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Estimating and Decomposing the TFP Growth of Service-Oriented Manufacturing in China: A Translogarithmic Stochastic Frontier Approach

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Abstract: By constructing a translogarithmic stochastic frontier production model, this study explores the total factor productivity (TFP) of service-oriented manufacturing in 30 provinces in China during 2004–2020. We carried out decomposition analysis to understand in greater depth the potential drivers of TFP growth. The results show that the overall TFP of service-oriented manufacturing continuously improved during the sample period; however, the overall growth rate showed a significant slowing trend, and the contribution of TFP growth to output growth is still low. The industrial growth of service-oriented manufacturing is mainly driven by capital input, and the transformation of its growth mode from extensive to intensive has not yet been realized. Furthermore, there exists significant regional and sub-sectoral heterogeneity in the TFP growth of the industry. The decomposition of TFP growth shows that technological progress and technical efficiency are the main sources of TFP growth, but the growth rate of technological progress is declining gradually, and its driving effect on TFP is weakening. The deterioration of both scale and allocation efficiency hinders the improvement of TFP in service-oriented manufacturing, and there is still room for the industry to improve its TFP level by improving scale efficiency and allocation efficiency.

Keywords: TFP growth; service-oriented manufacturing; stochastic frontier analysis; decomposition analysis

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1. Introduction

With the intensification of international competition, China's manufacturing industry is facing increasing pressure to undertake structural transformation and upgrading. The original competitive advantages of the manufacturing industry have been weakened, and the traditional simple production mode can no longer meet the requirements of the internationalization of the manufacturing industry. The necessity of accelerating the transformation and upgrading of the manufacturing industry is becoming increasingly pressing.

As a new manufacturing paradigm integrating "products + service", service-oriented manufacturing is an effective way to achieve the innovative, cost-effective, and high-quality development of the manufacturing industry, and to help manufacturing enterprises form new competitive advantages in the international market [1]. Advanced manufacturing countries, such as the United States and Germany, have already realized the servitization of their manufacturing industries, which is a powerful trend in the development of the global manufacturing industry [2]. To accelerate the transformation and upgrading of China's manufacturing industry, the Chinese government put forward the "Made in 2025" plan in 2015, which clearly indicates that the development of service-oriented manufacturing should be accelerated, driving the manufacturing industry to achieve the specialization and high-end extension of the global value chain. Subsequently, in July 2016, the Chinese Ministry of Industry and Information Technology and the National Development and Reform

Commission jointly formulated and issued the "Special Action Guide for the Development of Service-oriented Manufacturing in China (2016–2018)", which further emphasizes the development of service-oriented manufacturing and plays an important guiding role in promoting the development of each region's service-oriented manufacturing.

Compared with the traditional simple production mode, service-oriented manufacturing integrates the production-based economy and consumption-based service economy and can better meet the needs of customers in an all-round way [3]. It improves the personalized production and services of enterprises, enhances their competitiveness, and extends to two ends of the "smile curve": that is, moving in the direction of high-added value through service investment or R&D innovation and creating more economic profits and a higher market share [4]. Furthermore, service-oriented manufacturing can overcome the problems of low-level repetitive construction and overcapacity that are experienced in the traditional manufacturing industry and guide the manufacturing industry to a new industrial production mode oriented around differentiation, diversification, and service efficiency [5]. Due to these clear advantages, it has attracted increasing attention from both scholars and entrepreneurs all around the world. Many theoretical and technical studies have been conducted on service-oriented manufacturing from different perspectives [6–9]; however, few studies have focused on the total factor productivity (TFP) of service-oriented manufacturing, especially in the context of China, the largest manufacturing country in the world.

Furthermore, to date, many scholars have proposed different methods and models for the measurement of TFP growth [10–14]. However, there are still some research gaps in this academic field. First, most of the studies adopt data envelopment analysis (DEA) for the measurement of TFP growth in China; however, the DEA method requires the construction of a production frontier for each cycle of the panel data, which requires high data accuracy [15] and is easily affected by sample outliers [16]. Moreover, since China is currently undergoing a rapid economic transition and is affected by some imperfectly controllable factors, such as institutional transitions and the international market environment, there are inevitably random disturbances and unobservable factors involved in the process of economic growth [17]. Therefore, a DEA method with deterministic boundaries may not be fully applicable to the TFP problem in China. Second, although a few studies have tried to evaluate TFP performance by utilizing stochastic frontier analysis (SFA), the frontier production function of these studies takes the Cobb–Douglas (C-D) form, and the assumptions of constant substitution elasticity and neutral technological progress are often too harsh, which may cause model missetting [18]. Third, the existing literature considers only two aspects of the decomposition of TFP growth: technological progress and efficiency changes. However, in a transition economy such as China, due to the imperfection of the factor market, the industrial sector has much more room to improve productivity through factor reallocation and scale adjustment than in mature economies [19]. Therefore, it is necessary to take factor allocation and the scale adjustment effect into account when analyzing the sources of TFP changes. Nevertheless, the existing literature often ignores these two aspects.

Accordingly, this study aims to make marginal contributions to the existing literature in the following three areas. First, following the work of Solow [20] and Kumbhakar et al. [21], we constructed a translogarithmic stochastic frontier production function, which has obvious advantages over the DEA method when dealing with statistical noise and the heterogeneity of reaction technology. We use this to assess the TFP performance of service-oriented manufacturing in China for the first time. Second, regarding the shortcomings of the C-D production function in TFP measurement, the translogarithmic stochastic frontier production function effectively addresses the binding of the functional form through a series of strict hypothesis tests and selects the most appropriate model for the TFP evaluation of China's service-oriented manufacturing. Third, unlike previous studies that consider only the two sources of TFP growth (i.e., technological progress and efficiency change), this study further decomposed TFP growth into four components: the factor allocation efficiency change, the scale efficiency change, technological progress, and the technical efficiency change. We analyzed the dynamic impacts of each component on TFP growth from the national, regional, and sectoral perspectives. A comprehensive consideration of the decomposition factors of TFP will help us to have a deeper understanding of the driving factors behind the growth of TFP, so as to formulate more specific and targeted policies to promote the growth of TFP in service-oriented manufacturing. Accordingly, this study has important practical significance. It allows for a deeper understanding of the dynamic evolution trend of TFP growth in China's service-oriented manufacturing industry and enables us to explore the potential drivers of TFP change and the reasons for the unbalanced development of service-oriented manufacturing between different regions and sub-sectors.

