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How does digital technology affect total factor productivity in manufacturing industries? Empirical evidence from China

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ABSTRACT

Extensive studies have discussed the relationship between digital technology and total factor productivity (T.F.P.) in manufacturing industries, but far less attention is paid to the nonlinear relationship. Based on the panel data of China's manufacturing industries and matching data of National Intellectual Property Public Service Network from 2000 to 2019, this article aims to explore how digital technology affects T.F.P. in manufacturing industries. The result demonstrates that a significant inverted U-shaped relationship is between digital technology and T.F.P. The threshold in high technology manufacturing industries is larger than that in low and middle technology manufacturing industries. With the progress of digital technology, the expenditure of technology and equipment upgrading is increasing. However, the marginal return of technology and equipment is decreasing, besides technology innovation. The case of China perhaps provides new insights into manufacturing industries in developing country to gain sustainable development.

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1. Introduction

Digital technology, such as artificial intelligence, Internet of things, cloud computing, big data, 3D printing, 5G, machine learning, virtual reality, is developing rapidly (Pagliosa et al., 2019; Sturgeon, 2002). According to the *Digital Economy Development* in China (2021) published by the Ministry of Industry and Information Technology, in 2020, the China's digital economy amounted to 5.83 trillion dollars, accounting for 38.6% of the national G.D.P. However, the growth rate of added value in China's manufacturing industries is decreasing year by year even though digital technology has been widely employed. In the context of digital economy, improving the total factor productivity (T.F.P.) in manufacturing industries can effectively reduce the resource input during economic process, which is crucial for developing circular economy. Although the relationship between digital technology and manufacturing

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T.F.P. has attracted much attention from academic researchers, there is no unified view.

There are mainly two viewpoints on this topic. One view is that information technology can significantly promote T.F.P. (Graetz & Michaels, 2018). Digital technology is conductive to the application of personalised and intelligent production system in manufacturing industries (Egger & Masood, 2020). It improves automatic control ability and promotes lean production in manufacturing industries (Rossini et al., 2022). Another view inherits the earlier productivity paradox about the impact of information technology on productivity. Some scholars believe that the rapid progress of digital technology has expanded the production scale in manufacturing industries, but it does not bring the improvement of production efficiency significantly (Jorgenson et al., 2008; Oliner & Sichel, 2000; Solow, 1987). The main reason is that, the exact effect and optimal level of factor inputs in the transformation between new and old system cannot be predicted accurately, due to the limitation of resources (Youssef & ElMaraghy, 2007). Therefore, redundancy of inputs will negatively influence the T.F.P. in manufacturing industries (Brynjolfsson & Milgrom, 2013).

For existing literature, most of them measure the digital technology by composite indicators, the measurement results cannot precisely reflect the rapid development of digital technology (Aly, 2022). And sample selection generally is listed company (e.g., Xu & Guan, 2022; Zeng & Lei, 2021; Zhang et al., 2022), which cannot reflect the overall effect of digital technology on the T.F.P. in manufacturing industries. As a result, they both discussed the benefits of digital technology while not noticed the challenges brought by it, thus ignoring the nonlinear relationship.

This research contributes to the previous literature from a especial perspective: First, this article explores in detail the challenges of rapid advances in digital technology to the sustainable development in manufacturing industries. Second, it provides a theoretical explanation of the inverted u-shaped relationship between digital technology and T.F.P. in manufacturing industries from the perspective of the cost for digital transformation. Third, based on the nonlinear relationship between digital technology and the T.F.P. in manufacturing industries, this article provides new insights into the sustainable development of the manufacturing industries in specific countries and regions.

The rest of this article is organised as follows. Part 2 is theory analysis and research hypothesis. Part 3 is mainly about methodology and variables. Part 4 principally analyses the empirical test results. Part 5 is the conclusions and policy implications.

