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# The Impact of Digital Transformation on Total Factor Productivity of Enterprises

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**Abstract**

In recent years, China's economic development has transitioned into a new phase, shifting from the pursuit of rapid growth to a period of high quality development that prioritizes the enhancement of total factor productivity. Historically, China predominantly relied on extensive growth methods to bolster economic efficiency. However, in light of economic policy uncertainty, trade protectionism, international political friction and other external shocks, there has been a notable deceleration in productivity growth. Consequently, promoting the deep fusion of digital technology and traditional economic modalities while ameliorating overall factor productivity within micro-enterprises has emerged as an imperative undertaking in this new stage. The study of micro-level digital transformation in enterprises holds significant theoretical and practical implications for enhancing productivity. This paper employs panel data of all Shanghai and Shenzhen A-share listed enterprises from 2011 to 2021 to construct a keyword matrix for digital transformation, conduct quantitative analysis on its impact on enterprise total factor productivity, and explore the relationship and influence mechanism between digital transformation, financing constraints, and organizational redundancy. Additionally, heterogeneity analysis is performed based on property rights nature, enterprise scale, and overseas background of senior executives to offer valuable insights for the government in formulating tailored policies for enterprises with different characteristics. This study also provides empirical evidence for enterprises to develop customized digital transformation strategies.

**Keywords:** digital transformation, total factor productivity, financing constraints, organizational redundancy

## 1. Introduction

The digital economy represents the future direction of global development. Accelerating the promotion of industrial digitalization and digital industrialization is a crucial measure for advancing the digital economy. Reinforcing traditional industries with advanced technologies can facilitate comprehensive digital transformations, leading to a substantial improvement in overall production efficiency. This digital transformation not only amplifies the impact of digital technologies on economic growth but also generates additive and multiplier effects. In recent years, with China's continuous improvement in network infrastructure, new generation information technologies like blockchain, and cloud computing have rapidly developed and been widely adopted. These digital technologies optimize not only underlying technical architecture but also innovate upper-level service models, injecting new vitality into traditional industries while propelling economic society towards intelligence and digitization to establish a new pattern for the digital economy. It is noteworthy that according to relevant data, China's digital economy scale accounted for 41.5% of GDP in 2022, fully demonstrating the significant position and immense potential of today's economy in relation to the digital economy. Therefore, it is imperative to continue deepening development within this sector to promote sustained and healthy overall economic growth.

The fundamental driving force of the digital economy is information technology. In the early stages of information technology development, the "information technology productivity paradox" posited that there was no significant correlation between information technology and productivity (David, 1990). However, with the widespread adoption of the Internet, the "paradox of information technology productivity" has been dispelled (Oliner & Sichel, 2000), and scholars have also observed that the utilization of the Internet and information technology contributes to enhanced productivity. With the advent of new generations of information technologies such as artificial intelligence and big data, enterprises' business models have gradually shifted towards digitalization and intelligence (Donghua Zhou & Yijian Wan, 2023), making digital transformation a key driver for Chinese enterprises to achieve sustainable high-quality development.

The primary financing channel for Chinese enterprises is debt financing. However, the impact of the COVID-19 epidemic and international political and trade frictions has led to a decrease in enterprise return on investment and a slowdown in capital turnover. This has resulted in challenges with timely loan repayment and even loan defaults. Additionally, commercial banks have increased risk premiums and raised financing thresholds due to heightened enterprise risks, leading to rejection of financing needs for small and medium-sized enterprises. On the other hand, the rough operation mode of enterprises in the early stage formed a lot of organizational redundancy in the organization, which occupied the space of other resources, reduced the efficiency of enterprise resource allocation, caused resource waste and increased management costs. However, the application of digital technology in enterprises can mitigate information asymmetry and enhance resource allocation efficiency. By leveraging digital technology to ensure transparency of asset data and information in business processes, it can minimize organizational redundancy, optimize resource utilization, and boost enterprise productivity.

Therefore, the academic debate continues regarding the research findings on the impact of digital transformation on enterprise total factor productivity, necessitating further analysis. This paper systematically examines the influence of digital transformation on overall factor productivity at the micro level, investigates the mediating role of financing constraints and organizational slack in this relationship, and explores the mechanism through which digital transformation affects total factor productivity. Heterogeneity analysis is conducted based on enterprise ownership nature, size, and executives' overseas educational background to discuss the varied impact of digital transformation on different enterprise and executive characteristics, providing valuable insights for government support policies and tailored transformation strategies for enterprises.