The remainder of the study is arranged as follows. Section 2 comprises a review of the related literature, and Section 3 presents the materials and methods. In Section 4, we carry out model hypothesis testing and analysis. Section 5 presents the empirical results and offers further discussion. In the last section, the research conclusions and policy implications are provided.

2. Literature Review

2.1. Overview of Service-Oriented Manufacturing

The research on service-oriented manufacturing can be considered an extension of the study of the manufacturing industry and the service industry. Vandermerwe and Rada [22] first proposed that service-oriented manufacturing is a new mode in which manufacturing enterprises can add value to their products by providing customers with a full range of services through continuous technological innovation and service extension that meet customers' individual needs. The research findings of Bathla [23] indicate that, with the expansion of the economic scale of the manufacturing sector, the demand for services will increase, and the interdependence of services and manufacturing will increase the productivity of service-oriented manufacturing. These viewpoints are supported by the work of Baines, et al. [24], who concluded that the adoption of service-integrated manufacturing strategies is effective not only in gaining customer acceptance but also in increasing revenue and reducing the cost of organizational change. Furthermore, another strand of the literature explored the key factors that facilitate the development of service-oriented manufacturing. For example, by studying Finland's manufacturing industry and service industry, Leiponen [25] found that research and development (R&D) can play a major intermediary role in promoting the integrated development of the service industry and the manufacturing industry. The research results of Lightfoot, et al. [26], show that the widespread application of information and communication technologies (ICTs) accelerates the integration of the manufacturing and service industries. In addition, a growing number of technical studies have also focused on service-oriented manufacturing in terms of system designs [1,27], supply chain management [6,8], key technologies [28,29], pricing strategies [30,31], outsourcing of maintenance services [3,5], customer impact [4,32], etc. However, there are few quantitative analyses of service-oriented manufacturing. Notably, no studies have assessed the total factor productivity of service-oriented manufacturing to date, even for China, the largest manufacturing country in the world.

2.2. Total Factor Productivity Measurement

Total factor productivity (TFP), also known as the "Solow residual", was first proposed by Solow [20]. It refers to the increase in output caused by technological progress and capability realization beyond the input of various factors (such as capital and labor); it is the residual obtained after excluding the contribution of factor inputs. In the literature, there are three methods commonly used to estimate the TFP: Solow residual analysis (SRA), data envelopment analysis (DEA), and stochastic frontier analysis (SFA). The traditional SRA method assumes that the economic entity is technically effective; that is, the economic entity under study is at the level of the optimum technological frontier of the production function [13]. However, as elements such as the market environment, technological level, and social institutions of most developing countries are imperfect and still need to be improved [33], it is difficult for these countries to meet the requirements of economic entities being at the forefront of technology [34]. For this reason, the SRA approach is not applicable to China, which is currently undergoing rapid economic transition. With respect to the DEA method, it evaluates the relative effectiveness of multiple inputs and outputs of decision-making units at the same time [35]. It has the advantages of dimensional processing and not needing to set a production function form [36]. However, this approach has some limitations; it requires the construction of a production frontier for each cycle of the panel data, which requires highly accurate data, and it is easily affected by sample outliers [18]. Furthermore, since China is currently undergoing a rapid economic transition and is affected by some imperfectly controllable factors, such as institutional transition and the international market environment, there are inevitably random disturbances and unobservable factors involved in the economic growth process [17,37]. Therefore, a DEA method with deterministic boundaries may not be fully applicable to the TFP of China. Unlike the SRA and DEA approaches, the SFA method requires the setting of a production function while allowing for the existence of error terms; additionally, it constructs one production front for the whole of the sample data, which is helpful for weakening the influence of abnormal data on the overall estimation results, reducing errors [38]. Because of these advantages, it has recently been endorsed by various scholars. For example, Rawat and Sharma [39] measured the TFP growth of the Indian manufacturing industry by employing the SFA approach and decomposed it into technical change and efficiency improvement. Based on the same method, Baležentis and Sun [40] explored the TFP growth of the Lithuanian dairy sector and found that the industry maintained an average annual TFP growth of 2%; additionally, the main sources of TFP growth were technical change and scale efficiency improvements. Although these studies attempted to calculate TFP growth based on the SFA approach, the frontier production function of these studies takes the Cobb–Douglas (C-D) form and the assumptions of constant substitution elasticity and neutral technological progress are often too harsh [41,42], which may cause model missetting [14,43]. Furthermore, the decomposition of TFP growth in these studies accounts for only two aspects: technological progress and efficiency changes. However, in a transition economy such as China's, due to the imperfection of the factor market, the industrial sector has much more room to improve productivity through factor reallocation and scale adjustment than in mature economies [44,45]. Therefore, it is necessary to take factor allocation and scale adjustment effect into account when analyzing the sources of TFP changes. Nevertheless, the existing literature often ignores these two aspects.

3. Materials and Methods

3.1. Model Setting

As discussed in Section 2.2, this study employs the SFA method to measure the total factor productivity (TFP) growth of China's service-oriented manufacturing industry. According to the work of Aigner, et al. [38], we assume that the form of the stochastic frontier production function is as follows:

$$y_{it} = f(x_{it}, t; \beta) \exp(v_{it} - u_{it}) \tag{1}$$

where y_{it} indicates the output value of region (or industry) i in year t; x_{it} refers to the factor input of region (or industry) i in year t; and β is the parameter to be estimated in the production function. The optimal output frontier of the production function is $f(x_{it}, t; \beta)$. The random disturbance term includes the following two terms: v_{it} and u_{it}. Specifically, v_{it} is a general disturbance term composed of the measurement error or other uncontrollable random factors, subject to the distribution of $iidN\left(0, \sigma_v^2\right)$, and u_{it} is the technical inefficiency term. These two disturbance terms are independent of each other. Furthermore, $TE_{it} = \exp(-u_{it})$ represents the technical efficiency, which measures the distance between the actual output caused by production inefficiency and the production front.