2. Literature review and hypotheses

Digital technology can reduce the cost of information transmission, improve the efficiency of market transactions and accelerate the diffusion of new knowledge as well as new technologies, which promotes technology progress in manufacturing industries (Brynjolfsson et al., 2014, 2019; Hulten & Nakamura, 2017; Lightfoot et al., 2013). And digital technology reduce the search costs and verification costs which is benefit to introduce advanced technology and equipment to meet the demand for digital transformation (Goldfarb & Tucker, 2019; Huang & Rust, 2017). In addition, digital technology can reduce the flowing barriers of production factors, avoiding the redundancy or insufficient of input and optimising the resource allocation efficiency, through the network effects of digital infrastructure (Acemoglu & Guerrieri, 2008; Ngai & Pissarides, 2007). For example, the implementation of big data solutions enables companies to better understand consumer buying behaviour and provide companies with decisions to improve product quality and optimise production processes, which improves economic sustainability and promotes T.F.P. in manufacturing (Elkhwesky et al., 2022; Koman et al.,2022). Combined with the rolling task, the ability of self-renewal in manufacturing systems can be improved by using artificial intelligence (Burke et al., 2017; Moeuf et al., 2020). Therefore, the adoption of digital technology can improve production efficiency, ensure the economic sustainability, and increase T.F.P. in manufacturing (Marino et al., 2022).

However, the relationship between digital technology and T.F.P. in manufacturing industries may not be simply positive linear, but an inverted U-shaped. As a general purpose technology, digital technology requires supporting from specific digital equipment and human resource (Toader et al., 2018). When digital technology in a low level, the requirements for equipment and human resources are relatively low, the adoption of digital technology can improve labour productivity and management efficiency (Ivanov et al., 2018). With the digital technology progress, the cost for digital transformation is more expensive, and the enterprises need new technology and equipment to product new productions to satisfy consumer before achieving cost optimisation, resulting in the mismatch and efficiency loss (Mandviwalla & Flanagan, 2021). At the same time, digital transformation requires the advance of production concept, absorption of transformation technology and redistribution of production resource, which puts forward higher requirements on the resource identification and integration ability (Barton & Thomas, 2009). If ignoring this ability and blindly pursuing the application of digital technology will lead to crowding effect of digital factors, which may negatively impact on T.F.P.

Hypothesis 1: There is an inverted U-shaped relationship between digital technology and T.F.P. in manufacturing industries.

The digital transformation in manufacturing industries is mainly reflected in technology and equipment upgrading (Gebauer et al., 2020). The adoption of digital technology in manufacturing industries requires technology upgrading, like technology innovation or introducing, absorbing and purchasing new technology. Also, replacing and renovating the equipment for digital production condition is necessary. Thus, a certain cost input is required for technology and equipment upgrading, which will affect the resource allocation efficiency (Brecher, 2015). As the growth of T.F.P. stems from the technology progress and the improvement of resource allocation efficiency (Lagos, 2006), it is feasible to explore the inverted U-shaped relationship between digital technology and T.F.P. in manufacturing from the investment for digital transformation.

The fast progress of digital technology and rapid change of market demand will drive manufacturing to expand the scale of technology and equipment upgrading (Savvides & Zachariadis, 2005). When the digital technology in a relatively low level, new technology and equipment meet the production conditions of the new products for improving the satisfaction of consumer demand and production efficiency, so the marginal return of technology and equipment upgrading is increasing, which positively effects the T.F.P. in manufacturing industries (Koman et al., 2022). When reaching a certain level, the adoption of digital technology greatly enriches the supply of products, which means that consumers can obtain more alternative products and lack of attention to a single product, resulting in a non-obvious growth of output in manufacturing industries (Rosato, 2016).

In a long term, technology and equipment upgrading require significant and sustained investment (Marino et al., 2022). When facing a certain production target, the effect of those investments may be reduced, i.e., the marginal return of technology and equipment upgrading may be decreased (Franke, 1987). Because technology upgrading may lead to insufficient absorption or low applicability (Lall, 2003), reducing the transformation effect and squeezing out other expenditures that could have been used in other places, such as improving employee skills (Mittal et al., 2020). Similarly, in the continuous equipment upgrading, the optimal process is difficult to be determined, so the equipment cannot be fully utilised, resulting the decrease of resource allocation efficiency (Applegate et al., 2006). At same time, the technological environment and digital equipment will face more cybersecurity risks, which forces the manufacturing industries to pay more attention and investment in cybersecurity management (Tvaronavičienė et al., 2020).

> Hypothesis 2: The development of digital technology can drive the manufacturing industries to expand the scale of technology and equipment upgrading, but when reaching a certain level, the marginal return for technology and equipment upgrading decreases, thus reducing the T.F.P. in manufacturing industries.