## 2. Literature Review

Porter et al. (2014) have emphasized the wide application of digital technology redefines the competition mode of enterprises by breaking the isolation of department data and establishing data collection groups, and delineates new competition boundaries. This is having a profound impact on internal management processes and could even upend the way companies operate. The development and application of digital transformation has changed the conventional industrial business model, promoted the transformation of enterprises from “vertical” structure to “flat” structure, promoted the collaborative development between departments (Yudong Qi & Xu Xiao, 2020), and realized the matching and integration of heterogeneous resources between different organizations (Yao Wu et al., 2022), thus improving the operation efficiency of enterprises. Some scholars argue that digital technology can not only offer intelligent production design ideas for enterprises during the manufacturing process, but also facilitate efficient coordination and circulation among production factors in material procurement and product sales, thereby enhancing overall factor productivity. Previous research has indicated that the financing capability, level of innovation, and other factors play a crucial role in influencing the total factor productivity of enterprises (Defeng Mao et al., 2013). As a result, whether digital transformation will affect total factor productivity has always been the focus of academic attention.

The impact of digital transformation on the total factor productivity of enterprises can be summarized as a positive promotional effect, a negative uncertainty effect, and a non-linear effect. On one hand, numerous scholars argue that through digital transformation, enterprises facilitate the flow and allocation of traditional production factors (such as labor, capital, organization, etc.), promote innovative activities and changes, realize the restructuring of traditional business processes and models, and enhance the total factor productivity of enterprises. Oliner et al. (2008) and Frank et al. (2019) proposed that the advancement of digital technology has driven enterprises to develop high-level data-driven strategies and utilize digital technologies such as intelligent production and unmanned production to gather unstructured and scattered data, including material procurement, fixed asset performance, process parameters, and the sales proportion of products or services. This is done in order to enhance the visualization level of business processes, optimize resource allocation efficiency, and increase productivity. Within the research framework of resource-based theory, digital transformation exerts a substantial positive influence on enterprise innovation and performance (Nwankpa et al. ,2016). Du et al. (2021) emphasized that most enterprises have significantly reduced production costs and improved production efficiency through the implementation of automation and intelligent production technologies. Furthermore, the synergy between data and traditional production factors enhances factor liquidity and allocation efficiency, thereby effectively boosting enterprise productivity. This integration of data into the production process has led to an optimization in factor utilization and overall operational performance within enterprises.

On the other hand, while China's digital infrastructure construction and development of digital technology have made significant progress, there remains considerable debate regarding their potential economic impact. As noted by Nobel Prize-winning economist Robert Solow in 1987, despite the substantial human, material, and financial investment in information technology, the United States has seen little impact on productivity. Solow then introduced the renowned Solow paradox: computers are ubiquitous except for total factor productivity. Subsequently, numerous scholars have delved into studying the influence of information technology on enterprise productivity and have expanded upon the Solow paradox from various perspectives and levels. With the advancement of information technology, some scholars have proposed the "productivity paradox" of IT investment, contending that IT investment is a necessary but not sufficient condition for enhancing production efficiency; meaning that while IT investment is not necessarily linked to increased productivity, improved productivity will directly affect IT investment. By examining over 150 articles, Brynjolfsson et al. (1996) discovered that only a minority of the articles provided evidence supporting the positive relationship between digital investment and productivity growth. Rei (2004) conducted a study on Portuguese enterprises and found that those with substantial and sustained investment in digital technology did not yield the anticipated enhancement in labor productivity. Consequently, it is inferred that there is no discernible direct causal relationship between digital technology and productivity. Hajli et al. (2015) observed only positive correlations between banking industry digitization in Nigeria & UK but not across other industries or enterprises. Destefano et al. (2018) noted increased corporate sales from digital transformation but without impacting total factor productivity improvement. Some scholars suggested a non-linear inverted U-shaped relationship exists between enterprise TFP &digital transformation providing new insights. Digital transformation reshapes production and operations, enhancing capabilities and potentially boosting productivity. However, excessive implementation without aligning with enterprise strategy may lead to resource misallocation and hinder the process (Changqi Wu et al.,2022). As digitalization continues to advance, enterprises are increasingly seeking improved business collaboration and data management capabilities. However, due to strategic misalignment, organizational inertia, and uncertainties in the external environment, fully realizing the positive impact of enterprise digitalization remains challenging (Pengfei Wang et al., 2023).

## 3. Theoretical Assumptions

### *3.1 Digital Transformation and Enterprise Total Factor Productivity*

In the digital economy era, traditional factor-driven and scale-driven growth models are no longer sufficient for high-quality development. Digital transformation has become increasingly essential as a support and driving force for enterprises to enhance productivity and promote the high-quality growth of economy. The key lies in transitioning the production process and management mode from traditional industrialization to digitalization, effectively improving the overall factor productivity of enterprises.

