Dual job	Non-dual job
	TFP_LP	TFP_LP	TFP_LP	TFP_LP	TFP_LP	TFP_LP
DCG	0.0134*** (0.00304)	0.00900* (0.00464)	0.00759** (0.00321)	0.0139*** (0.00295)	-0.00945* (0.00509)	0.0199*** (0.00314)
left	-0.00174** (0.000740)					
DCG*left	-0.000619** (0.000286)					
dual				0.0181 (0.0111)		
DCG*dual				-0.0138*** (0.00490)		
asset	0.560*** (0.00673)	0.533*** (0.0119)	0.586*** (0.00862)	0.559*** (0.00674)	0.596*** (0.0135)	0.537*** (0.00832)
roa	3.107*** (0.0814)	3.313*** (0.157)	2.956*** (0.0951)	3.104*** (0.0815)	3.143*** (0.158)	2.971*** (0.0962)
growth	-0.000310 (0.000246)	-0.000774 (0.00231)	-0.000289 (0.000239)	-0.000314 (0.000246)	0.00304 (0.00274)	-0.000325 (0.000243)
assetdebt	0.531*** (0.0324)	0.535*** (0.0561)	0.472*** (0.0412)	0.542*** (0.0324)	0.490*** (0.0685)	0.511*** (0.0383)

lev	-0.00379** (0.00174)	-0.00238 (0.00323)	-0.00524** (0.00205)	-0.00380** (0.00174)	0.00253 (0.00546)	-0.00326* (0.00183)
managefinc	0.0339*** (0.00639)	0.0202* (0.0115)	0.0349*** (0.00778)	0.0340*** (0.00640)	0.0252** (0.0126)	0.0410*** (0.00761)
cashflow	0.0258*** (0.00326)	0.0229*** (0.00579)	0.0236*** (0.00395)	0.0259*** (0.00326)	0.0226*** (0.00620)	0.0266*** (0.00389)
Constant	-4.575*** (0.125)	-3.862*** (0.225)	-5.099*** (0.160)	-4.577*** (0.125)	-5.340*** (0.250)	-4.054*** (0.158)
Id	yes	yes	yes	yes	yes	yes
Observations	7,247	2,505	4,742	7,247	2,076	5,171
R-squared	0.729	0.687	0.739	0.728	0.754	0.696

Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

Table 5 shows the moderating effect of financing constraints and agency costs. The increase in agency costs leads to an increase in operating costs in the manufacturing industry, and digital transformation cannot play a good role, limiting the optimization effect of digital technology and thereby reducing the total factor productivity level of manufacturing enterprises. In the full sample regression results of column (4), *turo* has a negative moderating effect. In the group regression of columns (5)-(6), the DCG coefficient is higher in the higher agency cost, indicating that agency cost does indeed affect the effect of digital transformation on total factor productivity of enterprises. Hypothesis 3 of this article is verified. The coefficient of the multiplication term (DCG*SA) between financing constraints and the degree of digital transformation in column (1) is -0.0361, which is significant at the level of P value 1%. This indicates that financing constraints have a positive moderating effect on the relationship between digital transformation and the upgrading of the manufacturing industry structure, verifying hypothesis 4 of this paper. However, at this point, the coefficient of SA is -0.2, which is significant at the 1% level, indicating that financing constraints and digital transformation are affecting TFP_LP has a substitution effect, that is, financing constraints will limit the role of digital transformation and require a large amount of funds in the early stages of digital construction. Financing constraints restrict the allocation of funds in the manufacturing industry, weakening the level of total factor productivity. However, financing constraints on digital infrastructure construction will reduce the inhibitory effect. In group regression, the coefficient of DCG is significantly lower and not significant in the regression of enterprises with higher financing constraints. Therefore, financing constraints can also affect the intensity of the impact of digital transformation on total factor productivity.