3. Methodology

3.1. Model setting

Panel data models mainly involves pooled model, fixed effects (F.E.) models and random effects (R.E.) models. The F.E. model assumes that individual effects are associated with an explanatory variable, while the R.E. model is the opposite. Under this assumption, the F.E. model is actually equivalent to the different intercept per individual (or per period), and the heterogeneity of the intercept is not random, which considers individual-varying or time-varying omitted variables (Bell et al., 2019). For avoiding the impact of unobserved heterogeneity on the estimation results, this article constructed a econometric model as follows:

$$lnTFP_{ijt} = \alpha + \beta lnDIG_{it} + \delta(lnDIG_{it})^2 + \gamma lnX_{ijt} + u_i + v_t + \varepsilon_{ijt} \tag{1}$$

where i, j, t subscript indicate provinces, manufacturing sub-sectors and time, respectively. TFP_{ijt} represents total factor productivity; $lnDIG_{it}$ is the logarithmic digital technology level; X_{ijt} is the control variable. α, u_i, v_t, ε_{ijt} are the constant term, individual F.E.s, time F.E.s and random error term, respectively. The applicability of this model will be further tested hereinafter.

Break point regression model was employed to test the inverted U-shaped relationship between digital technology and T.F.P. in manufacturing industries for robustness. The slope of the part in lower DIG value should be positive, while the slope of the part in higher DIG value should be negative. Therefore, this article divides the sample into two parts conducting linear regression, respectively. The breakpoint is DIG_c, then the regression model was set as follows.

$$TFP_{ijt} = \alpha + \beta ln(l\_DIG_{it}) + \delta ln(h\_DIG_{it}) + \rho H_{it} + \gamma ln X_{ijt} + u_i + v_t + \varepsilon_{ijt} \tag{2}$$

If $DIG_{it} \leq DIG_c$, $l\_DIG_{it} = DIG_{it} - DIG_c$, otherwise it is zero, if $DIG_{it} \geq DIG_c$, $h\_DIG_{it} = DIG_{it} - DIG_c$, H_{it}=1, otherwise it is zero. For the setting of breakpoint, this article set them by the threshold of the benchmark model and using Robin Hood algorithm based on research of Simonsohn (2018). The main idea of Robin Hood algorithm is to redivide the sample interval to change the model from the regression with higher significance to the lower one.

3.2. Variable selection

Digital technology. Referring to Xu and Guan (2022), digital technology (*DIG*) is measured by the number of authorised public invention patents of digital technology. Details are as follow: First, digital technology keywords, applicants' country (province), patent application type, I.P.C. classification and open (announcement) day were edited into index type. Second, the index was matched in the National Intellectual Property Public Service Network (N.I.P.P.S.N.), a patent retrieval and analysis database. Third, the invention patents of result were selected to obtain the number of digital technology invention patents granted per year in each region.

Total factor productivity. The measurement of T.F.P. mainly include parametric and non-parametric methods (Brandt et al., 2012). The measurement of T.F.P. by the production function beyond logarithmic stochastic frontier (S.F.A.) can better reflect the authenticity of it. Input factors mainly include the capital stock and labour stock. The output factor is the main business income of the manufacturing sub-sectors. The labour force data is the average number of manufacturing workers employed in each province (10,000). The capital stock is measured by the total number of fixed assets in each province by the perpetual inventory method. Referring to Huang et al. (2019), the depreciation rate was set at 5%.

Mechanism variable. According to hypothesis 2, the mechanism variables mainly involve technology upgrading (*Tup*), equipment upgrading (*Eup*) and marginal return of *Tup* and *Eup*. Referring to Pece et al. (2015) and Sharma et al. (2018), technology and equipment upgrading are measured by the logarithmic expenditure. Where, technology upgrading includes technology innovation (*Tin*), technology purchase (*Tpu*), technology absorption (*Tab*) and technology importation (*Tim*). And marginal return of technology and equipment upgrading is calculated by the ratio of added sales revenue to their current expenditure, expressed as *Mar_tup*, *Mar_eup*, *Mar_tin*, *Mar_tpu*, *Mar_tab*, *Mar_tim*, respectively.

