

Mechanisms and Heterogeneity of the Impact of Digital Economy on Total Factor Productivity in Manufacturing Based on DEA-Malmquist Method

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Abstract. Based on provincial panel data of 30 provinces from 2013-2019, this paper measures the total factor productivity of China's manufacturing industry using the DEA-Malmquist method, and also employs the generalized least squares (GLS) method to study the impact of the digital economy on total factor productivity in manufacturing. The study finds that the digital economy can promote manufacturing productivity growth, and this growth is driven by technological progress, and at the same time, the digital economy can enhance manufacturing productivity by improving technological innovation and resource allocation efficiency. From different dimensions of the digital economy, the infrastructure of the digital economy, the industrialization of the digital economy and the intelligitization of the industry can significantly contribute to manufacturing productivity.

Keywords: Digital economy; Manufacturing industry; Digitalization; Resource allocation efficiency.

1. Introduction

After entering the 21st century, the information technology industry has gradually developed and the digital economy has gradually received attention from various countries. First of all, digital economy is a multidimensional concept, including digital infrastructure, integration of real economy and digital technology, digital industry, digital governance, etc. However, few existing studies start from the intrinsic structure of digital economy and dig into the impact of different dimensions of digital economy on total factor productivity (TFP) of manufacturing industry and the impact effect. In this paper, we will take a multidimensional perspective to study the impact of digital economy on total factor productivity (TFP) of manufacturing industry, decompose TFP into technical efficiency and technical progress, and decompose digital economy into digital infrastructure, digital industrialization, digitalization of industry and digital governance, and deeply analyze the effect of digital economy on total factor productivity from a vertical perspective.

2. Elaboration of theoretical mechanisms and measurement of productivity in the digital economy

2.1 Elaboration of theoretical mechanism

With the gradual development and growth of the digital economy, the production, consumption and distribution methods of society have changed and the efficiency of economic operation has improved significantly. First, the digital economy can reduce the risk of information asymmetry, reduce the search cost, production cost and transaction cost of enterprises, improve the efficiency of transactions, expand the scale of transactions, improve the efficiency of resource allocation, and thus promote the growth of total factor productivity. Secondly, big data can greatly promote the efficiency of optimal factor allocation and the level of collaboration among factors, and production enterprises can quickly adjust to changes in market demand, break the shackles of traditional factor markets, and reconfigure the way resources are allocated. Finally, the digital economy can also give rise to a networked collaborative manufacturing model, strengthen the cooperation and communication of

enterprises in each production supply chain, and enhance the ability of enterprises to divide and collaborate. The principle diagram of the impact of digital economy on TFP is shown in Figure 1.