We construct the following translogarithmic stochastic frontier production function by taking the logarithm of Equation (1):

$$\ln y_{it} = \alpha_0 + \sum_{j=1}^{2} \alpha_j \ln x_{itj} + \frac{1}{2}\sum_{j=1}^{2}\sum_{i=1}^{2} \alpha_{jl} \ln x_{itj} \ln x_{lit} + \beta_1 t + \frac{1}{2}\beta_2 t^2 + \sum_{j=1}^{2} \rho_j t \ln x_{itj} + v_{it} - u_{it} \tag{2}$$

where x_{itj} and x_{itl} denote the j and l input factors of region (or industry) i in year t, representing capital and labor, respectively. t is the time trend variable that represents the technological change. In Equation (2), the cross term (i.e., $tlnx_{itj}$) of the time trend and factor input is introduced to represent the possible non-neutral technological progress in production.

The technical inefficiency term (i.e., u_{it}) can be expressed as follows by referring to the work of Battese and Coelli [46]:

$$u_{it} = u_i \eta_{it} = u_i \exp[-\eta(t-T)] \tag{3}$$

where u_i follows a non-negative truncated normal distribution $N^+(\mu, \sigma_u^2)$. η represents the change rate of the technical efficiency index; if $\eta > 0$, it indicates that technical efficiency is improving over time, and if $\eta < 0$, it indicates the deterioration of technical efficiency. Meanwhile, $\eta = 0$ indicates that the technical efficiency does not change over time.

The maximum likelihood (ML) approach is employed to jointly estimate the parameters of the stochastic frontier model determined by Equations (2) and (3). The variance parameters in the likelihood function can be constructed as follows:

$$\gamma = \sigma_u^2 / \sigma^2 \tag{4}$$

$$\sigma^2 = \sigma_u^2 + \sigma_y^2 \tag{5}$$

We separate the estimated value of the technical inefficiency term from the composite error ($e_{it} = v_{it} - u_{it}$) by following the work of Jondrow, et al. [47]:

$$\hat{u}_{it} = E[u_{it}|e_{it}] = E[u_{it}\eta_{it}|e_{it}] = E[u_i|e_i]\eta_{it} = [u_i^* + \sigma_i^* \frac{\Phi(-\mu_i^*/\sigma_i^*)}{\Phi(\mu_i^*/\sigma_i^*)}] \exp[-\eta(t-T)] \tag{6}$$

$$\mu_i^* = \frac{\mu\sigma_v^2 - \sigma_u^2 \sum_1^T \eta_{it} e_{it}}{\sigma_v^2 + \sigma_u^2 \sum_1^T \eta_{it}^2} = \frac{\mu(1-\gamma) - \gamma \sum_1^T \eta_{it} e_{it}}{(1-\gamma) + \gamma \sum_1^T \eta_{it}^2} \tag{7}$$

$$\sigma_i^{*2} = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_u^2 \sum_1^T \eta_{it}^2} = \frac{(1-\gamma)\gamma\sigma^2}{(1-\gamma) + \gamma \sum_1^T \eta_{it}^2} \tag{8}$$

Therefore, the estimated technical efficiency of region (or industry) i in year t can be expressed as

$$TE_{it} = E[\exp(-u_{it})|e_{it}] = \frac{\Phi(\mu_i^*/\sigma_i^* - \eta_{it}\sigma_i^*)}{\Phi(\mu_i^*/\sigma_i^*)} \exp(-\eta_{it} u_i^* + \frac{1}{2}\eta_{it}^2 \sigma_{\mathrm{i}}^{*2}) \tag{9}$$

Combined with the two main input factors in this study (i.e., capital (K) and labor (L)), the specific form of the translogarithmic stochastic frontier production function can be represented as follows:

$$\begin{gathered}\ln y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_T t + \tfrac{1}{2}\beta_{KK}(\ln K_{it})^2 + \tfrac{1}{2}\beta_{LL}(\ln L_{it})^2 \\ + \beta_{\mathrm{KL}} \ln K_{it} \ln L_{it} + \tfrac{1}{2}\beta_{TT} t^2 + \beta_{TK} t \ln K_{it} + \beta_{TL} t \ln L_{it} + v_{it} - u_{it}\end{gathered} \tag{10}$$

To test the rationality and feasibility of the translogarithmic stochastic frontier model selected in this study, we proposed the following hypotheses:

(i) $H_0 : \beta_{KK} = \beta_{LL} = \beta_{KL} = \beta_{TT} = \beta_{TK} = \beta_{TL} = 0$; this means that the frontier production function should be in the form of the Cobb–Douglas (C-D) production function.
(ii) $H_0 : \beta_T = \beta_{TT} = \beta_{TK} = \beta_{TL} = 0$; that is, there is no technological progress.
(iii) $H_0 : \beta_{TK} = \beta_{TL} = 0$; this indicates that technological progress is Hicks-neutral.
(iv) $H_0 : \gamma = \eta = \mu = 0$; that is, there is no technical inefficiency term.
(v) $H_0 : \eta = 0$; this indicates that technical inefficiency does not change with time.
(vi) $H_0 : \mu = 0$; this means that u_i obeys the $N^+(0, \sigma_u^2)$ distribution.
(vii) H_0 : the terms with insignificant coefficients in the primary selection model are 0.

All hypotheses were tested using generalized likelihood ratio (LR) statistics. The calculation formula of LR statistics is: $LR = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ represent the likelihood function values of constrained and unconstrained models, respectively. When the null hypothesis H_0 is true, the LR statistics obey the mixed χ^2 distribution, and the degree of freedom is the number of constrained variables.

3.2. Decomposition of Total Factor Productivity Growth

By following the work of Kim and Han [48], we decompose the changes in TFP into the following four parts: technological progress (TC), technological efficiency change (TEC), scale efficiency change (SEC), and allocation efficiency change (AEC). We first take the logarithm of both sides of the production function Equation (1), and then take the derivative of t:

$$\frac{d \ln y_{it}}{dt} = \frac{\partial \ln f(x_{it}, t; \beta)}{\partial t} + \sum_{j=1}^{2} \frac{\partial \ln f(x_{it}, t; \beta)}{\partial \ln x_{itj}} \frac{d \ln x_{itj}}{dt} - \frac{du_{it}}{dt} \tag{11}$$

where $\varepsilon_{\text{itj}} = \frac{\partial \ln f(x_{it}, t; \beta)}{\partial \ln x_{itj}}$ indicates the output elasticity of the j th factor. Then, Equation (11) can be expressed as

$$y_{it} = \frac{\partial \ln f(x_{it}, t; \beta)}{\partial t} + \sum_{j=1}^{2} \varepsilon_{itj} x_{itj} - \frac{du_{it}}{dt} \tag{12}$$