Internally, the application of digital technology reconfigures various dimensions and connections in the process of delivering products or services. Enterprises leverage the interoperability of information elements to drive the transformation of traditional operational models, enhance inter-departmental coordination and management, and facilitate organizational change as needed to enhance total factor productivity. They empower conventional production tools with data resources, achieving integration, automation, and intelligence in production, procurement, and sales processes while significantly enhancing output efficiency. The data information platform with decentralized characteristics has been continuously enhanced for external use, transcending geographical and spatial limitations to facilitate information sharing among enterprises and industries. This fosters collaboration among market traders, enriches product structures and types, and increases the potential for innovation in products or services. Furthermore, third-party e-commerce platforms reduce user resistance to product information search, enabling enterprises to capture and predict market demand more effectively. They also improve the customer experience by accurately capturing consumer preferences, providing personalized needs, and driving economies of scale.

However, blindly promoting digital transformation while ignoring the integration with the existing production mode and strategy may destroy the original operation system, lead to high integration costs of management mode and increase the difficulty of coordination. Furthermore, an abundance of irrelevant data can lead to internal information overload and hinder the effectiveness of enterprise resource allocation(KARHADE，2021). First of all, digital transformation is still in the initial stage of innovation in China. As the basis of successful transformation, the integration of digital technology and industrial system has high requirements on the data integration ability of enterprises, and the risk of failure is high. Secondly, some enterprises simply understand digital transformation as the simple utilization of digital technology, resulting in digital strategy and business development are not aligned at an equivalent level. Ultimately, while digital transformation has the potential to reduce operational costs, it is essential to consider the increased costs associated with integrating new technologies into existing structures. As digital transformation progresses, the number of stakeholders involved continues to grow. The forced integration of digital technology into established business processes often leads to compatibility issues within systems, resulting in a virtual increase in coordination and management costs. The negative impact of rising management costs may counteract the positive effects of reduced operating costs for enterprises, ultimately diminishing the overall impact of digital transformation on enterprise total factor productivity (TFP). Therefore, this article proposes Hypothesis 1:

H1: There is an inverted U-shaped relationship between digital transformation and enterprise TFP.

### *3.2 Digital Transformation, Financing Constraints and Total Factor Productivity*

The company's own financing capacity and the openness of the external financial environment will affect its ability to obtain sufficient and stable financial resources to support normal production and operation and technological innovation (Hottenrott,2022). However, in the process of serving the real economy, financial institutions usually give priority to enterprises with low asset-liability ratio and strong financial strength as the objects of financing. Consequently, a significant number of small and medium-sized enterprises are compelled to resort to less favorable financing options and confront the challenge of exorbitant financing expenses (Jinsong Lv, 2015). However, the establishment of digital infrastructure and the management of digital transformation require a large amount of financial support. Insufficient corporate financing will make it difficult for firms to make optimal investment decisions, resulting in a decline in productivity. In recent years, digital finance generated by the deep fusion of digital technology and financial field has fully realized the mutual exchange and matching of corporate financing needs and loan information of financial institutions, provided new ideas for alleviating corporate financing constraints, and provided strong support for enterprises to enrich human resource structure and purchase and construction of digital infrastructure, thus facilitating the enhancement of enterprises' efficiency in developing and utilizing resources. Therefore, this article proposes Hypothesis 2:

H2: Digital transformation improves enterprises' total factor productivity by alleviating financing constraints.

### *3.3 Digital Transformation, Organizational Redundancy and Enterprise Total Factor Productivity*

At present, there is no consensus in academia on whether organizational slack promotes or inhibits enterprise productivity. Scholars pointed out that organizational slack can be used as resources for enterprises to freely use in daily activities, which can not only help enterprises to operate normally, but also broaden the scope of enterprise investment and enhance enterprise value (Voss et al.,2008). Pollock et al. (2004) pointed out that the redundant idle resources in the organization provided convenience for operators' over-investment and blind investment, which harmed the interests of owners. Nohria (2005) posited a conclusion divergent from organizational theory, contending that organizational redundancy leads to agent fatigue, increases the likelihood of selecting secondary investment projects, and diminishes enterprise development and emergency response capabilities. Incumbents often resort to one-size-fits-all layoffs to reduce or eliminate redundancies. However, digital transformation is a process that has high requirements on workers' professional skills and digital knowledge level. Some enterprises also use the "Internet +" thinking to "datalize" the resource age, value, quantity and other factors, rebuild the resource system, clarify the resource requirements in the production process, eliminate ineffective resources, reduce the resource inventory on the premise of ensuring the daily production needs, and avoid the delay of production schedule due to insufficient resources or the slowdown of resource allocation efficiency due to resource accumulation. Therefore, this article proposes Hypothesis 3:

H3: Digital transformation improves total factor productivity by reducing organizational redundancy.

