The Impact of Digital Transformation on the Total Factor Productivity of Manufacturing Firms: The Mediating Effect of Dynamic Capabilities

Diandong Zhang[1], and Sheng Zhao[1,*]

[1] School of Management, Zhengzhou University, Zhengzhou, 450001, China
*zhao@zzu.edu.cn

Abstract. The 14th Five-Year Plan for the Development of the Digital Economy issued by the China State Council emphasizes the importance of digital transformation in improving total factor productivity and promoting high-quality economic development. An empirical investigation of how digital transformation affects the total factor productivity of manufacturing firms can help provide motivation and guidance for their digital transformation. The paper selects the manufacturing firms listed on China's A-share market from 2015 to 2022 as the research sample, and constructs a two-way fixed-effects model for empirical testing, which shows that digital transformation plays a significant role in boosting the total factor productivity of manufacturing firms, and dynamic capabilities play a partly mediating role in it. The effect of digital transformation on total factor productivity also shows differences in firms with different sizes and holding nature. The study helps manufacturing firms recognize the advantages of digital transformation and provides informative management recommendations for the government on how to promote digital transformation in different types of manufacturing firms.

Keywords: Digital transformation, Manufacturing firms, Dynamic capabilities, Total factor productivity, Empirical research.

1 INTRODUCTION

China's economy is in a phase of transition from rapid growth to high-quality growth. With serious challenges such as increasingly constrained resources, fierce international competition and serious environmental pollution, the traditional growth mode dominated by resource consumption and low-cost advantages is no longer sustainable. In order to achieve sustainable, healthy and stable economic development, China urgently needs to change its economic development mode, and improving total factor productivity (TFP) has become the key to the change. An increase in TFP will help to improve the competitiveness and sustainable development capability of China's economy, thus transitioning to the high-quality and high-efficiency development mode.

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The digital transformation of China's manufacturing is necessary for China to transition to high efficiency development. But there are significant differences in the digitalization levels among the variety of manufacturing firms. Many firms, especially small and medium-sized ones, continue to use traditional approaches in production and management, lacking awareness and capabilities for digital transformation.

It is important to examine how digital transformation affects the TFP of manufacturing firms. It will help to see clearly the actual role of digital transformation in production activities of firms, thus to motivate and guide firms towards digitalization. Furthermore, it will provide theoretical support and practical direction for the government to formulate effective policies on digital transformation.

The main contributions of the paper are: (1) To examine how digital transformation affects TFP, the paper constructs a correlation model about digital transformation, dynamic capabilities, and TFP, followed by an empirical testing to determine whether dynamic capabilities play a mediating role between digital transformation and the TFP. (2) The measurement of dynamic capabilities is more comprehensive and reliable. Most of the existing studies related to dynamic capabilities use questionnaires or case studies together with the measurement scales to quantitatively analyze dynamic capabilities, which is limited in the amount of data obtained and often affected by the subjective views of the investigators. The paper collects data from A-share listed manufacturing firms from 2015-2022, which is much wider and more objective.

The rest of the paper is organized as follows: Sect.2 reviews the literature and presents the hypotheses; Sect.3 introduces the research design; Sect.4 illustrates the empirical results and analysis; and Sect.5 presents the conclusions.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Literature Review

Total Factor Productivity (TFP) is an indicator used to measure the efficiency of production process in which inputs are used to generate output. It represents the portion of output growth that cannot be attributed to the growth of traditional inputs such as labor and capital. TFP reflects technological progress and innovation in a firm, industry, or economy.

There is a debate in the academic community on whether digital transformation can have a positive impact on TFP. Some scholars believe that digital transformation does not have a significant effect on TFP and may even have a negative correlation. The proponent of TFP, Solow, proposed Solow's paradox in 1987 in response to information disclosed by the U.S. Bureau of Labor Statistics. With the emergence of information technology, TFP has not increased or even declined to some extent. Syverson et al. (2017) [1] found that productivity growth in the United States has been slowing since 2004, despite the widespread adoption of ICTs. And the growth created by digital technologies has fallen far short of the losses caused by the productivity slowdown. Capello et al. (2022) [2] conducted further research on Solow's paradox, which showed that new technologies typically have a positive effect on the productivity of the sectors that adopt them. However, the extension of this effect to the entire regional economy is dampened by the reallocation of employment towards less productive sectors.