TFP is the part of output growth that cannot be explained by the growth of factor input. Then, the TFP growth rate can be expressed as

$$TFP_{it} = y_{it} - \sum_{j=1}^{2} s_{itj} x_{itj} \tag{13}$$

where $s_{itj} = w_{itj} x_{itj} / \sum_{j=1}^{2} w_{itj} x_{itj}$ represents the cost share of the j th input factor, $\sum_{j=1}^{2} s_{itj} = 1$. Then, by substituting Equation (12) into Equation (13), we can obtain

$$\begin{aligned} TFP_{it} &= \tfrac{\partial \ln f(x_{it}, t; \beta)}{\partial t} - \tfrac{du_{it}}{dt} + \sum_{j=1}^{2} (\varepsilon_{itj} - s_{itj}) x_{itj} \\ &= \tfrac{\partial \ln f(x_{it}, t; \beta)}{\partial t} - \tfrac{du_{it}}{dt} + (RTS_{it} - 1) \sum_{j=1}^{2} \lambda_{itj} x_{itj} + \sum_{j=1}^{2} (\lambda_{itj} - s_{itj}) x_{itj} \end{aligned} \tag{14}$$

where $RTS_{\text{it}} = \sum_{j=1}^{2} \varepsilon_{itj}$ represents the elasticity of the input scale, which measures the scale effect. $\lambda_{\text{itj}} = \frac{\varepsilon_{itj}}{RTS_{it}}$ indicates the relative output elasticity of the input factor j.

By combining Equation (14) with Equation (10), we decompose the TFP growth into the following four terms:

(1) Technical progress (TC). This refers to the change rate of output over time when the input factors are fixed; that is, the output growth brought about by technological progress.

$$TC_{it} = \frac{\partial \ln f(x_{it}, t; \beta)}{\partial t} = \beta_T + \beta_{TT} t + \beta_{TK} \ln K_{it} + \beta_{TL} \ln L_{it} \tag{15}$$

(2) Technical efficiency change (TEC). This represents the change in the gap between the actual output and the maximum possible output at a given level of technology and factor inputs.

$$TEC_{it} = \frac{\partial \ln TE_{it}}{dt} = -\frac{du_{it}}{dt} \tag{16}$$

(3) Scale efficiency change (SEC). This refers to the productivity changes caused by economies of scale or diseconomies of scale.

$$\begin{aligned} SEC_{it} = (RTS_{it} - 1)\sum_{j=1}^{2} \lambda_{itj}x_{itj} = (\beta_K + \beta_{KK}\ln K_{it} + \beta_{KL}\ln L_{it} + \beta_{TK}t + \beta_L + \beta_{LL}\ln L_{it} + \beta_{KL}\ln K_{it} \\ +\beta_{TL}t - 1) \times (\tfrac{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t}{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t+\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t}\dot{K}_{it} \\ +\tfrac{\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t}{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t+\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t}\dot{L}_{it}) \end{aligned} \tag{17}$$

(4) Allocation efficiency change (AEC). This measures productivity changes caused by structural changes in factor inputs.

$$\begin{aligned} AEC_{it} = \sum_{j=1}^{2} (\lambda_{itj} - s_{itj})x_{itj} = \\ (\tfrac{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t}{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t+\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t} - S_{itK})\dot{K}_{it} \\ +(\tfrac{\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t}{\beta_K+\beta_{KK}\ln K_{it}+\beta_{KL}\ln L_{it}+\beta_{TK}t+\beta_L+\beta_{LL}\ln L_{it}+\beta_{KL}\ln K_{it}+\beta_{TL}t} - S_{itL})\dot{L}_{it} \end{aligned} \tag{18}$$

(5) Total factor productivity change ($T\dot{F}P$):

$$T\dot{F}P = TC + TEC + SEC + AEC \tag{19}$$

3.3. Variable Selection and Data Sources

For empirical analysis, this study employs a panel dataset of the service-oriented manufacturing industries in 30 Chinese provinces from 2004 to 2020. Due to the unavailability of data, Tibet, Hong Kong, Macao, and Taiwan are not included in the sample. Referring to the work of Wu, et al. [49] and Jiang, et al. [50], seven industries, including communication equipment, computer and other electronic equipment manufacturing (I_1), transportation equipment manufacturing (I_2), food manufacturing (I_3), general equipment manufacturing (I_4), instrumentation and culture, office machinery manufacturing (I_5), special equipment manufacturing (I_6), and electrical machinery and equipment manufacturing (I_7) were selected as the statistical objects. These manufacturing industries usually provide more professional after-sales services and customized design than other manufacturing industries, and their value-added services account for a high proportion [50].

We took the total output value of service-oriented manufacturing industry in each province as the proxy of the output variable and converted it according to the 2003 fixed price index to eliminate the impact of price fluctuation. The input variables included capital (K) and labor (L). Labor input was proxied by the number of employees in the service-oriented manufacturing industry at the end of the year, and capital input was measured by capital stock. We employed the perpetual inventory method to estimate the capital stock. In addition, it was also necessary to calculate the cost share of each input factor when using the stochastic frontier approach. The cost of capital input was measured by the depreciation of fixed assets and the interest expenditure of the service-oriented manufacturing industry in each province, and the total labor remuneration was used to measure the cost of labor input [51]. The data for all the above variables were taken from the China Statistical Yearbook, the China Industrial Statistical Yearbook, the China Labor Statistical Yearbook, and the China Science and Technology Statistical Yearbook.

4. Model Hypothesis Test and Analysis

To create an effective and suitable model for the TFP evaluation of service-oriented manufacturing, we carried out a series of model hypothesis tests using the maximum likelihood estimation (MLE) method. All hypotheses in Section 2.1 were tested using the generalized likelihood ratio (LR) statistics. The test results are shown in Table 1. From Table 1, it can be seen that Hypothesis 1 is rejected at the significance level of 1%, which indicates that the frontier production function in its translogarithmic form is more suitable for explaining the production technology structure of service-oriented manufacturing than the C-D production function. Hypotheses 2 and 3 are also rejected at the significance level of 1%, indicating that there was technological progress in the sample period, and that it was not Hicks-neutral. In other words, technology is not independent of production factors but is embedded in them, and changes in input factors will also cause changes in technological progress. Furthermore, the LR statistics of Hypothesis 4 caused the null hypothesis to be rejected at the significance level of 1%, which implies that there exists a technical inefficiency term in the benchmark model. This again supports the suitability of adopting the stochastic frontier model. For Hypothesis 5, the null hypothesis is rejected at the 1% confidence level, indicating that the time-varying efficiency model should be selected if the technical efficiency changes with time during the sample period. Hypothesis 6 and Hypothesis 7 are both accepted at the significance level of 1%, indicating that u_i follows a semi-normal distribution. Therefore, μ = 0 should be set when estimating the stochastic frontier model, and the non-significant coefficient in the primary model should be excluded.