## 4. Research Methods

### *4.1 Samples and Data*

The research samples selected in this paper are all enterprises listed on Shanghai and Shenzhen A-shares from 2010 to 2021, and the sample data are processed as follows :(1) Data of delisted or IO year and before are excluded; (2) Remove ST enterprise data; (3) Excluding financial enterprise data; (4) Remove missing values; (5) Carry out 1% tailing treatment for continuous variables. The data of digital transformation in this paper mainly comes from the annual reports of enterprises disclosed by Shenzhen Stock Exchange and Shanghai Stock Exchange. Corporate financial information comes from CSMAR database and this article uses Stata 16.0 software to process and analyze the data.

### *4.2 Variable Measurement*

#### 4.2.1 Dependent Variable

The current measurement methods for total factor productivity (TFP) in micro enterprises are relatively well-established, primarily including the OLS method based on the Cobb-Douglas production function setting, semi-parametric LP method and OP method, and generalized moment GMM method. This paper utilizes the LP method to estimate the TFP of enterprises, while also testing the robustness of results calculated by the GMM method and OLS method.

$$Y_{it} = \delta_0 + \delta_1 K_{it} + \delta_2 L_{it} + \delta_3 M_{it} + \mu_i + v_t + \varepsilon_{it} \tag{1}$$

4.2.2 Independent Variable

This paper applies the currently widely used quantitative research method to use the frequency of keywords as the measurement index of enterprise digital transformation (DT). Referring to the practice of Wu et al. (2021), the digital transformation keyword matrix is constructed, and the text mining method is used to quantitatively measure the degree of enterprise digital transformation (DT). The main steps are as follows: first, use Python crawler function to summarize and sort out the annual reports of A-share listed companies to be disclosed from Shenzhen Stock Exchange and Shanghai Stock Exchange; Second, referring to previous research, the digital transformation is structured and classified into two levels: "underlying technology application" and "technology practice application", and "underlying technology application" is further subdivided into four categories: artificial intelligence, blockchain, cloud computing and big data. The data pool formed by Python crawler technology and Java PDF box matching text extraction is used to summarize the frequency of the above five keywords, and this frequency is used as the original measurement index of the degree of enterprise digital transformation. In order to avoid the impact of the right-skewness of the statistical frequency of keywords on the regression results, this paper converts it into logarithm.

4.2.3 Intermediate Variable

Financing constraints (SA). According to the theory of information asymmetry and credit rationing, digital transformation can effectively help enterprises relieve financial pressure and gain social trust with better qualifications. This paper adopts the SA index model to measure financial constraints. Compared with KZ index and WW index, SA index can effectively avoid the reverse causality in the calculation process, has no endogeneity problem, and can accurately measure the results of financial constraints with certain robustness. Where Size is the enterprise size and Age is the enterprise age.

$$SA = -0.737Size - 0.04Age + 0.043Size^2 \tag{2}$$

Organizational Slack. Referring to the measurement method of organizational balance by Chen Xiaohong et al. (2012), this paper mainly adopts the average value of the three indexes after standardization, namely, current ratio, equity/liability ratio and sales period expense ratio.

$$Slack = (\text{liquidity ratio} + \text{asset-liability ratio} + \text{fee-income ratio})/3 \tag{3}$$

4.2.4 Conrol Variables

Table 1. Control variable explanation

| Name of variable | Definition of variables | Method of construction | Explanation of variables |
|---|---|---|---|
| ROE | Return on equity | Net profit/owners' equity | The higher the value is, the stronger the profitability of the enterprise is, and the more sufficient the funds to invest in digital technology are. |
| Age | Age of enterprise | Year - Year of establishment +1 | The older the firm is, the higher the level of corporate risk-taking and the higher the financing availability. |
| Top1 | Concentration of ownership | Shareholding ratio of the largest shareholder | The higher the value is, the management will excessively advocate or resist digital transformation, which is not conducive to the improvement of total factor productivity. |
| Nature | Nature of property rights | State-owned enterprises are marked as 1, and non-state-owned enterprises are | Compared with non-state-owned enterprises, state-owned enterprises will take more initiative in digital transformation. |

| | | | |
|---|---|---|---|
| | | marked as 0 | |
| Size | Size of enterprise | Log value of total assets | The larger the enterprise scale, the stronger the motivation to introduce digital technology to achieve automation, unmanned, and intelligent. |
| Lev | Financial leverage | Total liabilities/total assets | The larger the value is, the greater the financial risk is and the greater the financing constraints are, which has a negative impact on the improvement of total factor productivity. |
| Growth | Operating income growth rate | (Income for the current year - income for the previous year)/income for the previous year | The higher the value of this index is, the faster the growth rate of the enterprise's operating income is, and the better the market development prospect of the enterprise is. |