Some studies have confirmed that digital transformation have a positive impact on TFP. The main mechanisms of the impact are to alleviate financing constraints, enhance innovation capacity, and improve resource allocation capacity. Chen et al. (2022) [3] found that the digitalization of financial services can alleviate the financing constraints of listed firms in cities with concentrated financial resources. Guo et al. (2022) [4] showed that the application of digital technology enhances the transparency of firms' financial and credit information, enabling financial institutions to screen out quality firms more quickly, which makes financial institutions more willing to grant loans to these firms and alleviates their financing constraints. Financing constraints directly limit the ability of firms to invest, but also limit their access to international markets or new areas of business [5]. Alleviating financing constraints can have a positive impact on TFP. According to Nwankpa et al. (2017) [6], the use of digital technologies in firms has led to the creation of open innovation platforms, facilitating the participation of consumers and external members in the firm's innovation process, and creating a closer innovation ecosystem. In addition, the impact of digital transformation lies in increasing returns to scale. By digital transformation, firms can better address innovation dilemmas and improve the TFP gains brought by increased innovation investment [7]. The study of Lyu et al. (2023) [8] confirmed that digital transformation can enhance the advantages in information collecting and processing during data production, and help firms improve the efficiency of resource allocation, such as improving the efficiency of investment, reducing the cost of external transactions, and broadening customer resources.

In summary, it is still debatable whether digital transformation can contribute to the improvement of TFP. In addition, although there have been many studies on the correlation between digital transformation and TFP, there are few on its impact path. The paper uses dynamic capabilities as a mediating mechanism to find out whether digital transformation can have a positive impact on TFP.

2.2 Research Hypothesis

Digital transformation can improve the TFP of manufacturing firms, which is mainly reflected in the role of digital technology in helping firms to acquire heterogeneous resources. Resource-based theory emphasizes that the heterogeneous resources and capabilities possessed by firms are the source of their competitive advantages [9]. Digital technology is a heterogeneous resource, and digital transformation helps firms to acquire and integrate resources, thus acquiring heterogeneous resources [10]. Acquiring heterogeneous resources is important for promoting the improvement of TFP. Heterogeneous resources can provide valuable competitive advantages for firms due to their uniqueness and differences, and play a unique role in the production and operation processes, which leads to differentiated results. These differentiated results may be reflected in product innovation, service enhancement or cost reduction, and help firms gain larger shares of the market and higher profits, affecting positively their TFP [11].

Therefore, we propose *Hypothesis 1*. Digital transformation positively affects the TFP of manufacturing firms.

Dynamic capability has been a hot research topic in the field of firm strategic management. First proposed by Teece(1994) [12], it indicates the ability of firms to fully utilize their internal and external resources when facing a complex external environment, and is a key factor for firms to maintain their core competitiveness under the pressure of market competition. The paper draws on the definition of dynamic capability by Wang et al (2007) [13], and divides dynamic capability into three dimensions: absorptive, adaptive, and innovative capabilities. Digital transformation will positively affect the absorptive, adaptive, and innovative capacities of firms from the dimensions of perception and resource integration capacities.

With application of information technology, firms are able to strengthen their ability to perceive the outside world [14]. Effective perception of the external environment enables firms to adjust their resources flexibly and efficiently. Firms adjust their competitive advantages dynamically to adapt to the changing market environment, customer demand and competition. Faster resource allocation implies the creation of heterogeneous resources [15]. Therefore, we propose *Hypothesis 2*. Digital transformation positively affects the TFP of manufacturing firms by enhancing their adaptive capacity.

Digital transformation provides firms with more data sources and information acquisition channels, enabling them to access a wider range of knowledge and cutting-edge technologies. It provides firms with powerful information analysis tools, which strengthen their ability to absorb knowledge and technology [16]. With strong absorptive capacity, firms are able to efficiently filter and integrate the acquired information and knowledge, and transform them into heterogeneous resources. Therefore, we propose *Hypothesis 3*. Digital transformation positively affects the TFP of manufacturing firms by enhancing their absorptive capacity.

Digital transformation enables firms to make decisions based on in-depth analysis and mining of data to understand market demand, consumer behavior and competitor dynamics, which points out the way for innovation [17]. And it improves the allocation efficiency of resources by introducing open innovation platforms, more efficient organizational structures and more open organizational cultures [18], thus enhancing innovation capability and promoting the generation of heterogeneous resources. Therefore, we propose *Hypothesis 4*. Digital transformation positively affects the TFP of manufacturing firms by enhancing their innovation ability.