Controlled variable. In order to avoid the impact of missing variables on the estimated results, the following important variables are controlled. Three variables are controlled at industry level. The profit margin of cost (*Rpce*) reflects the profitability. It means that the products are consistent with the customer's underlying utility, enabling the manufacturing to capture more value and improve value recognition ability, increasing the T.F.P. in manufacturing (Comin et al., 2020; Zeithaml et al., 2001). The capital–labour ratio (*Clr*) is the total net value divided by the worker numbers, reflecting the investment bias of the region to manufacturing and positively affecting the T.F.P. (Kakkar, 2002). Higher main business income growth rate (*Irmbr*) will translate into higher market demand, which is correlated with T.F.P. (Pilling et al., 1999). Five variables were controlled at macro level. Trade openness (*To*) is expressed as the proportion of total imports and exports to G.D.P. Opening can obtain technology spillover, thus improving T.F.P. (Ramzan et al., 2019). The intensity of government spending (*Gfe*) is measured by the proportion of public finance expenditure in regional G.D.P. The government's public infrastructures and the construction of colleges and universities have a certain effect on promoting T.F.P. (Bardaka et al., 2021). Land urbanisation rate (*Ul*) is measured by the proportion of urban built-up area to the total area of municipal districts. The higher the degree of land urbanisation, the higher the factor intensity, which has an impact on the T.F.P. of manufacturing (Kumar & Kober, 2012). The degree of intellectual property protection (*Rds*) is measured by technology market turnover as a percentage of G.D.P. Intellectual property protection can guarantee digital technology transformation and ultimately improve T.F.P. (Habib et al., 2019). The density of traffic network (*Rnd*), measured by the number of roads and railways per unit area, can reduce transportation costs, eliminate field segmentation, weaken the market power of enterprises, and improve T.F.P. (Graham et al., 2003).

3.3. Data sources

This article uses the manufacturing panel data of 30 provincial administrative regions in China from 2000 to 2019. Among them, there are many missing data in Tibet region, thus no data statistics are conducted. The data source are mainly as follows: N.I.P.P.S.N.; Provincial statistical yearbooks; China Industrial Statistical Yearbook; Enterprise research database; China Science and Technology Statistical Yearbook. The China Industrial Statistical Yearbook has not released the 2005, 2018 and 2019 edition. In this article, the corresponding data were supplemented by referring to the statistical yearbooks of each province, and the missing data of some provinces were estimated by linear interpolation method. Moreover, there were many missing data of the subdivided manufacturing in some provinces which were removed, a sample of 12,530 valid observations was finally obtained. The year 2000 was taken as the base period for price adjustment of all currency unit data. The descriptive statistics of each variable are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable name	Obs.	Mean	S.D.	Min.	Max.
TFP	12530	0.5751	1.4252	0.0004	19.0700
lnDIG	12530	4.3938	2.0563	0.0000	9.7810
To	12530	1.0374	0.7827	0.0100	2.9966
Gfe	12530	0.8541	0.1056	0.4246	0.9899
Ul	12530	1.8882	0.7005	0.8474	4.4306
Rds	12530	1.0545	0.1539	0.5966	1.5966
Rnd	12530	0.1160	0.4301	0.0001	3.0799
Rpce	12338	0.0565	0.0810	−1.8710	2.3333
Clr	12360	0.0957	0.2609	0.0012	15.6780
Irmbr	12530	0.1526	0.3123	−0.9000	1.9990

Source: calculated by authors with the original data of Chinese statistical yearbook.

Table 2. The regression results of panel data model.

Variable	(1) Pooled model	(2) RE model	(3) FE model
DIG	0.246***	0.101***	0.117***
	(8.99)	(3.46)	(3.38)
DIG^2	−0.021***	−0.009***	−0.013***
	(−7.43)	(−4.67)	(−4.43)
To	0.262***	0.075*	0.075*
	(9.24)	(1.83)	(1.94)
Gfe	−0.620***	−0.548***	−0.916***
	(−4.67)	(−3.94)	(−3.48)
Ul	0.073**	0.005	0.033
	(2.24)	(0.17)	(0.66)
Rds	0.1768*	0.071	0.070
	(1.69)	(0.55)	(0.57)
Rnd	0.087***	0.009	0.003
	(3.11)	(0.70)	(0.71)
Rpce	0.2045	0.096	0.024
	(1.23)	(0.59)	(0.21)
Clr	0.039	0.029	0.024
	0.79	(1.08)	(0.92)
Irmbr	0.007*	0.022	−0.015
	(1.72)	(0.47)	(−0.66)
Cons	0.439**	0.682***	0.903**
	(2.40)	(3.34)	(2.90)
F test			21.32***
			(0.0000)
Breusch-Pagan LM test		1260.77***	
		(0.0000)	
Hausman test		78.38***	
		(0.0000)	
Individual fixed	No	Yes	Yes
Time fixed	No	Yes	Yes
R^2	0.0208	0.0820	0.0927
Observations	12295	12295	12295

Note: ***, ** and * are significant at the level of 1%, 5% and 10%, and the values in parentheses are the t-value, similarly hereinafter.
Source: calculated by authors with the original data of Chinese statistical yearbook.