*4.3 Model Building*

Model setting.When $\beta_1$<0 and $\beta_1$ is different from $\beta_2$, it represents that digital transformation has an inverted U-shaped relationship with enterprise TFP. In order to control the impact of industry factors and time factors on TFP, this paper also adds industry fixed effects $\delta_i$ to the equation. And year fixed effects $\lambda_Y$.

$$\mathrm{TFP_{it}} = \alpha + \beta_{1it}\mathrm{DT}^2 + \beta_{2it}\mathrm{DT} + \gamma\mathrm{Controls_{it}} + \delta_i + \lambda_Y + \varepsilon_{it} \tag{4}$$

Intermediate effect model.In order to test the mediating effect of financing constraints and organizational slack, the following model is constructed:

$$\mathrm{TFP_{it}} = a_0 + a_{1it}\mathrm{DT}^2 + a_{2it}\mathrm{DT} + \gamma\mathrm{Controls_{it}} + \delta_i + \lambda_Y + \varepsilon_{it}$$

$$INTER_{it} = b_0 + b_{1it}\mathrm{DT}^2 + \gamma\mathrm{Controls_{it}} + \delta_i + \lambda_Y + \varepsilon_{it}$$

$$\mathrm{TFP_{it}} = c_0 + c_{1it}DT^2 + c_{2it}DT + \mu INTER_{it} + \gamma Controls_{it} + \delta_i + \lambda_Y + \varepsilon_{it} \tag{5}$$

Among them, when $b_1$ and $\mu$ is significant, it means that the variable has a mediating effect.

## 5. Empirical Results

*5.1 Descriptive Statistical Analyze*

The average total factor productivity (TFP) stands at 8.487 with a variance of 1.046, indicating a generally favorable level among the sample firms but significant heterogeneity across them. The mean enterprise digital transformation degree (DT) is 10.46, with a wide range from 0 to 547 and a high variance of 28.343, suggesting that Chinese enterprises overall exhibit low levels of digital transformation with uneven degrees among them. Even some enterprises have not begun to apply digital technology to management, and realizing digital transformation is still an important strategic goal for the future development of enterprises. The maximum financing constraint (SA) is recorded at 11.620, while the minimum is at 1.995, and the average sits relatively high at 4.189, signifying common financing constraints in Chinese enterprises with noticeable disparities among them. Furthermore, the maximum organizational redundancy (Slack) value is observed at 10.865, whereas the minimum value registers at 0.326; meanwhile, the variance stands at an appreciable level of 0.849—indicating discernible differences in winter enterprises' organizational redundancy levels. Similarly, through the maximum, minimum and mean of other variables, it can be found that there is a large gap between different companies, which is caused by different industrial characteristics and individual characteristics to a certain extent.

Table 2. Descriptive statistics and correlation analysis

| Variables | Mean | Std | Min | Max |
|---|---|---|---|---|
| TFP-LP | 8.487 | 1.046 | 5.367 | 14.120 |
| DT | 10.460 | 28.343 | 0 | 547 |
| SA | 4.189 | 1.567 | 1.995 | 11.620 |
| Slack | 1.037 | 0.849 | 0.326 | 10.865 |
| ROE | 0.094 | 0.070 | -0.204 | 0.421 |
| Age | 2.148 | 0.787 | 0.693 | 3.367 |
| Top1 | 35.114 | 14.664 | 8.920 | 75.420 |
| Nature | 0.368 | 0.482 | 0.000 | 1.000 |
| Size | 22.282 | 1.291 | 19.692 | 26.497 |
| Lev | 1.390 | 1.095 | -0.088 | 11.864 |
| Growth | 0.203 | 0.429 | -0.674 | 5.009 |

### *5.2 Analysis of Regression Results*

According to the regression results in Table 3, simultaneous inclusion of the first term (DT) and square term ($DT^2$) of digital transformation reveals a significant impact on total factor productivity at a 1% significance level. Specifically, the coefficient for the square term ($DT^2$) of digital transformation is negative and significant, while the coefficient for the primary term (DT) is positive and significant. This suggests an inverted U-shaped relationship between enterprise digital transformation and total factor productivity, thus confirming hypothesis H1.