3 RESEARCH DESIGN

3.1 Data Source

Based on the 2012 industry classification of the China Securities Regulatory Commission (CSRC), and considering the availability of sample data, the paper selects A-share listed manufacturing firms from 2015 to 2022 as the research sample. The sample selection process involves the following steps: (1) excluding ST, *ST, PT-type firms from the sample; (2) removing firms with abnormal or missing data; (3) excluding firms that have changed in industry type during the sample period. The data is winsorized at the

1% and 99% percentiles. Finally, 1924 eligible firms that meet the criteria are obtained, forming panel data with a total of 11,608 observations.

The data sources used for the empirical analysis are as follows: the word frequency of digital transformation, the data of R&D expenditure, number of R&D personnel, capital expenditure, and advertising expenditure required to measure dynamic capabilities are all sourced from the annual reports of the sample firms. The data on firm age, nature of equity, proportion of independent directors, equity concentration, and number of employees are obtained from the CSMAR（China Stock Market & Accounting Research） database, which is a comprehensive research-oriented database focusing on China Finance and Economy. The financial data used to calculate TFP and some control variables are obtained from the WFT and CNRDS databases. WFT（Wind Financial Terminal）is a leading platform in China, which provides global financial data, information and insights on all asset classes as well as commercial data in macroeconomics, industry sectors and corporate operations. CNRDS (Chinese Research Data Service Platform) is a high-quality, open, and comprehensive data platform for economic, financial, and business research in China.

3.2 Definitions of Variables

(1) Explained variables

Total Factor Productivity (TFP): Currently, the most commonly used methods for measuring TFP are OLS (Ordinary Least Squares), FE method (Fixed Effects method), OP method (Olley and Pakes method), and LP method (Levinsohn and Petrin method). Among them, LP method is used more frequently, which overcomes the problems of simultaneity bias and sample selection bias that are common in the process of measuring TFP. The paper uses the LP method to measure the TFP of the sample firms.

$$lnY_{i,t} = \beta_0 + \beta_1 lnL_{i,t} + \beta_2 lnK_{i,t} + \beta_3 lnM_{i,t} + \beta_4 age_{i,t} + \sum_m \delta_m year_m + \sum_j \gamma_j reg_j + \varepsilon_{i,t} \tag{1}$$

$$TFP_{i,t} = Exp(lnY_{i,t} - \beta_1 lnL_{i,t} - \beta_2 lnK_{i,t}) \tag{2}$$

Where, Y is the firm's outputs, L is the labor inputs, K is the capital inputs, M is the intermediate inputs. Drawing on Song et al. (2021) [19], labor inputs are measured using the number of employees in the firm, capital inputs are measured using the firm's fixed assets, and intermediate inputs are measured using sales minus value added, where value added is the sum of depreciation, workers' compensation, net production tax and operating surplus.

(2) Explanatory variables

Digital Transformation Index (DTI): The paper draws on Wu et al.'s (2021) [20] feature word mapping, and uses python to count the keyword frequencies of digital technology and its application scenarios in the annual reports of sample firms. The word frequencies are summed, and the logarithm is taken after adding 1 to overcome the right-biased distribution of the data to obtain the DTI data.

(3) Mediating variables

The paper takes into account the reliability and measurability of data, and measures the three dimensions of dynamic capabilities using the research method of Yang et al. (2020) [21].

Absorptive capacity (AP) = R&D expenditure/total firm assets

Adaptive Capacity (AC) = the intensity of R&D expenditure and the proportion of R&D personnel normalized separately and summed up

Innovative Ability (IA) = $-\frac{\sigma}{mean}$ (where σ is the standard deviation of the three main expenditure intensities, R&D, capital and advertising, and *mean* is the mean of the three expenditure intensities)

(4) Control variables

The control variables selected in the study include firm age (age), nature of equity (stata), asset-liability ratio (lev), proportion of independent directors (Indep), equity concentration (top5), Tobin's Q value (TobinQ), Rate of Return on Common Stockholders' Equity (roe), number of employees (size), management expense ratio (Mfee), and growth rate of operating income (growth).

The definition of all the above variables are shown in table 1.

Table 1. Variable definition.