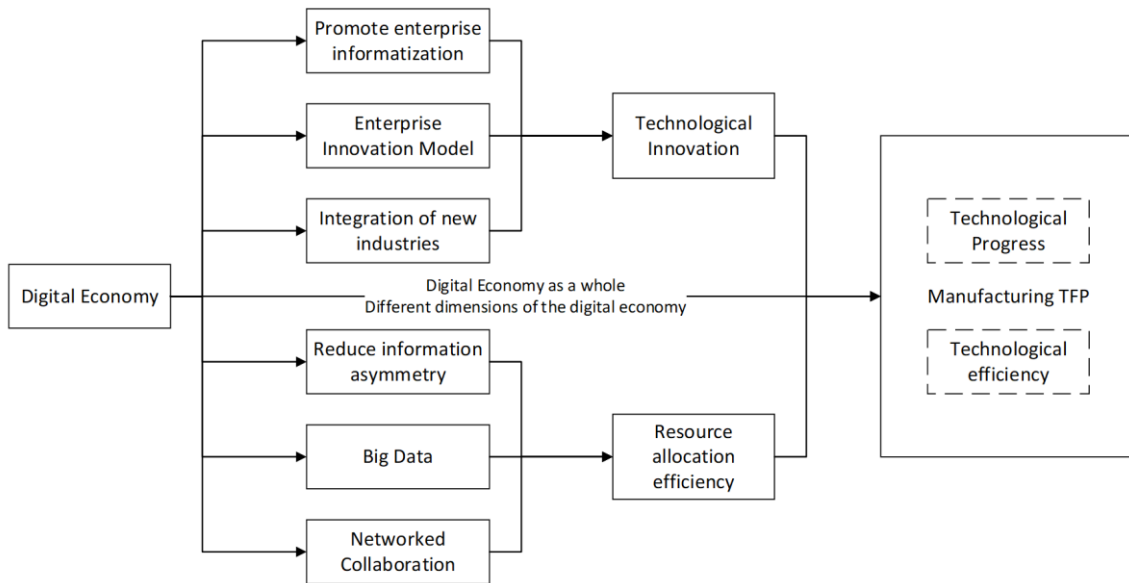


Fig 1. Schematic diagram of the impact of the digital economy on TFP

2.2 Measurement of development level

In this paper, the entropy weight method is used to determine the evaluation index weights when measuring the development level of digital economy. First, the *j*th indicator of the *i*th region in year *t* is defined as *X_{itj}*. Since the units of the indicators are not consistent and comparable, this paper performs dimensionless processing, i.e., the original indicators are standardized.

The next step is to determine the indicator weight, which is calculated as $Y_{itj} = \frac{X_{itj}^{\wedge}}{\sum_i X_{itj}^{\wedge}}$; next, the entropy value of the indicator is calculated as shown in Equation (1).

$$e_j = -k \sum y_{ij} \ln(Y_{itj}) \tag{1}$$

The comprehensive digital economy indicators of each province are calculated as shown in Equation (2)

$$Digital_{it} = \sum_j (w_j X'_{itj}) \tag{2}$$

2.3 TFP and its decomposition results

In this paper, DEA-Malmquist index is used to measure manufacturing TFP, and the change in technical efficiency indicates the distance between current production efficiency and the optimal production frontier, and the change in technical progress indicates the change in the optimal production frontier.

The sample time selected in this paper is 2013-2019, referring to Qiu Ailian et al. and Li Lianshui et al. Total output is expressed using gross manufacturing output, capital input is measured using net fixed assets in manufacturing, and labor input is expressed by the average annual number of workers in manufacturing, and the description and treatment of each index are as follows.

(1) Total output. In this paper, the total output value of manufacturing industry is used to measure the total output. Since the China Industrial Statistics Yearbook counts the total industrial output value, the total industrial output value from the China Industrial Statistics Yearbook is used minus the output value of six of the non-manufacturing industries. In this paper, we take 2013 as the base period and use the ex-factory price index of industrial producers to do index deflations of total manufacturing output to eliminate the influence of prices.

(2) Capital input. This paper uses the net value of fixed assets in manufacturing industry as a proxy variable for capital input. The net value of industrial fixed assets minus the net value of fixed assets in non-manufacturing industries is used in the China Industrial Statistics Yearbook, and the fixed asset investment price index is used to make an index deflator for the net value of fixed assets in manufacturing.

(3) Labor input. In this paper, the annual average number of workers in manufacturing industry is chosen to measure labor input.

Based on the input-output data of manufacturing industry in 30 provincial-level regions of China from 2013 to 2019, this paper measures the dynamic index of total factor productivity of manufacturing industry with the measurement software DEAP2.1 (constant scale payoff, radial input), and the results are shown in Table 1.

Table 1. Total Factor Productivity Changes in China's Manufacturing Industry and Its Decomposition, 2013-2019

| Age | tfp | effch | tech | pech |
|-----------|-------|-------|-------|-------|
| 2013-2014 | 1.037 | 1.017 | 1.020 | 0.990 |
| 2014-2015 | 1.028 | 0.919 | 1.119 | 0.960 |
| 2015-2016 | 1.056 | 1.062 | 0.995 | 1.040 |
| 2016-2017 | 1.184 | 0.878 | 1.349 | 0.915 |
| 2017-2018 | 1.153 | 0.796 | 1.449 | 0.860 |
| 2018-2019 | 1.024 | 0.956 | 1.071 | 0.968 |

3. Data indicator selection and processing analysis

3.1 Description of sample variables and data sources

In order to examine the impact of digital economy on total factor productivity in manufacturing industry, the following model is set in this paper to investigate, as shown in equation (3)(4)(5).

$$tfp_{i,t} = \beta_1 Digital_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (3)$$

$$tech_{i,t} = \beta_1 Digital_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (4)$$

$$effch_{i,t} = \beta_1 Digital_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (5)$$

where tfp, tech, and effch denote total factor productivity, technical progress, and technical efficiency of manufacturing industry, respectively; Digital denotes the level of development of digital economy; control_(i,t) is a series of control variables, including the level of foreign openness, the level of economic development, and R&D investment; μ_i is the individual effect; and $\varepsilon_{(i,t)}$ is the disturbance term of the model.