Table 1. Hypothesis test results of the stochastic frontier model.

Null Hypothesis H_0	LR Statistic	Critical Value (CV)	Inspection Conclusion
1. $H_0 : \beta_{KK} = \beta_{LL} = \beta_{KL} = \beta_{TT} = \beta_{TK} = \beta_{TL} = 0$	107.94	16.81	refuse
2. $H_0 : \beta_T = \beta_{TT} = \beta_{TK} = \beta_{TL} = 0$	67.01	13.28	refuse
3. $H_0 : \beta_{TK} = \beta_{TL} = 0$	11.75	9.21	refuse
4. $\mathrm{H}_0 : \gamma = \eta = \mu = 0$	464.1	11.34	refuse
5. $H_0 : \eta = 0$	80.87	6.63	refuse
6. $H_0 : \mu = 0$	0.94	2.71	accept
7. H_0 : The coefficient insignificance term in the primary model is 0.	1.64	4.61	accept

Note: the critical value corresponds to the significance level of 1%.

Based on the above hypothesis test results, we carried out model estimation for Equation (10), and Table 2 reports the corresponding results. In Table 2, Model 1 is the unrestricted model, Models 2 and 3 are restricted models, and the restraint conditions are β_L = 0, μ = 0, and β_L = 0. The coefficients of parameter μ and $\ln L_{it}$ in Model 1 are not significant, and the coefficient of μ is still not significant after removing the non-significant term (i.e., $\ln L_{it}$) in Model 2. Therefore, Model 3 is selected as the benchmark model for the estimation of the translogarithmic stochastic frontier production function (i.e., Equation (10)). According to the estimation results of Model 3, it can be seen that the LR test results of the translogarithmic stochastic frontier model are significant at the level of 1%, and the γ value is above 95%, indicating that the production fluctuations under the given conditions of factor input mainly arise due to technological inefficiency. Furthermore, the time-varying parameter (i.e., η) of technical efficiency in Model 3 is significantly positive, indicating that the technical efficiency of service-oriented manufacturing gradually improved during the sample period.

Table 2. Estimation results of the stochastic frontier model.

Variable	Coefficient	Model 1	Model 2 ($\beta_L = 0$)	Model 3 ($\mu = 0, \beta_L = 0$)
Cons_	β_0	1.5498 *** (4.94)	1.5060 *** (4.66)	1.4046 *** (5.08)
$\ln K_{it}$	β_K	0.9406 *** (6.82)	1.0270 *** (16.59)	1.0266 *** (16.43)
$\ln L_{it}$	β_L	0.0959 (0.70)	0	0
t	β_T	0.1461 *** (6.49)	0.1391 *** (6.86)	0.1441 *** (7.55)
$\frac{1}{2}(\ln K_{it})^2$	β_{KK}	−0.3111 *** (−5.72)	−0.3360 *** (−8.55)	−0.3399 *** (−8.80)
$\frac{1}{2}(\ln L_{it})^2$	β_{LL}	−0.4181 *** (−7.46)	−0.4354 *** (−8.80)	−0.4378 *** (−8.87)
$\ln K_{it} \ln L_{it}$	β_{KL}	0.3520 *** (6.51)	0.3742 *** (8.74)	0.3790 *** (9.05)
$\frac{1}{2}t^2$	β_{TT}	−0.0114 *** (−8.65)	−0.0114 *** (−8.59)	−0.0116 *** (−8.92)
$t \ln K_{it}$	β_{TK}	0.0220 *** (2.46)	0.0226 ** (2.55)	0.0233 *** (3.62)
$t \ln L_{it}$	β_{TL}	−0.0276 *** (−3.20)	−0.0276 *** (−3.18)	−0.0289 *** (−3.47)
σ^2		0.0847 ** (2.60)	0.0833 ** (2.72)	0.1346 *** (3.72)
γ		0.9691 *** (36.09)	0.9712 *** (49.19)	0.9867 *** (65.83)
μ		0.2043 (1.35)	0.2299 (1.57)	0
η		0.0583 *** (9.71)	0.0570 *** (9.44)	0.0578 *** (9.91)
Likelihood function logarithm		171.75	169.79	169.21
LR statistics		468.49 ***	494.93 ***	493.80 ***

Note: **, *** represent the significance level at 5%, and 1%, respectively; T values in brackets.

In addition, we further carried out the hypothesis test and model selection procedure for the sub-sectors of service-oriented manufacturing in the same way as described above. The results are shown in Table 3. Table 3 shows that the LR test results of the stochastic frontier final selection model are significant in all sub-sectors; the time-varying parameters of technical efficiency are negative in the I_1, I_5, and I_7 sub-sectors and positive in the other sectors. This shows that, although the overall time-varying parameter (i.e., η) of the service-oriented manufacturing industry is positive (as shown in Table 2), the development of each sub-sector is different.

Table 3. Estimation results of the subdivided service-oriented manufacturing industry.