Variable Type	Variable Name	Variable definition
Explained Variable	TFP	Measuring the TFP of an firm using the LP method
Explanatory Variable	DTI	$\ln(\text{Total word frequency of feature words} + 1)$
Control Variable	age	$\ln(\text{firm age} + 1)$
	state	1 for state-controlled, 0 otherwise
	lev	Total liabilities at year-end/total assets at year-end
	Indep	Proportion of independent directors to the total number of board members
	top5	Shareholding ratio of top 5 shareholders
	TobinQ	(Market value of outstanding shares + number of shares not in circulation × net assets per share + book value of liabilities)/Total assets
	roe	Net profit/average balance of shareholders' equity
	size	$\ln(\text{number of employees} + 1)$
	Mfee	Administrative expenses/operating income
	growth	Current year's operating income/previous year's operating income - 1
Mediating Variable	AP	R&D expenditure/total business assets
	IA	R&D expenditure intensity and R&D headcount ratios normalized and summed separately
	AC	$-\frac{\sigma}{mean}$, where σ is the standard deviation of the three main expenditure intensities, R&D, capital and advertising, and *mean* is the mean of the three expenditure intensities

3.3 Model Setup

In order to verify the mediating effect of dynamic capabilities (absorptive capacity, innovative capacity, and adaptive capacity) in the impact of digital transformation on TFP, the paper uses the three-step test model of mediating effect established by Wen et al. (2014) [22].

(1) Basic regression model

TFP taken as the explained variable, DTI the explanatory variable, and with control variables, model (3) is established to test the relationship between digital transformation and TFP.

$$TFP_{i,t} = \alpha_0 + \alpha_1 DTI_{i,t} + \alpha Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{3}$$

(2) Mediation effects model

Models (4), (5), (6) are developed to verify whether digital transformation can positively affect the adaptive, absorptive, and innovative capabilities.

$$AC_{i,t} = \beta_0 + \beta_1 DTI_{i,t} + \beta Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{4}$$

$$AP_{i,t} = \beta_0 + \beta_2 DTI_{i,t} + \beta Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{5}$$

$$IA_{i,t} = \beta_0 + \beta_3 DTI_{i,t} + \beta Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{6}$$

Models (7), (8), (9) are developed to test whether adaptive capacity, absorptive capacity, and innovative capacity play mediating roles in the impact of digital transformation on TFP.

$$TFP_{i,t} = \gamma_0 + \gamma_1 DTI_{i,t} + \gamma_4 AC_{i,t} + \gamma Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{7}$$

$$TFP_{i,t} = \gamma_0 + \gamma_2 DTI_{i,t} + \gamma_5 AP_{i,t} + \gamma Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{8}$$

$$TFP_{i,t} = \gamma_0 + \gamma_3 DTI_{i,t} + \gamma_6 IA_{i,t} + \gamma Con_{i,t} + \mu_t + \mu_i + \varepsilon_{i,t} \tag{9}$$

4 Empirical Results

4.1 Descriptive Statistical Analysis

Table 2. Results of the descriptive statistics

Variable	Obs	Mean	SD	Min	Mediam	Max
TFP_LP	11608	8.3453	0.9238	6.3532	8.3147	10.8943
DTI	11608	1.4811	1.2811	0	2.4584	4.7701
AC	11608	-0.7701	0.322	-0.8475	-0.6268	-0.0757
IA	11608	0.1075	0.1311	0.0000	0.0845	0.1424
AP	11608	0.0273	0.0203	0.0091	0.0215	0.2762
age	11608	2.4361	0.5261	0.6721	2.4974	3.4582
state	11608	0.3024	0.4890	0	0	1
lev	11608	0.3893	0.1781	0.0560	0.4351	0.8252
Indep	11608	0.3767	0.0538	0.2857	0.4251	0.6354
top5	11608	0.5329	0.1429	0.1876	0.3564	0.8920
TobinQ	11608	2.2035	2.3995	0.8024	3.2535	16.6445
roe	11608	0.1386	0.1227	0.0096	0.1447	0.4151
size	11608	7.8677	1.1377	4.5432	7.7421	13.2547
Mfee	11608	0.0471	0.0535	0.0068	0.0447	0.1462
growth	11608	0.1861	0.3536	-0.4653	0.1879	3.8940

Table 2 shows the results of the descriptive statistics of the explained variables, explanatory variables, mediating variables, and control variables in the sample. It can be seen that there are some differences in the TFP of the firms in the sample. The data distribution of the DTI of the firms is skewed, with a small number of firms having a high degree of digital transformation, but majority of firms having a low degree of transformation. The DTI data shows that the sample firms are generally not highly digitally transformed and that there are vast variations among firms. Some firms have undergone active digital transformation, whereas majority still have been in the early stages of the transformation or have not started at all. The polarization is consistent with the fact that China's manufacturing firms started digital transformation relatively late.