Table 3. Regression analysis results

| Variables | (1)<br>TFP-LP | (2)<br>TFP-LP |
|---|---|---|
| DT2 | -5.2684***<br>(-8.0024) | |
| DT | 9.5090***<br>(12.5898) | 4.4507***<br>(10.7514) |
| ROE | 2.1388***<br>(39.0949) | 2.1367***<br>(39.0064) |
| Top1 | 0.0017***<br>(6.6704) | 0.0017***<br>(6.5179) |
| Nature | 0.0548***<br>(6.0960) | 0.0524***<br>(5.8240) |
| Lev | 0.0105***<br>(3.0501) | 0.0100***<br>(2.8960) |
| Growth | 0.0938***<br>(11. 1423) | 0.0955***<br>(11.3422) |
| Age | 0.0266***<br>(4.7222) | 0.0264***<br>(4.6782) |
| Size | 0.6295***<br>(185.8145) | 0.6303***<br>(185.8509) |
| Fixed industry | Yes | Yes |
| Fixed year | Yes | Yes |
| Observations | 23115 | 23115 |
| R2 | 0.735 | 0.735 |

*Note.* *, **, *** respectively indicate significant levels at 0.1, 0.05, and 0.01; the standard error of regression coefficients in parentheses.

### *5.3 Mesomeric Effect*

Table 4, the coefficient for digital transformation is -2.06 and statistically significant at the 1% level, indicating that digital transformation can effectively mitigate financial constraints. Table 4 adds financing constraints as explanatory variable in the model setting. The results show that compared with the correlation coefficient of the regression model, the correlation coefficient between digital transformation and TFP decreases slightly, which indicates that financial constraints play a negative mediating role in the relationship between digital transformation and TFP.

The coefficient of digital transformation in Table 4(5) is -1.88, significant at the 1% level, indicating that digital transformation can reduce organizational redundancy. In Table 4 (6), organizational redundancy is included as an explanatory variable in the model. The results of the intermediary effect test for organizational redundancy show a significant negative correlation between total factor productivity of enterprises and the square term of digital transformation at the 1% level, and a significant positive correlation with the linear term of digital transformation at the 1% level. This confirms that the inverted U-shaped relationship between digital transformation and total factor productivity of enterprises remains valid. However, there is a correlation coefficient of -0.102 between enterprise TFP and organizational redundancy, and compared to the regression model, there is a slight decrease in the correlation coefficient between digital transformation and TFP, indicating that organizational redundancy plays a partial mediating role between digital transformation and enterprise TFP.

Table 4. Mesomeric effect

| | Chanel=SA | | | Chanel=Slack | | |
|---|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| | TFP-LP | SA | TFP-LP | TFP -LP | Slack | TFP -LP |
| DT2 | -5.2684*** | -2.0556*** | -5.2416*** | -5.2684*** | - 1.0725** | -5.3437*** |
| | (-8.0024) | (-3.2131) | (-7.9641) | (-8.0024) | (-2. 1504) | (-8. 1984) |
| DT | 9.5090*** | | 9.4288*** | 9.5090*** | | 9.4624*** |
| | (12.5898) | | (12.4841) | (12.5898) | | (12.6542) |
| Chanel | | | -0.1541*** | | | -0.1019*** |
| | | | (-4.2441) | | | (-22.0994) |
| Conrol variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 23115 | 23115 | 23115 | 23115 | 23115 | 23115 |
| R2 | 0.735 | 0.996 | 0.735 | 0.735 | 0.180 | 0.741 |

*Notes*. *, **, *** respectively indicate significant levels at 0.1, 0.05, and 0.01; the standard error of regression coefficients in parentheses.

### *5.4 Robustness Test*

This paper will adopt two methods to conduct robustness tests. Firstly, we will replace the explained variable. We use GMM method and OLS method to recalculate total factor productivity and conduct regression analysis. The results show that in the first and second columns of Table 5, the square term of digital transformation is negatively correlated at the significant level of 1%, and the quadratic term is positively correlated at the significant level of 1%, while the direction and significance of other control variable coefficients are consistent with the original regression results. Therefore, it can be indicated that the model setting has a certain robustness. Secondly, the samples of municipalities directly under the Central Government and autonomous regions are excluded due to their significant advantages in financial strength, policy support, innovation input, talent introduction, and other aspects. Table 5(3) demonstrates that the square term of digital transformation is significantly negative at a 1% level, while the quadratic term is significantly positive at a 1% level. This aligns with the regression results and indicates the robustness of the regression model.