The digital economy also affects the total factor productivity of manufacturing industry from different dimensions, therefore, this paper constructs the following econometric model based on the benchmark model, as shown in equation (6)(7)(8).

$$tfp_{i,t} = \beta_1 Dimension_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (6)$$

$$tech_{i,t} = \beta_1 Dimension_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (7)$$

$$effch_{i,t} = \beta_1 Dimension_{i,t} + \beta_2 control_{i,t} + \mu_i + \varepsilon_{i,t} \quad (8)$$

where Dimension_(i,t) refers to digital economy infrastructure, digital industrialization, industry digitization, and digital governance indicators, respectively, and the remaining variables are explained as above.

Based on the mechanism analysis above, this paper tests the mechanism of digital economy affecting total factor productivity in manufacturing industry, and selects two mediating variables, technological innovation and resource allocation efficiency, to test the mechanism. The following mediating mechanism test model is established in this paper, as shown in equation (9) (10).

$$Med_{i,t} = \beta_1 Digital_{i,t} + \beta_2 control_{i,t} + u_i + \varepsilon_{i,t} \tag{9}$$

$$tfp_{i,t} = \alpha_1 Med_{i,t} + \beta_1 Digital_{i,t} + \beta_2 control_{i,t} + u_i + \varepsilon_{i,t} \tag{10}$$

where Med_(i,t) is the mediating variable, including technological innovation (innov), resource allocation efficiency (res), and other variables are explained as above. Technological innovation is measured by the number of effective patent applications; resource allocation efficiency is measured by the resource mismatch index, including capital mismatch index and labor mismatch index, and it should be noted that the index is less than 0 indicates under-allocation of resources and more than 0 indicates over-allocation of resources.

3.2 Variable descriptions and data sources

(1) Explanatory variable: Total factor productivity of manufacturing industry and its decomposition index. Based on the DEA-Malmquist index method, the Malmquist index can be decomposed into technical progress and technical efficiency, which is convenient to explore the source of TFP changes in manufacturing industry. Since the Malmquist index measures the rate of change relative to the previous year, the approach of this paper, transforms the change in TFP into absolute TFP. In this paper, absolute total factor productivity in manufacturing is used as the explanatory variable.

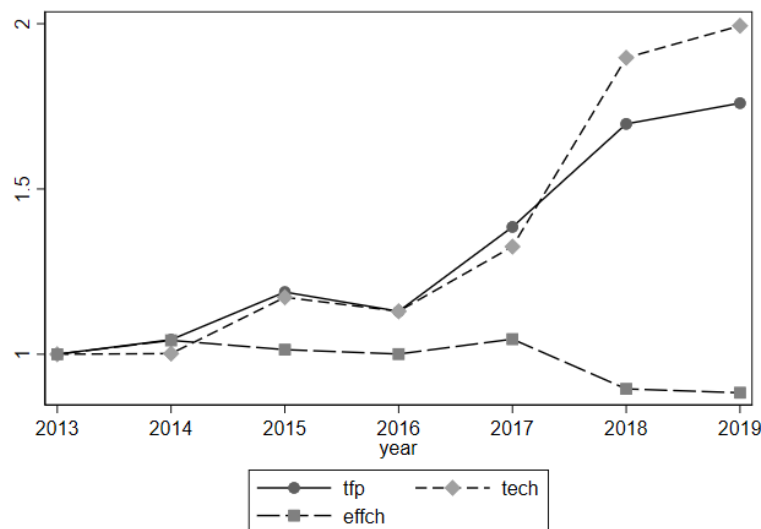


Fig 2. Folding line graph of absolute total factor productivity change in China's manufacturing industry, 2013-2019

From Figure 2, we can see that total factor productivity shows an increasing trend, and the fluctuation state of technical progress and overall TFP growth is basically the same. From the total factor productivity decomposition, technical efficiency contributes weakly to the growth of total factor productivity, while technical progress contributes most of the total factor productivity growth. It is the growth of technological progress that is the main cause of TFP progress in China's manufacturing industry.

(2) Core explanatory variable: the level of development of the digital economy. Since the development of digital economy has dynamic development characteristics, this paper constructs a multi-dimensional indicator system of digital economy. Drawing on Pan Weihua et al.'s study, the level of digital economy development is measured in four dimensions: digital infrastructure, digital industrialization, industrial digitization, and digital governance.