4. Results and discussion

4.1. Panel data model

Columns (1) to (3) in Table 2 report the regression results of Pooled Model, R.E. Model and F.E. Model, respectively. Through the result of F test, the null hypothesis is rejected, choosing F.E. model over Pooled model. From the result of B-P LM test, the p-value is significantly zero, which means the R.E. model is more appropriate. It illustrates that there is a significant individual effect. By the result of Hausman test, the p-value is significantly zero, which means to reject the null hypothesis to choose F.E. model over R.E. model.

It can be found in column (1) to (3) that the coefficient of digital technology is significantly positive, while its squared term is significantly negative, indicating an inverted U-shaped non-linear relationship between digital technology and T.F.P. in manufacturing industries. Hypothesis 1 is confirmed. The thresholds are 5.857, 5.611 and 4.500, respectively. When digital technology level is lower than the threshold, the digital technology progress will increase the T.F.P. in manufacturing industries. And when digital technology level is higher than the threshold, the digital technology progress will decrease the T.F.P.

For the control variable, the coefficient of trade openness is significantly positive, indicating that the technology spillover effect obtained from opening to the outside world significantly increases the T.F.P. in manufacturing industries. Government fiscal expenditure intensity decreases the T.F.P. The possible reason is that in the present stage China's infrastructures has been relatively mature, and the local government to the traditional infrastructures spending is mainly in terms of operation and maintenance, but the economic effect of new infrastructures investment such as the inter-city rail transit construction has yet to embody. On the other hand, traditional infrastructures spending can crowd out private investment and reduce regional market dynamism. The coefficient of land urbanisation rate is not significant, indicating that the cost effect caused by land rent and production factors is significantly stronger than the market proximity effect, thus it does not increase the T.F.P. in manufacturing.

4.2. Robustness test

Breakpoint regression testing the inverted U-shaped relationship. Columns (1) to (2) in Table 3 report the results using the threshold as the breakpoint, and column (3) to (4) report the results using Robin Hood algorithm to calculate the breakpoint. It can be found that the regression coefficient is significantly positive on the left side of the breakpoint, while it is significantly negative on the right side, indicating that the inverted U-shaped relationship is robust.

Replacing explained variable. The T.F.P. is reflected the efficiency in production, which takes into account the number of resources utilised in the production process.

Table 3. Robustness test results of breakpoint regression method.

	(1)	(2)	(3)	(4)
	The breakpoint is 4.500		The breakpoint is 3.921	
Variable	Left side	Right side	Left side	Right side
DIG	0.0764*	−0.120*	0.046***	−0.199*
	(2.39)	(−1.79)	(3.34)	(−2.21)
Control variable	Yes	Yes	Yes	Yes
R^2	0.0945	0.1367	0.0912	0.1501
Observations	6465	5830	5362	6933

Source: calculated by authors with the original data of Chinese statistical yearbook.

Table 4. Robustness test results.

Variable	(1) Replacing explained variable	(2) Replacing explanatory variable	(3) Tailor processing	(4) Additional control variables
DIG	0.040***	0.092*	0.119**	0.180*
	(7.84)	(1.97)	(3.30)	(2.05)
DIG^2	−0.005**	−0.010*	−0.013***	−0.016*
	(−2.89)	(−1.96)	(−4.11)	(−1.78)
Additional control variable	No	No	No	Yes
Control variable	Yes	Yes	Yes	Yes
R^2	0.6869	0.4330	0.0920	0.3249
Observations	12295	12295	12183	12295

Source: calculated by authors with the original data of Chinese statistical yearbook.

Referring to the measurement method of efficiency by Korshenkov and Ignatyev (2020), this article replaces the explained variable with the efficiency in manufacturing industries for robustness test. Columns (1) of Table 4 shows the parameter estimation results. It can be found that the coefficient of digital technology is significantly positive, while its squared term is significantly negative, which is consistent with the results of Table 2.

Replacing explanatory variable. The integration of digital technology with economy and society promotes the digital transformation of manufacturing, so its development is basically consistent with the growth of digital enterprise. This article selects the annual number of digital enterprises in China (N_{cdt}), the number of enterprises above designated size in each province (N_{pst}), to calculate the proportion of the number of enterprises. Then, the N_{cdt} is multiplied by the proportion of the N_{pst} to approximate the number of digital enterprises in each province (N_{pdt}), which is regarded as a substitute variable of digital technology for robustness test. Column (2) of Table 4 reports the parameter estimation results of digital technology and its squared term. The results show that the coefficient of digital technology is significantly positive, while its squared term is significantly negative, which is consistent with the benchmark test.