Table 5 Financing constraints and the moderating effect of agency costs

VARIABLES	Overall	High financing constraints	Low financing constraints	Overall	High agency costs	Low agency costs
	TFP LP	TFP LP	TFP LP	TFP LP	TFP LP	TFP LP
DCG	-0.133*** (0.0370)	0.00408 (0.00376)	0.0163*** (0.00399)	-0.0185*** (0.00306)	0.0106*** (0.00377)	0.00944*** (0.00303)
SA	-0.200*** (0.0315)					
DCG*SA	-0.0361*** (0.00973)					
<i>turo</i>				0.965*** (0.0107)		
DCG*turo				0.0339*** (0.00402)		
asset	0.519*** (0.00828)	0.555*** (0.00993)	0.573*** (0.0105)	0.678*** (0.00431)	0.569*** (0.00974)	0.596*** (0.00815)
roa	3.104*** (0.0810)	3.424*** (0.134)	2.743*** (0.105)	1.439*** (0.0527)	1.967*** (0.120)	2.998*** (0.105)
growth	-0.000301 (0.000244)	0.00347 (0.00377)	-0.000346 (0.000222)	-0.000246 (0.000151)	-0.000518 (0.00199)	-0.000290 (0.000217)

assetdebt	0.561*** (0.0322)	0.640*** (0.0507)	0.332*** (0.0485)	0.0870*** (0.0204)	0.447*** (0.0483)	0.299*** (0.0387)
lev	-0.00322* (0.00173)	0.000912 (0.00209)	-0.00566* (0.00338)	-0.00300*** (0.00107)	0.000634 (0.00251)	-0.00408** (0.00199)
managefinc	0.0339*** (0.00636)	0.0333*** (0.00948)	0.0242*** (0.00900)	0.0229*** (0.00393)	0.0257*** (0.00895)	0.0393*** (0.00751)
cashflow	0.0236*** (0.00325)	0.0227*** (0.00467)	0.0206*** (0.00442)	0.00719*** (0.00201)	-0.00131 (0.00465)	0.0290*** (0.00373)
Constant	-4.380*** (0.131)	-4.492*** (0.185)	-4.650*** (0.208)	-7.219*** (0.0817)	-3.773*** (0.184)	-5.588*** (0.153)
Id	yes	yes	yes	yes	yes	yes
Observations	7,247	3,628	3,619	7,247	2,887	4,360
R-squared	0.732	0.723	0.673	0.897	0.747	0.767

Standard errors in parentheses ***p<0.01,**p<0.05,*p<0.1

3.2.5 Endogeneity testing

To avoid endogeneity interference, this article uses internet popularity as the instrumental variable for regression. Table 6 column (2) is the first stage regression, and the correlation coefficient between the instrumental variable and the explanatory variable is significant at the 1% level. Secondly, we conduct weak instrumental variable tests and over identification tests. The weak instrumental variable test for inter is 327.834, which is significantly higher than the critical value. Secondly, the Sargan test value is 0.000, which belongs to just identification. Therefore, it is reasonable for us to use it as an instrumental variable for testing. According to the results of column (1), the coefficient of DCG is 0.557, which is significant at the 1% level, indicating that the promotion effect of digital transformation on total factor productivity in the manufacturing industry is still valid.

To further address the potential endogeneity issue, this article first performs PSM matching on the data, followed by a common support hypothesis test. After matching, the parallel trend hypothesis is passed. On this basis, we proceed to the next step of regression. The results are showed in Table 7. Column (1) represents the regression of matched weight samples, with DCG coefficients being significantly 0.0995 at the 1% level. Column (2) represents the samples that satisfy the common support hypothesis, with DCG coefficients being 0.0944, which is also significant at the 1% level. Column (3) has a fixed effects regression result of 0.0934 at the 1% significant level. Explain that the results of this article in the benchmark regression section are valid.