4.2 The Results of Baseline Regressions

Table 3. Base regression and mediation effect test results

Variabe	(1) TFP	(2) AC	(3) TFP	(4) AP	(5) TFP	(6) IA	(7) TFP
DTI	0.062***	0.105***	0.053***	0.010***	0.060***	0.015***	0.059***
	(7.54)	(7.52)	(6.98)	(4.12)	(5.43)	(5.14)	(6.91)
AC			0.086***				
			(12.03)				
AP					0.216***		
					(11.97)		
IA							0.174***
							(12.57)
age	0.048*	-0.027	0.054*	0.012	0.051*	0.013	0.057*
	(1.83)	(-0.43)	(1.94)	(0.98)	(1.76)	(0.87)	(1.88)
lev	0.796***	0.147***	0.833***	0.011***	0.798***	0.031***	0.896***
	(14.57)	(3.11)	(12.38)	(4.36)	(14.68)	(3.15)	(14.67)
roe	1.358***	0.911***	1.274***	0.098*	1.014***	0.354**	1.342***
	(13.84)	(4.34)	(13.71)	(1.87)	(14.65)	(2.05)	(15.36)
state	0.957***	-0.099*	0.984***	-0.074*	0.973***	-0.087*	0.871***
	(28.77)	(-1.74)	(31.88)	(-1.71)	(28.73)	(-1.74)	(28.63)
Mfee	0.124*	-0.173	0.121**	-0.084	0.162**	-0.145	0.140**
	(1.77)	(-1.15)	(1.97)	(-1.42)	(2.07)	(-1.23)	(2.31)
growth	0.132***	0.051**	0.114***	0.041*	0.165***	0.052*	0.147***
	(13.75)	(2.53)	(14.78)	(1.84)	(17.66)	(1.92)	(17.65)
top5	0.059	0.048	0.073	0.007	0.063	0.015	0.077
	(0.57)	(0.16)	(0.47)	(0.42)	(0.51)	(0.27)	(0.64)
size	0.159***	0.006***	0.191***	0.003**	0.167***	0.004**	0.176***
	(5.92)	(3.04)	(5.96)	(2.34)	(5.83)	(2.41)	(6.87)
indep	0.274**	-0.035	0.259**	-0.068	0.276**	-0.081	0.294**
	(2.04)	(-0.14)	(2.43)	(-0.37)	(2.29)	(-0.47)	(2.36)
TobinQ	-0.019***	-0.007	-0.028***	-0.009	-0.031***	-0.007	-0.024***
	(-3.34)	(-1.19)	(-3.33)	(-1.42)	(-3.14)	(-1.51)	(-3.41)
_cons	6.117***	-0.982**	6.134***	0.011*	6.221***	0.046**	6.645***
	(29.27)	(-2.14)	(29.17)	(1.69)	(30.23)	(2.26)	(30.21)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11608	11608	11608	11608	11608	11608	11608
Adj.R2	0.576	0.241	0.527	0.237	0.575	0.213	0.447

Note: *, ** and *** are significant at the level of 10%, 5% and 1% respectively

Column (1) in Table 3 shows the result of the baseline regression between the DTI and TFP. The regression result indicates that the DTI is significantly and positively correlated with TFP, with each unit increase in DTI increasing TFP by 0.062 units. The regression results verify the correctness of Hypothesis 1.

4.3 Path Analysis

Columns (2) to (7) in Table 3 demonstrate the results of the mediation mechanism test. Columns (2), (4) and (6) show that the regression coefficients between DTI and adaptive, absorptive, and innovative capacities are all positive and significant at the 1% level, which suggests that digital transformation plays a positive role in improving the adaptive, absorptive, and innovative capacities. Columns (3), (5) and (7) show that the regression coefficients between DTI and TFP, and between adaptive, absorptive, innovative capacities and TFP are all significantly positive at the 1% level, indicating that adaptive, absorptive, and innovative capacities play a certain degree of positive influence. Columns (1) to (7) together verify *Hypothesis 2*, *Hypothesis 3*, *Hypothesis 4*, that is, digital transformation positively affects the TFP of manufacturing firms by improving their adaptive, absorptive, and innovative capacities.