To eliminate the influence of sample outliers on the benchmark model and verify the robustness of it, this article also conducted regression on the samples after tail shrinking at 1% and 99% levels. Column (3) of Table 4 reports the parameter estimation results of digital technology and its squared term. In order to reduce the influence of omitted variables on the regression results, control variables such as the proportion of insured persons (reflecting the degree of social security in the region), the number of enterprises (reflecting the degree of competition among enterprises in the region) and the Herfindahl index of employed persons in regions (reflecting the degree of monopoly in manufacturing) were added to further proof the robustness. The parameter estimation results are reported in column (4) of Table 4.

Endogeneity may lead to biased parameter estimation results. Due to the non-linear relationship between digital technology and T.F.P., when the T.F.P. increases, the growth rate of manufacturing is faster, which is conducive to the R&D (research and development) of digital technology. Therefore, there may be endogeneity problems in the benchmark model. On the other hand, because of the limitation of the data, the matching index may exist measurement error which is related to the unobservant

Table 5. Regression results of 2SLS and Heckman two-stage method.

Variable	(1) IV1	(2) IV2	(3) First stage	(4) Second stage
DIG	0.292***	0.214*		0.126***
	(11.95)	(1.78)		(3.24)
DIG^2	−0.027***	−0.015***		−0.016***
	(−10.48)	(−3.05)		(−4.58)
Imr				0.963**
				(2.59)
Adt			0.027***	
			(9.66)	
Control variable	Yes	Yes	Yes	Yes
K-P LM statistic	734.271***	241.239***		
K-P Wald F statistic	905.924***	44.246***		
R^2	0.1565	0.2089	0.6330	0.0943
Observations	12295	11158	11441	11441

Note: The Kleibergen-Paap rk LM statistic and Kleibergen-Paap rk Wald F statistic are the tested value for inadequate identification of tool variable and weak identification.
Source: calculated by authors with the original data of Chinese statistical yearbook.

factors that affect the T.F.P. This makes the endogenous problems of estimation. Therefore, this article takes the interaction items of the logarithm of the distance from the provincial capital city to the coastal port ($lnDis_{pt}$) and digital enterprise stock (lnN_{pdt}), the relief (Slo_{pt}) and digital enterprise stock as instrumental variables (I.V.1) to solve the endogeneity problems (Bai, 2021). In addition, in order to solve the endogenous problem of mutual causation mentioned above, the lagging term (*L.DIG*) and the lagging phase of the squared term ($L.\ DIG^2$) are also adopted as instrumental variables (I.V.2.).

Columns (1) to (2) in Table 5 report the results of two-stage least square method with I.V.1. and I.V.2.. The results show that there is a significant inverted U-shaped relationship between digital technology and T.F.P., and reject the null hypothesis of insufficient recognition of I.V.s and weak I.V.s, indicating that the tools selected are relatively appropriate. Therefore, the inverted U-shaped relationship between digital technology and T.F.P. is still robust with the consideration of endogeneity.

Treatment of the sample self-selection bias. The surplus funds for digital transformation may increase T.F.P. in manufacturing industries, which causes sample self-selection bias. Referring to Boese et al. (2021), Heckman two-stage model is employed to solve this problem. For the first stage, the Probit model is constructed to calculate the inverse Mills ratio (*Imr*), where the ability of digital transformation (*Adt*) is as an exclusivity constraint variable measured by the ratio of the total profit (the sum of main business and other business profits) to the digital transformation cost, and the explained variable is a binary variable set as below:

$$\begin{cases} Digital\ \ transfomation1 = 1\ \ if\ \ digital\ \ technology\ \ level\ \ > average\ \ value \\ Digital\ \ transfomation1 = 0\ \ otherwise \end{cases}$$

When the digital technology level is above the average, manufacturing enterprises tend to promote the digital transformation after weighing the profits and digital transformation costs, improves the level of digital technology. The second stage requires to calculate the *Imr* from the Probit regression result and add it into Model (1) to eliminate sample self-selection bias.

Columns (3) in Table 5 reports the results of the first stage, which indicate that the improvement of digital transformation ability can promote digital technology progress. Columns (4) in Table 5 reports the results of the second stage, where the coefficient of *Imr* is significantly positive and the vif value of *Imr* is 8.03, indicating that there is a sample self-selection bias and no multicollinearity. The inverted U-shaped relationship between digital technology and T.F.P. is still robust.