3.2.6 Heterogeneity test

Below is an analysis of the heterogeneity under different characteristic sample groups such as the region where the enterprise is located, high-tech industry, and property rights nature. Firstly, in terms of regional differences, there are significant differences in the economic development levels among the three traditional regions of China, namely the East, West, and Central regions. On this basis, there are significant differences in digital technology infrastructure required to develop the digital economy, and the level of digital economy development varies. The gradient pattern in the East, West, and East, as well as the heterogeneity of regional resource endowments, result in heterogeneity in the impact of digital transformation on the total factor productivity of the manufacturing industry among different regions. The analysis of the impact of digital transformation in the eastern, central, and western regions on total factor productivity in table 8 columns (1)-(3) of this article shows that the digital transformation in the central region is not significant, while the coefficient in the western region is 0.378, which is much higher than the coefficient in the eastern region of 0.0934, and both are significant at the 1% P-value level, indicating a higher promoting effect in the western region. Secondly, compared to other industries, the high-tech industry already has management system differences brought about by technological factors, which can adapt to the changes in personnel management methods brought about by digital transformation more quickly. Moreover, the high-tech industry already has a certain technological and personnel

foundation,so transformation efficiency is higher.Therefore,we believe that digital transformation has a higher investment efficiency for high-tech enterprises compared to non high-tech enterprises.The columns (4) - (5) in Table 9 are grouped based on sub samples of high-tech characteristics.The results show that the DCG coefficient of column (4) is significantly 0.138 at the 1% level,while the DCG coefficient of column (5) is not significant,indicating that digital transformation has a more significant impact on the investment efficiency of high-tech enterprises.

Finally,the operational uncertainty of state-owned enterprises is covered by government,and the scale and financial strength of enterprises at a high level. At the same time,the bank oriented capital market will also concentrate more funds on state-owned enterprises,resulte in lower financing constraints. Maintaining current investment business already can meet investment needs. The market environment in which non-state-owned enterprises is highly uncertain,the degree of operational risks and financing constraints limit their development path. Therefore,we speculate that digital transformation has a more significant impact on the total factor productivity of state-owned enterprises.Columns (6)-(7) in Table 8 show the heterogeneity regression results between private and state-owned enterprises.The coefficient of DCG in column (7) is 0.260,which is significant at the 1% level.It is more significant in the regression group of state-owned enterprise samples,indicate that the impact of digital transformation on state-owned enterprises is more significant.

3.2.7Robustness check

This paper replace the explained variables,regression method and changed samples to do robustness test.In tabel 9 columns (1)-(2),explained variables were replaced by OLS and fixed effect method respectively to calculate the total factor productivity (TFP_OLS and TFP_fe).Column (3) use Tobit method to regression;Column (4) changes the sample time interval from 2015 to 2021.Compared the result with benchmark regression part,the coefficient and significance did not change much.The robustness test of the model proves that the hypothesis in this paper is valid.

4. Conclusions and policy recommendations

This paper takes A-share manufacturing listed enterprises from 2011 to 2021 as research object,analyzes the impact of different types of enterprises' digital transformation on the total factor productivity of enterprises,and then inspection and analysis from three perspectives:financing constraints,governance mechanism and agency costs.The results show that:(1)Digital transformation can effectively promote the total factor productivity of manufacturing industry;(2)The degree of financing constraints on enterprises' digital transformation will restrict digital infrastructure investment and inhibit its promotion effect on TFP,so financing constraints will reduce the promotion effect of digital transformation on TFP;(3)The management structure changes the effect of digital transformation on the total factor productivity of enterprises.There is a tradeoff space between the centralization or decentralization of power in the management structure,and the preference setting will lead to the weakening of the promotion effect of digital technology.Secondly,the existence of agency costs will also limit the promotion effect of digital technology on total factor productivity.(4)Heterogeneity test shows that the promotion effect of digital transformation on total factor productivity is more significant in state-owned enterprises and high-tech enterprises,and the impact of digital transformation on enterprises in the eastern and western regions is more obvious.

Based on above conclusions,this paper put forward following policy recommendations:First,enterprises should actively adopt digital technology to complete digital transformation.After the enterprises have passed the stage of high investment on the early stage of digital technology application,they can better exert the technical effects brought by digital transformation,alleviate the financing constraints of enterprises,optimize the management structure,reduce agency costs and improve operation efficiency of enterprises.Second,the government can provide pilot digital transformation preferential policies,which in line with local

development based on the regional market environment, to promote regional enterprises to actively complete digital transformation and upgrading. Third, the enterprise and governments can cooperate to build a platform which the information is more transparent and open. Improve the information exchange mechanism of factor market and product market, reduce the cost of investors to obtain the information of enterprise operation and the degree of digital transformation.

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