Variable	Coef.	I_1	I_2	I_3	I_4	I_5	I_6	I_7
Cons_	β_0	2.2358 *** (12.27)	2.3626 *** (10.82)	1.1105 *** (11.01)	1.3350 *** (7.05)	0.8094 *** (4.88)	1.5705 *** (9.31)	1.0588 *** (6.93)
$\ln K_{it}$	β_K	0.6085 *** (9.61)	0.3629 *** (2.74)	0.6077 *** (12.65)	0.4774 *** (15.72)	0.6073 *** (5.12)	0	0.6049 *** (12.86)
$\ln L_{it}$	β_L	0.4807 *** (5.92)	1.2137 *** (8.53)	0.3987 *** (11.57)	0.7337 *** (15.02)	0.7586 *** (5.02)	1.1351 *** (23.20)	0.2604 *** (5.86)
t	β_T	0.1635 *** (10.54)	0.3173 *** (15.07)	0.1756 *** (16.40)	0.2178 *** (12.65)	0.2293 *** (14.10)	0.2843 *** (17.48)	0.3076 *** (29.13)
$\frac{1}{2}(\ln K_{it})^2$	β_{KK}	−0.0221 *** (−3.03)	0.6771 *** (11.02)	0.0882 *** (5.11)	0	0.0872 ** (2.91)	0.4186 *** (6.51)	0.0987 *** (8.32)
$\frac{1}{2}(\ln L_{it})^2$	β_{LL}	0.1528 *** (10.89)	0.6660 *** (10.68)	0	−0.2261 *** (−7.24)	0.2525 *** (2.96)	0.3508 *** (3.86)	0
$\ln K_{it} \ln L_{it}$	β_{KL}	0	−0.6416 *** (−10.49)	0	0.0620 *** (5.09)	−0.1283 ** (−2.18)	−0.4032 *** (−5.28)	0
$\frac{1}{2}t^2$	β_{TT}	0	0	−0.0018 ** (−2.05)	−0.0123 *** (−10.14)	−0.0061 *** (−3.40)	−0.0086 *** (−4.21)	−0.0082 *** (−7.22)
$t \ln K_{it}$	β_{TK}	−0.0266 *** (−5.37)	−0.0897 *** (−14.00)	−0.0235 *** (−8.53)	0	−0.0216 *** (−9.08)	−0.0432 *** (−3.64)	−0.0317 *** (−11.82)
$t \ln L_{it}$	β_{TL}	0.0113 ** (2.11)	0.0841 *** (12.78)	0	−0.0106 *** (−4.67)	0	0.0352 *** (2.49)	0
σ^2		1.8694 *** (3.57)	0.3012 *** (3.55)	0.1367 *** (4.01)	0.0648 *** (6.29)	0.6422 *** (3.56)	0.1869 *** (3.37)	0.04726 ** (2.80)
γ		0.9213 *** (40.40)	0.8032 *** (12.88)	0.6448 *** (6.59)	0.9275 *** (48.03)	0.890 *** (18.45)	0.748 *** (6.98)	0.8848 *** (21.23)
μ		0	0	0	0.2445 *** (2.71)	0	0	0
η		−0.0371 *** (−5.87)	0.0496 *** (6.457)	0.0134 ** (2.33)	0.0800 *** (7.56)	−0.0388 ** (−2.01)	0.0514 *** (4.88)	−0.1908 ** (−2.61)
Likelihood function logarithm value		−208.91	−48.15	21.00	−62.70	−351.08	−59.47	−82.90
LR statistics		398.79 ***	351.44 ***	169.17 ***	275.89 ***	106.35 ***	244.36 ***	231.9 ***

Note: **, *** represent the significance level at 5%, and 1%, respectively; T values in brackets.

5. Empirical Results and Discussion

5.1. Changes in the TFP Growth of China's Service-Oriented Manufacturing Industry

According to the estimation results of the translogarithmic stochastic frontier model (i.e., Equation (10)) in Section 4, we can calculate the TFP growth of China's service-oriented manufacturing industry; Figure 1 shows the changing trend of TFP growth over the period 2004–2020. We can see from Figure 1 that TFP growth at the national and regional levels is always positive during the study period, with the exception of some individual years. The overall TFP keeps improving; however, the overall growth rate shows a significant slowing trend. Nevertheless, it is noteworthy that the gap between different regions exhibits a gradual narrowing trend. In addition, TFP declined sharply in 2008 due to the impact of the financial crisis, and all three regions were affected to different degrees, with the largest decline in the central region, followed by the western region, and the smallest decline in the eastern region. Driven by a series of economic revitalization measures taken by local governments in the face of the financial crisis, the TFP growth of each region rebounded again in 2009. However, due to the continuity of the negative impacts of the financial crisis, the TFP growth rate still experiences small fluctuations after 2009. Finally, when COVID-19 broke out in 2020, it had a significant impact on the development of the manufacturing industry and other economic sectors; therefore, the growth of TFP both at national and regional levels (i.e., eastern, central, and western regions) fell again in 2020. In summary, the TFP growth of service-oriented manufacturing in the east is very close to that of the whole country; that of the western region is higher than the national average, while that of the central region is lower than the national average. On the whole, the difference in TFP growth between different regions exhibited a gradual narrowing trend over the sample period.

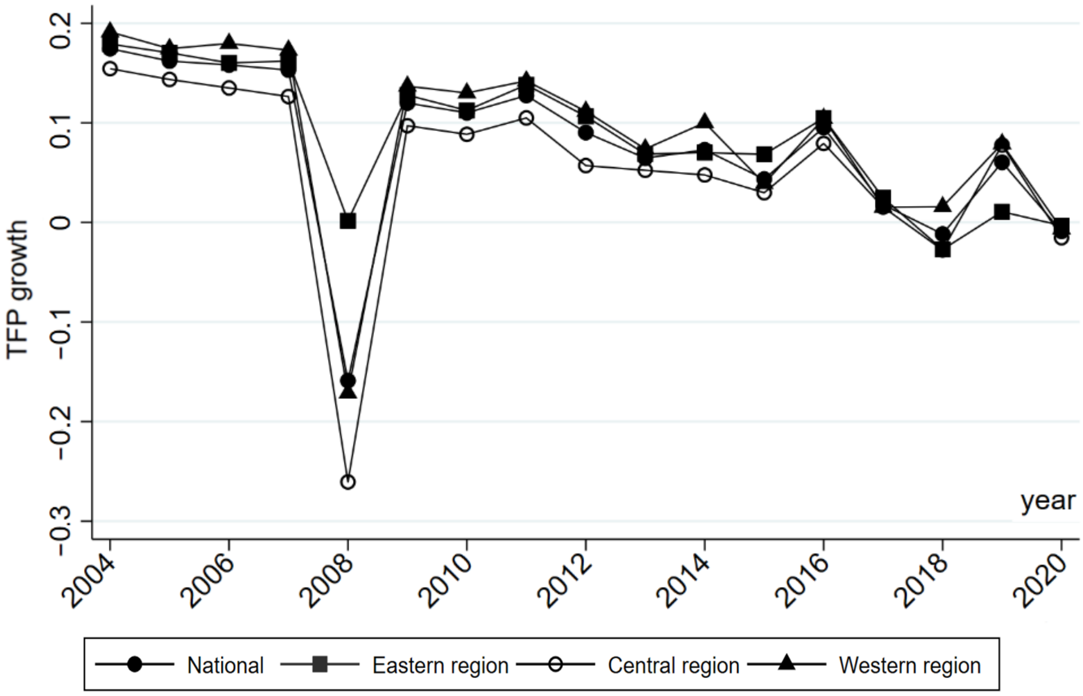

Figure 1. TFP growth of service-oriented manufacturing industry in different regions of China (2004–2020).