Table 5. Robustness test

| Variables | Model(1) | Model(2) | Model(3) |
|---|---|---|---|
| | TFP-GMM | TFP-OLS | TFP-LP |
| DT2 | -6.4583*** | - 1.9250*** | -5.5859*** |
| | (-8.0484) | (-3.0663) | (-5.8382) |
| DT | 11.5164*** | 3.6549*** | 9.3455*** |
| | (12.5099) | (5.0747) | (9.9738) |
| ROE | 1.8997*** | 2.0461*** | 1.9957*** |
| | (28.4901) | (39.2221) | (32.8175) |
| Age | 0.0220*** | 0.0365*** | 0.0317*** |
| | (3. 1936) | (6.7808) | (4.9713) |
| Top1 | 0.0006** | 0.0021*** | 0.0016*** |
| | (2.0662) | (8.7293) | (5.4352) |
| Nature | 0.0239** | 0.0737*** | 0.0339*** |
| | (2. 1836) | (8.5922) | (3.3323) |
| Size | 0.1761*** | 0.8439*** | 0.6351*** |
| | (42.6421) | (261. 1981) | (157.5275) |
| Lev | 0.0007 | 0.0230*** | 0.0099*** |
| | (0. 1706) | (7.0157) | (2.6118) |
| Growth | 0.1494*** | 0.0758*** | 0.0931*** |
| | (14.5634) | (9.4455) | (9.7790) |
| Fixed industry | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes |
| Observations | 23115 | 23115 | 18449 |
| R2 | 0.370 | 0.350 | 0.726 |

*Notes*. *, **, *** respectively indicate significant levels at 0.1, 0.05, and 0.01; the standard error of regression coefficients in parentheses.

### *5.5 Heterogeneity Analysis*

Nature of property rights. The nature of property rights dictates the division of enterprises into two types: state-owned and non-state-owned. State-owned enterprises, in response to national strategic initiatives, are able to leverage policy preferences and financial support from stakeholders due to their capital, talent, and policy advantages. This creates a conducive environment for digital transformation, resulting in a stronger impact on total factor productivity. The absolute value of the $DT^2$coefficient is significant at 5% for non-state-owned enterprises and at 1% for state-owned enterprises as shown in Table 6(Columns 1 and 2). Chow test results indicate that the inverse U-shaped relationship between digital transformation and total factor productivity remains valid across different property rights groups, with a more pronounced effect observed in state-owned enterprises. The difference between soes and non-soes in digital transformation may be mainly due to the different self-positioning and strategic goals of the two parties. In addition to pursuing economic benefits, state-owned enterprises also undertake more social responsibilities and actively respond to the call of national strategy. In addition, soes can obtain more policy preference and financial support from stakeholders such as the government and state-owned banks. These advantages enable state-owned enterprises to improve total factor productivity more actively and effectively in the process of digital transformation.

Enterprise size difference. This paper divides the sample into small and medium-sized enterprises and large enterprises for heterogeneity analysis, in order to explore the impact of firm size on the relationship between digital transformation and total factor productivity. Unlike small enterprises, larger enterprises have a specialized division of labor, are able to achieve economies of scale easily, and have the capacity to engage in high-risk research and development activities, thereby promoting improvements in enterprise productivity levels. Table 6(3) and (4) demonstrate that the inverted U-shaped effect of digital transformation on total factor productivity of enterprises is more significant in large enterprises. Compared to large firms, SMEs face challenges in paying high audit fees and disclosing financial conditions due to their small size, limited establishment period, and lack of collateral assets. As a result, they are more susceptible to being marginalized by banks and other financial institutions, leading to greater difficulties in obtaining financing. Constrained by external financial limitations, small and medium-sized enterprises lack the incentive to pursue digital transformation, resulting in lower quantity and quality of transformation compared to larger enterprises. Additionally, factors such as scale, geographical location, and growth prospects make SMEs less appealing to external investors and digital technology talents. Consequently, they lack the necessary conditions for digital transformation which leads to a relatively slower process of digitization. Therefore, the impact of digital transformation on TFP is more pronounced for large enterprises than for small and medium-sized enterprises.

Executive overseas background. Senior executives with international experience play a pivotal role in formulating and executing corporate strategies, exerting a significant impact on the overall productivity of enterprises. This encompasses factors such as their overseas education, work experience, and executive compensation. Table 6 (5) and (6) demonstrate that companies led by senior executives with overseas education exhibit a higher absolute value for the coefficient of digital transformation square compared to those without such background. Furthermore, the chow test's P value rejects the null hypothesis at a 1% significance level, indicating that the influence of digital transformation on total factor productivity is more pronounced for companies led by senior executives with international experience. From an individual perspective, the strategic cognition of executives will have a significant impact on enterprises' investment in digital technology. Executives with overseas education are exposed to leading global digital construction strategies and top digital transformation designs, making them more inclined to increase investment in digital technology when formulating corporate strategies. From a network perspective, enterprises led by executives with overseas backgrounds can access resources through domestic and international networks, providing innovation advantages and convenient conditions for carrying out digital transformation. Therefore, they offer valuable insights for the digital transformation of Chinese enterprises.