4.3. Heterogeneity analysis

At present, 70% of China's manufacturing is low and middle technology processing manufacturing (Li et al., 2021). Therefore, the inverted U-shaped relationship between digital technology and T.F.P. of manufacturing may be due to the large overall scale of low and middle technology manufacturing industry. Considering the heterogeneity of manufacturing industries, it has a periodical effect on T.F.P. Therefore, this article groups the samples based on the density of input and technology for discussing the heterogeneity of the inverted U-shaped relationship between digital technology and T.F.P. (Dai et al., 2018). The regression results are shown in Table 6.

Columns (1) to (3) of Table 6 report the regression results classified by intensity of factor input. The results show that there is a significant inverted U-shaped relationship between digital technology and T.F.P. in labour, capital and technology intensive manufacturing. According to the calculation, the digital technology threshold of labour, capital and technology intensive manufacturing are 0.436, 3.333 and 7.409, respectively. It means that digital technology has not improved the T.F.P. in labour-intensive manufacturing. When the value of digital technology is lower than the threshold, it can significantly increase T.F.P. in capital and technology intensive manufacturing. On the contrary, it will show a inhibitory effect.

Columns (4) to (6) of Table 6 report the regression results of technology intensity. The results show that there is a significant inverted U-shaped relationship between digital technology and T.F.P. in low, middle and high technology manufacturing industries. According to the calculation, the digital technology threshold values in low, middle and high technology manufacturing industries are 0.500, 3.154 and 8.222, respectively. It indicates that digital technology negatively influences the T.F.P. in low technology manufacturing. For the middle and high technology manufacturing, only

Table 6. The results of industry heterogeneity.

Variable	(1) Labour intensive	(2) Capital intensive	(3) technology intensive	(4) Low technology	(5) Middle technology	(6) High technology
DIG	0.0157	0.152***	0.163**	0.040	0.164**	0.148**
	(0.29)	(3.99)	(3.24)	(0.98)	(3.31)	(2.64)
DIG^2	−0.018***	−0.024***	−0.011***	−0.020***	−0.026***	−0.009***
	(−3.56)	(−6.58)	(−3.92)	(−5.04)	(−5.65)	(−4.57)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
F-value	72.52	138.55	55.24	110.35	112.81	75.50
R^2	0.3551	0.3106	0.2673	0.3439	0.3122	0.2787
N	3382	6086	4339	5364	5456	3209

Source: calculated by authors with the original data of Chinese statistical yearbook.

when the values of digital technology is lower than threshold, it will increase the T.F.P.

At present, the average level of digital technology in China is 7.131, higher than the threshold level of capital and middle technology manufacturing, lower than that of technology intensive and high technology manufacturing, which can be demonstrated that digital technology is still increasing the T.F.P. of technology intensive and high technology manufacturing. For other manufacturing industries (capital and labour intensive, low and middle technology), digital technology decreases T.F.P.

4.4. Mechanism test

Table 7 reports the effect of digital technology on the expenditure of technology and equipment upgrading. In column (1), the coefficient of digital technology and its squared term are significantly positive, indicating a U-shaped relationship between digital technology and technology upgrading. The result in column (2) manifests a positive linear relationship between digital technology and equipment upgrading expenditure, indicating the continuously growing demand for equipment upgrading. Therefore, with the development of digital technology, the scale of technology and equipment upgrading is increasing. It can be found in column (3) that digital technology has a significant U-shaped relationship with the technology innovation, and the threshold is less than 0. It demonstrates that the adoption of digital technology has significantly promoted the input of technology innovation. In column (4), the coefficient of digital technology is significantly positive while the squared term is negative, which means an inverted U-shaped relationship between digital technology and technology purchase. The threshold is 8.370, larger than the current average 7.400. From the result of column (5) and (6), it shows that digital technology is positively correlated with expenditure of technology absorption and importation. With the progress of digital technology, it requires more spending on technology absorption and importation for the digital transformation in manufacturing.

Table 8 reports the effect of digital technology on the marginal return of technology and equipment upgrading. The result in column (1) manifests an inverted U-shaped relationship between digital technology and the marginal return of technology upgrading, and the threshold is 5.25. Column (2) manifests that the coefficient of digital technology is positive and the squared term is negative, indicating that an inverted U-shaped relationship between digital technology and the marginal return of equipment upgrading, and the threshold is 2.00, far less than the threshold between

Table 7. The effect of digital technology on technology and equipment upgrading.