5.2. Decomposition of TFP Growth in the Service-Oriented Manufacturing Industry

According to the discussion in Section 2.1, we decompose TFP growth into the following four parts: technological progress (TC), technical efficiency change (TEC), scale efficiency change (SEC), and allocation efficiency change (AEC). Table 4 displays the decomposition results. Table 4 shows that the four decomposition terms of each province have different characteristics. First, the technological progress (TC) in all provinces shows positive values, indicating that service-oriented manufacturing in each province achieved obvious technological progress during the sample period, playing a positive role in promoting the growth of TFP. Second, the technical efficiency change (TEC) also shows positive values in all provinces, a result that is consistent with the estimation results of the time-varying parameter (i.e., η) (as shown in Table 2) of the final selection, Model 3, in Section 4; this factor played a positive role in promoting the improvement of TFP. Third, the scale efficiency change (SEC) varies among different provinces. Apart from six provinces and cities, including Shanghai, Tianjin, Shanxi, Guizhou, Inner Mongolia, and Ningxia, which exhibit positive SEC values, all other provinces are negative, and the decline in scale efficiency hinders the growth of TFP. A moderate expansion of enterprise scale will reduce the cost of unit product and help to achieve economies of scale, which is conducive to the improvement of TFP, while an excessively small enterprise scale will increase the cost of unit product, resulting in diseconomies of scale, which is not conducive to the improvement of TFP. Fourth, the allocation efficiency change (AEC) presents negative values in all provinces except for Shandong and Hubei, and the deterioration of factor allocation efficiency negatively contributes to the growth of TFP. In summary, technological progress and technical efficiency contribute positively to the improvement of TFP in service-oriented manufacturing in each province, while scale efficiency and allocation efficiency vary among the different provinces.

Table 4. Decomposition of TFP growth in service-oriented manufacturing by provinces.

Province	TFP	TC	TEC	SEC	AEC	Province	TFP	TC	TEC	SEC	AEC
Anhui	0.0631	0.0659 (1.046)	0.0196 (0.311)	−0.0029 (−0.046)	−0.0196 (−0.310)	Jiangxi	0.0939	0.0647 (0.689)	0.0372 (0.396)	−0.0013 (−0.013)	−0.0067 (−0.072)
Beijing	0.0845	0.0613 (0.726)	0.027 (0.320)	−0.0018 (−0.021)	−0.0021 (−0.024)	Liaoning	0.0872	0.0682 (0.782)	0.0294 (0.337)	−0.0008 (−0.010)	−0.0095 (−0.109)
Fujian	0.0529	0.0556 (1.050)	0.0051 (0.096)	−0.0028 (−0.054)	−0.0049 (−0.092)	InnerMongolia	0.0987	0.0815 (0.826)	0.0228 (0.231)	0.0010 (0.010)	−0.0066 (−0.067)
Gansu	0.1130	0.0696 (0.616)	0.0625 (0.553)	−0.0006 (−0.005)	−0.0185 (−0.164)	Ningxia	0.0961	0.0811 (0.844)	0.0491 (0.510)	0.0016 (0.016)	−0.0356 (−0.370)
Guangdong	0.0276	0.0421 (1.526)	0.0012 (0.042)	−0.0046 (−0.168)	−0.0110 (−0.400)	Qinghai	0.1067	0.0858 (0.805)	0.0602 (0.564)	−0.0002 (−0.002)	−0.0391 (−0.366)
Guangxi	0.0191	0.0672 (3.517)	0.0200 (1.048)	−0.0006 (−0.030)	−0.0675 (−3.534)	Shandong	0.0670	0.0571 (0.852)	0.0041 (0.061)	−0.0043 (−0.064)	0.0101 (0.151)
Guizhou	0.0726	0.0681 (0.939)	0.0536 (0.739)	0.0015 (0.021)	−0.0507 (−0.699)	Shanxi	0.1178	0.0641 (0.544)	0.0618 (0.525)	0.0001 (0.0004)	−0.0081 (−0.069)
Hainan	0.0743	0.0875 (1.178)	0.0093 (0.125)	−0.0026 (−0.035)	−0.0199 (−0.268)	Shaanxi	0.0996	0.0648 (0.651)	0.0439 (0.441)	−0.0008 (−0.008)	−0.0084 (−0.084)
Hebei	0.0793	0.0634 (0.799)	0.0324 (0.409)	−0.0022 (−0.027)	−0.0143 (−0.181)	Shanghai	0.0596	0.0676 (1.134)	0.0043 (0.072)	0.0001 (0.001)	−0.0124 (−0.208)
Henan	0.0703	0.0556 (0.790)	0.0277 (0.394)	−0.0047 (−0.067)	−0.0083 (−0.117)	Sichuan	−0.0430	0.0757 (−1.762)	0.0029 (−0.068)	−0.0015 (0.035)	−0.1201 (2.795)
Heilongjiang	0.0942	0.0705 (0.748)	0.0404 (0.429)	−0.0002 (−0.002)	−0.0165 (−0.175)	Tianjin	0.0689	0.0711 (1.032)	0.0059 (0.086)	0.0001 (0.001)	−0.0083 (−0.120)
Hubei	0.0901	0.0652 (0.723)	0.0254 (0.281)	−0.0015 (−0.017)	0.0011 (0.012)	Xinjiang	0.0916	0.0932 (1.018)	0.0353 (0.385)	−0.0010 (−0.010)	−0.0360 (−0.393)
Hunan	0.0818	0.0641 (0.783)	0.0329 (0.403)	−0.0020 (−0.025)	−0.0132 (−0.161)	Yunnan	0.0985	0.0681 (0.691)	0.0422 (0.428)	−0.0008 (−0.008)	−0.0109 (−0.111)
Jilin	0.0836	0.0765 (0.914)	0.0080 (0.095)	−0.00001 (−0.00003)	−0.0008 (−0.009)	Zhejiang	0.0491	0.0506 (1.030)	0.0164 (0.335)	−0.0042 (−0.086)	−0.0137 (−0.279)
Jiangsu	0.0506	0.0558 (1.102)	0.0087 (0.172)	−0.0064 (−0.126)	−0.0075 (−0.148)	Chongqing	0.0769	0.0629 (0.818)	0.0234 (0.305)	−0.0019 (−0.025)	−0.0075 (−0.097)

Note: The contribution of each decomposition term to the TFP growth is shown in brackets.