4.4 Robustness Test

Table 4. Robustness test results

Variable	TFP_OP	AC	TFP_OP	AP	TFP_OP	IA	TFP_OP
DTI	0.041***	0.105***	0.033***	0.010***	0.034***	0.015***	0.038***
	(4.31)	(7.52)	(4.24)	(4.12)	(4.35)	(5.14)	(4.32)
AC			0.076***				
			(7.27)				
AP					0.711***		
					(7.86)		
IA							0.214***
							(7.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	8.017***	-0.982**	4.783***	0.011*	4.978***	0.046**	4.895***
	(32.16)	(-2.14)	(27.94)	(1.69)	(27.62)	(2.26)	(26.80)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11608	11608	11608	11608	11608	11608	11608
Adj.R2	0.561	0.241	0.557	0.237	0.565	0.213	0.576

The robustness of the regression results can be verified by replacing the explained variables. The explained variable TFP, originally measured by the LP method, is replaced with the value of TFP measured by the OP method to verify the robustness of the regression results. The results of the baseline regression and the mediation effect test after replacing the explained variables are shown in Table 4. The results of the robustness test show that the regression coefficient between DTI and TFP measured using the OP method is positive and significant at the 1% level, which verifies the robustness of the benchmark regression results. The regression coefficients of the mediation mechanism test for adaptive, absorptive, and innovative capacities after replacing the explained variables are all positively significant at the 1% level.

4.5 Heterogeneity Test

Table 5. Heterogeneity test results

Variable	TFP_SOFs	TFP_nSOFs	TFP_large	TFP_Small
DTI	0.043*	0.058***	0.049***	0.031**
	(1.85)	(5.29)	(4.12)	(2.15)
_cons	6.848***	6.023***	6.423***	7.236***
	(17.86)	(27.98)	(32.56)	(29.22)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	3510	8108	5804	5804
Adj.R2	0.573	0.623	0.623	0.587

Considering the heterogeneity of listed manufacturing firms, the paper divides the sample firms into state-controlled and non-state-controlled firms, large-scale and small-scale firms, and conducts regression analyses separately. The regression results show that the digital transformation of state-owned firms (SOFs) has a lower and less significant positive effect on TFP than that of non-state-owned firms (non-SOFs). This may be due to the fact that the digital transformation of SOFs is subject to more institutional mechanism constraints than that of non-SOFs, resulting in a less significant effect of digital transformation on TFP. In contrast, non-SOFs usually have more flexible mechanisms and shorter decision-making chains, and are able to respond to technology changes and implement digital transformation more effectively. Another reason may be that many of SOFs belong to heavy industry, and tend to have lower resources efficiency and meet with greater difficulty in the process of digital transformation. For these reasons, SOFs have lower marginal returns for the same resource investment on digital transformation.

The positive effect of digital transformation on TFP is higher for large firms than for small firms. This may be due to the fact that large firms are more experienced in digital transformation and have more corporate resources, and that the utilization in large firms of R&D funds, engineering staff and innovation investments, which are necessary to enhance dynamic capabilities, is much higher than in small firms, resulting in much higher marginal returns of digital transformation investments on TFP in large firms than in small firms.

5 CONCLUSIONS

The paper empirically tests the research hypotheses and ensures that they are robust and reliable by using panel data of A-share listed manufacturing firms from 2015 to 2022 as the sample. Through the heterogeneity test, the paper examines the variability of the research hypotheses for firms with different holding natures and sizes. Final conclusion is drawn as follows: (1) Digital transformation improves TFP of manufacturing firms. (2) Dynamic capability plays a mediating role in the impact of digital transformation on TFP of manufacturing firms. (3) In terms of the effect of digital transformation on TFP, non-state-owned firms are better than state-owned firms, so are large firms than small ones.

The study has management implications at both corporate and government levels: (1) For firms, firms should integrate digital transformation into their development strategies, and cultivate dynamic capabilities from the dimensions of perception capability and resource integration capability in pursuing digital transformation. (2) For the government, the government should differentiate the policies towards digital transformation for manufacturing firms with different sizes and holding nature. For small manufacturing firms, the government should provide favorable policies and services to facilitate their digital transformation. For the state-owned manufacturing firms, the government should emphasize their digital transformation from the perspectives of technological progress and organizational changes. actively seeking their reforms so as to facilitate the transformation of their organizational structures and management approaches towards greater efficiency.

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