Variable	(1) *Tup*	(2) *Eup*	(3) *Tin*	(4) *Tpu*	(5) *Tab*	(6) *Tim*
DIG	0.058**	0.041***	0.187***	0.385***	0.576***	0.016
	(2.49)	(3.20)	(4.75)	(7.20)	(9.09)	(0.38)
DIG^2	0.009***	−0.006	0.002*	−0.023***	−0.051	0.013***
	(3.51)	(−1.56)	(1.78)	(−4.17)	(−1.15)	(5.64)
Control variable	12295	Yes	Yes	Yes	Yes	Yes
R^2	0.2372	0.0946	0.1436	0.0849	0.0981	0.1158
N	12295	12295	12295	12295	12295	12295

Source: calculated by authors with the original data of Chinese statistical yearbook.

Table 8. The effect of digital technology on the marginal return.

Variable	(1) *Mtup*	(2) *Meup*	(3) *Mtin*	(4) *Mtpu*	(5) *Mtab*	(6) *Mtim*
DIG	0.105**	0.040***	0.039***	0.006	−0.008***	−0.004***
	(2.10)	(10.53)	(11.52)	(1.24)	(−3.88)	(−5.28)
DIG^2	−0.010***	−0.010**	−0.002***	−0.001***	0.048	−0.003
	(2.81)	(−2.56)	(−5.71)	(−5.24)	(1.22)	(−0.78)
Control variable	0.5870	Yes	Yes	Yes	Yes	Yes
R^2	0.5870	0.5999	0.5806	0.5858	0.5402	0.6224
Observations	0.5870	12,295	12,295	12,295	12,295	12,295

Source: calculated by authors with the original data of Chinese statistical yearbook.

digital technology and T.F.P. In column (3), the coefficient of digital technology is significantly positive while the squared term is negative, indicating an inverted U-shaped relationship between digital technology and the marginal return of technology innovation. The threshold is 9.75, higher than the current average. From column (4) to (6), the results show that digital technology is negatively correlated with the marginal return of technology purchase, absorption and importation.

5. Conclusions and implications

This article aims to study the effect of digital technology on T.F.P. in manufacturing industries. The result shows a significant inverted U-shaped relationship between digital technology and T.F.P. in manufacturing industries. Digital technology has heterogeneous effects on the T.F.P. in different technology-intensive manufacturing. The threshold in high technology manufacturing industries is larger than that in low and middle technology manufacturing industries. With the progress of digital technology, the expenditure of technology and equipment upgrading is increasing. However, the marginal return of technology purchase, absorption and importation is decreasing. There is an inverted U-shaped relationship between digital technology and the marginal return of technology upgrading, as well as the marginal return of equipment innovation. The threshold of the marginal return of technology and equipment upgrading is approximate to that of T.F.P., indicating the decline of T.F.P. in manufacturing is due to the decrease of the marginal return. However, the threshold of the marginal return of technology innovation is larger than current average level of digital technology, shows that technology innovation can bring higher sales revenue.

Based on the above research results, this study also has several practical implications to develop the circular economy and improve the threshold level of inverted U-shaped curve between digital technology and T.F.P. in manufacturing. First, the efficient production in manufacturing requires optimising the industrial structure, that is, to support the transformation of labour- and capital-intensive manufacturing to technology intensive, and transformation of low technology and middle technology manufacturing to high technology manufacturing. Second, improving the T.F.P. in manufacturing industries needs to create a good environment for technology innovation and support innovation activity. Third, promoting the digital transformation progressively can avoid the insufficient absorption of technology and inadequate usage of equipment, optimise the resource allocation efficiency and increase the marginal return of technology and equipment upgrading.

This article unavoidably has some limitations, which reveal opportunities for further study. In this article, the inverted U-shaped relationship was examined. Since the sample period is in the expansion period of the digital transition, this phenomenon may be cyclical. So further studies can focus on the effect of digital technology after digital transformation basically finished. This article mainly focuses on the effect of digital technology on T.F.P. in manufacturing. However, the adoption of digital technology can improve the efficiency of resource utilisation and reduce pollution emissions, which is crucial to the develop circular economy. This article did not discuss the impact of digital technology on circular economy, but it is worthy to be explored further. Due to the limited availability of data related to equipment upgrading in manufacturing industries, this article did not discuss the effect of digital technology on the specific aspect of equipment upgrading, like replacing and renovating the equipment. More detailed industry data is necessary.

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