(3) Mediating variables: (1) Technological innovation: This paper uses the number of effective patent applications to measure technological innovation. Most scholars use the number of patent applications to indicate technological innovation, but the number of effective patent applications is a better measure of the actual technological innovation capability of enterprises, so this paper uses the number of effective patent applications to indicate technological innovation. (2) Resource allocation efficiency: This paper uses the resource mismatch index to measure, which includes capital mismatch index and labor mismatch index. In this paper, the H-K model proposed by Hsieh et al. is used to calculate the resource mismatch index, and the capital mismatch index and labor mismatch index (taul) are calculated for each province by referring to Chen Yongwei and Cui Shuhui et al. It is worth noting that if the index is greater than 0, it means that the resources are under-allocated, and vice versa indicates that the resources are over-allocated; the larger the absolute value of the index, the greater the degree of resource mismatch, and vice versa indicates that the degree of resource mismatch is decreasing.

(4) Control variables: level of external openness: the ratio of total import and export to regional GDP is used to measure the level of external openness; since the unit of total import and export in China Statistical Yearbook is billion dollars, this paper converts its unit into billion dollars by using the average of exchange rate of US dollars in previous years; level of economic development: GDP per capita is used to measure the level of regional economic development; R&D investment: the R&D expenditure of each province is used to measure the R&D investment; industrial expenditure to measure R&D investment; industrial structure rationalization: using the Thiel index to measure the industrial structure rationalization of each province.

3.3 Empirical Results and Analysis of the Model

In this paper, the manufacturing TFP is decomposed, and its decomposition terms, technological progress (tech) and technical efficiency (effch), are also used as the explanatory variables, and the regression analysis of model (1)(2)(3) is conducted using FGLS. Because FGLS can alleviate the heteroskedasticity and serial correlation problems to some extent, the results obtained are more robust. The regression results are shown in Table 2.

Table 2. Regression results of all factors and decomposition terms of manufacturing industry

| Explanatory variables | tfp | tech | effch |
|-----------------------|----------------------|----------------------|----------------------|
| Digital | 0.017*** (3.25) | 0.008*** (3.72) | -0.013 (-1.29) |
| open | -0.718*** (-4.60) | -1.025*** (-5.27) | 0.277** (2.45) |
| pgdp | 0.072*** (5.23) | 0.072*** (6.00) | -0.023*** (-3.85) |
| rd | -0.663* (-1.78) | -0.327*** (-2.67) | 0.363 (1.29) |
| indr | 0.170*** (2.92) | 0.061 (1.56) | 0.078* (1.88) |
| Constant term | 0.800*** (11.83) | 1.014*** (10.72) | 0.966*** (14.41) |
| Number of samples | 240 | 240 | 240 |

Observing Table 2, it can be found that the coefficient of the level of development of digital economy is 0.017 and significant at the 1% level, which indicates that the development of digital economy can significantly promote total factor productivity in manufacturing industry and is beneficial to the development of manufacturing enterprises. The result of observing the decomposition term shows that the coefficient of digital economy on technical progress is 0.008 and significant at 1% level, while the coefficient of digital economy on technical efficiency is -0.013 but not significant, which indicates that digital economy significantly promotes the growth of technical progress and has an insignificant effect on technical efficiency, and the positive effect of digital economy on total factor productivity of manufacturing industry is mainly through promoting technological progress to achieve. The reason that the digital economy fails to significantly promote technical efficiency may be that enterprises do not make good use of digital technology to improve their own labor productivity, their digital production management and operation management systems are not perfect, resources are not well allocated, and digital dividends are not well released.

4. Conclusion

In this paper, based on provincial panel data from 2013-2019, the entropy weight method was used to measure the digital economy; and the Malmquist index method was used to measure manufacturing TFP, which was decomposed into technical progress and technical efficiency to deeply explore the impact of the digital economy on total factor productivity in manufacturing. This paper analyzes different dimensions of the digital economy from the perspective of different dimensions of the digital economy to study the effect of different dimensions of the digital economy on manufacturing TFP, and uses the mediation model to test. The research results show that the digital economy can significantly promote manufacturing TFP, and it is through the enhancement of technological progress to enhance manufacturing TFP, and the digital economy can promote manufacturing TFP growth through two paths: enhancing enterprises' technological innovation capability and improving resource allocation efficiency. governance inhibits manufacturing TFP growth.

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