Table 6. Heterogeneity analysis

| Variables | (1) Non-state-owned enterprises | (2) State-owned enterprises | (3) Small and medium-sized enterprises | (4) large enterprises | (5) no overseas education background | (6) Have overseas education background |
|---|---|---|---|---|---|---|
| DT2 | -3.1647*** | -19.3238*** | -3.6828*** | -7.5948*** | -4.2659*** | -5.7322*** |
| | (-4.7693) | (-8.5694) | (-3.3543) | (-9. 1204) | (-5.6371) | (-4.6414) |
| DT | 6.5194*** | 22.3707*** | 3.9726*** | 15.3753*** | 6.8586*** | 10.9893*** |
| | (8.2560) | (10.4762) | (3.8981) | (13.0008) | (6.0522) | (10. 1338) |
| Nature | | | 0.0459*** | 0.0695*** | 0.0582*** | 0.0583*** |
| | | | (3.3407) | (5.4387) | (4. 1618) | (4.5094) |
| Controls vriables (Ex Nature) | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Fixed year | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 15241 | 8867 | 12054 | 12054 | 11693 | 12415 |
| R2 | 0.710 | 0.727 | 0.425 | 0.616 | 0.702 | 0.764 |
| Chow Test | ChowTest = 13.43; P-Value> F(2,24070)= 0.0000 | | Chow Test =21.61; P-Value> F(3,24069) = 0.0000 | | Chow Test =7. 12; P-Value> F(3, 24069) = 0.0001 | |

*Note*. *, **, *** respectively indicate significant levels at 0.1, 0.05, and 0.01; the standard error of regression coefficients in parentheses.

## 6. Conclusion and Discussion

### *6.1 Research Conclusions*

The study utilizes data from 2011 to 2021 of all A-share listed enterprises in the Shanghai and Shenzhen Stock exchanges as samples. It constructs a keyword matrix for digital transformation, conducts quantitative analysis on digital transformation, and further explores its relationship with corporate TFP and the influencing mechanism. The study illustrates an inverted U-shaped correlation between digital transformation and corporate total factor productivity. During the initial phases of digital transformation, the influence on TFP is negligible. However, as organizations deepen their digital investments, the impact becomes increasingly conspicuous. Nevertheless, excessive digital investment may lead to a decline in TFP due to heightened coordination costs, amplified investment outlays, and other related factors. In terms of the influencing mechanism, the external financial constraints encountered by firms and the internal redundancy stock within organizations are two crucial mediating factors affecting digital transformation's impact on total factor productivity. The integration of digital technology and the financial industry has given rise to a new form of digital finance, which serves to eliminate the information and distance barriers inherent in traditional finance. This facilitates long-tail enterprises in accessing financing information more effectively, identifying viable financing avenues, and enhancing their chances of securing funds. It also significantly alleviates financing constraints, empowering enterprises to proactively invest in innovation and enhance productivity, thereby fostering a virtuous cycle. On the other hand, the low production efficiency of China's early manufacturing industry and extensive operation led to the formation of more organizational redundancy within the organization. In the absence of efficient governance means, these organizational redundancies make the enterprise management cost high, and finally lead to the decline of the enterprise total factor productivity. The using of digital technology can promote the remodeling of the resource system to a certain degree, improve the transparency and informatization of resources, and build a multi-dimensional enterprise resource database, so as to improve the efficiency of resource allocation and risk management, and drive the growth of enterprise factor productivity. Heterogeneity analysis shows that the impact is more significant in large enterprises, state-owned enterprises and enterprises with overseas background.

### *6.2 Research Suggestion*

Firstly, the government should proactively adapt to the rapid development of digital technology and implement targeted support, fiscal and tax policies to incentivize enterprises to adopt digital technology. Simultaneously, by establishing a big data platform to facilitate seamless collaboration among financial institutions, enterprises, and Internet platforms, efficiently matching financing needs, enhancing financing success rates, reducing costs, and effectively addressing the financing challenges faced by smaller businesses. Emphasize the recruitment and development of versatile talent with international education backgrounds to provide Chinese enterprises with a more global mindset and management approach. Secondly, Enterprises should proactively integrate digital technology into all aspects of their operations, enhance information infrastructure, and achieve transparency in the production process. They should also tailor their transformation strategies to their unique characteristics instead of blindly imitating leading enterprises. Neglecting the distinctiveness and limitations of their own business transformation strategy may hinder enterprise development. Research indicates that excessive digital investment can impede productivity growth. Therefore, enterprises need to determine an appropriate investment scale based on their specific circumstances, recognize the importance of digital transformation, and gradually leverage the advantages of digital technology. Different types of enterprises have varying economic impacts from digital transformation. Non-state-owned enterprises should vigorously pursue transformation and development to address potential issues arising from strategic mismatches. SMEs must carefully allocate investment to avoid problems stemming from insufficient or excessive funding. Enterprises led by executives lacking international experience should develop digital transformation plans tailored to their characteristics, foster innovation, enhance flexibility, and optimize production efficiency for multiplied effects.

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**Data sharing statement**

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