In addition, the contribution of these four decomposition terms to TFP growth also varies significantly across different provinces, and the following four types can be obtained by ranking the absolute value of the contribution rate: (i) 21 provinces and cities, such as Zhejiang and Chongqing, present the TC > TEC > AEC > SEC order; (ii) 4 provinces and cities (Shanghai, Tianjin, Hainan, and Xinjiang) present the TC > AEC > TEC > SEC order; (iii) the order of TC > AEC > SEC > TEC includes Shandong and Guangdong provinces; (iv) only Hubei province presents the TC > TEC > SEC > AEC order; and (v) the order of AEC > TC > TEC > SEC includes Sichuan and Guangxi provinces. It can be seen that most provinces present the first type of contribution ranking. The positive contribution of TC and TEC to TFP growth is greater than the negative contribution of AEC and SEC, indicating that technological progress and technical efficiency are the two main drivers for TFP growth. Furthermore, only the Sichuan and Guangxi provinces experienced TFP decrement due to the serious deterioration of allocation efficiency. Notably, Gansu, Shanxi, and Qinghai provinces presented a relatively high TFP growth, which was driven by significant technological progress and efficiency improvement.

We also decomposed the TFP growth of service-oriented manufacturing into three typical regions (i.e., the eastern, central, and western regions) and conducted growth accounting analysis. The results are shown in Table 5, which indicates that the average TFP growth of service-oriented manufacturing at the national level was 0.0742. TC made the largest contribution of 0.910, and TEC contributes 0.365; meanwhile, AEC and SEC make negative contributions of −0.254 and −0.020, respectively. The contribution of the four decomposition terms to TFP was in the order of TC > TEC > AEC > SEC. At the regional level, the average growth rates of TFP in the central and western regions are close to each other and higher than that in the eastern region; this is mainly driven by technological progress and technical efficiency change. However, the deterioration of allocation efficiency and scale efficiency in the eastern region is relatively serious, hindering the growth of TFP. Therefore, it can be concluded that the TFP growth of China's service-oriented manufacturing mainly comes from technological progress and technical efficiency, among which technological progress is the main driving source. In addition, the growth accounting results show that China's service-oriented manufacturing achieved relatively fast growth during the sample period, with an average annual output growth of 16.58%; specifically, the contributions of capital and labor input reached 7.47% and 2.80%, respectively, and the contribution of TFP growth was 4.47%, far lower than the comprehensive contribution of the input factors. From the regional perspective, capital input in all three regions (i.e., eastern, central, and western) made the largest contribution to output growth. This implies that the growth mode of China's service-oriented manufacturing is still in extensive growth mode, and the rapid increase in output is mainly driven by capital input factors. There is still room for the service-oriented manufacturing industry to improve the structure of production factors and accelerate the transformation of the growth mode from extensive to intensive.

Table 5. Decomposition of TFP growth in service-oriented manufacturing by regions and growth accounting.

Region	TFP Growth Decomposition				Output Growth Rate	Capital Growth Rate and Contribution	Labor Growth Rate and Contribution	TFP GrowthRate and Contribution
	TC	TEC	SEC	AEC				
eastern	0.0632 (1.211)	0.0109 (0.209)	−0.0027 (−0.051)	−0.0192 (−0.369)	0.1582	0.1242 (0.785)	0.0544 (0.344)	0.0521 (0.330)
central	0.0658 (0.758)	0.0316 (0.364)	−0.0016 (−0.018)	−0.0090 (−0.104)	0.1856	0.1259 (0.678)	0.0374 (0.201)	0.0869 (0.468)
western	0.0731 (0.840)	0.0400 (0.460)	−0.0003 (−0.004)	−0.0257 (−0.295)	0.1818	0.1196 (0.658)	0.0237 (0.130)	0.0870 (0.479)
national	0.0675 (0.910)	0.0271 (0.365)	−0.0015 (−0.020)	−0.0189 (−0.254)	0.1658	0.1239 (0.747)	0.0465 (0.280)	0.0742 (0.447)

Note: In brackets are the contributions of each variable, of which the last three columns are the contributions of capital, labor, and TFP growth to output growth, and the first four columns are the contributions of TFP decomposition terms to TFP growth rate.

Furthermore, to better understand the dynamic impacts of the four decomposition terms on TFP growth, we further depicted the changing trends of the four components from 2004 to 2020 in different regions in China (as shown in Figure 2). It can be seen in Figure 2 that there exists significant heterogeneity in the dynamic changing trends of the four components. First, the technological progress (TC) rate of each region presents a decreasing trend, and its driving role in TFP growth is gradually weakening. Second, technical efficiency change (TEC) in each region also shows a decreasing trend; however, unlike TC, it tends to gradually become flat over time, and, in the sample period, it maintained a positive value. Although TEC has not entered the rising stage, the positive value nevertheless implies that technical efficiency is still gradually improving and moving closer to the production frontier. Third, the scale efficiency change (SEC) in different regions is undergoing significant fluctuations and deteriorates in most years, which indicates that the development of SEC is not ideal. Fourth, the allocation efficiency change (AEC) of each region is negative for most years, indicating significant deterioration during the sample period. The changing trend of AEC is generally consistent across different regions over the years, with a more serious decline in 2008 and significant fluctuations after 2011. Although AEC significantly improved in 2019, it dropped again in 2020 due to the impact of the COVID-19 pandemic. The outbreak of COVID-19 in 2020 has had a great impact on all aspects of the economy, and the production chain was almost in a state of stagnation during the year, which resulted in a steep decline in TC, TEC, SEC and AEC. In summary, the changing trends of technological progress and technical efficiency are relatively stable, while scale efficiency and allocation efficiency show significant fluctuations. The gradual decline of technological progress and the gradual stabilization of technical efficiency, on the other hand, imply the importance of improving both scale efficiency and allocation efficiency to promote the industry's TFP growth.

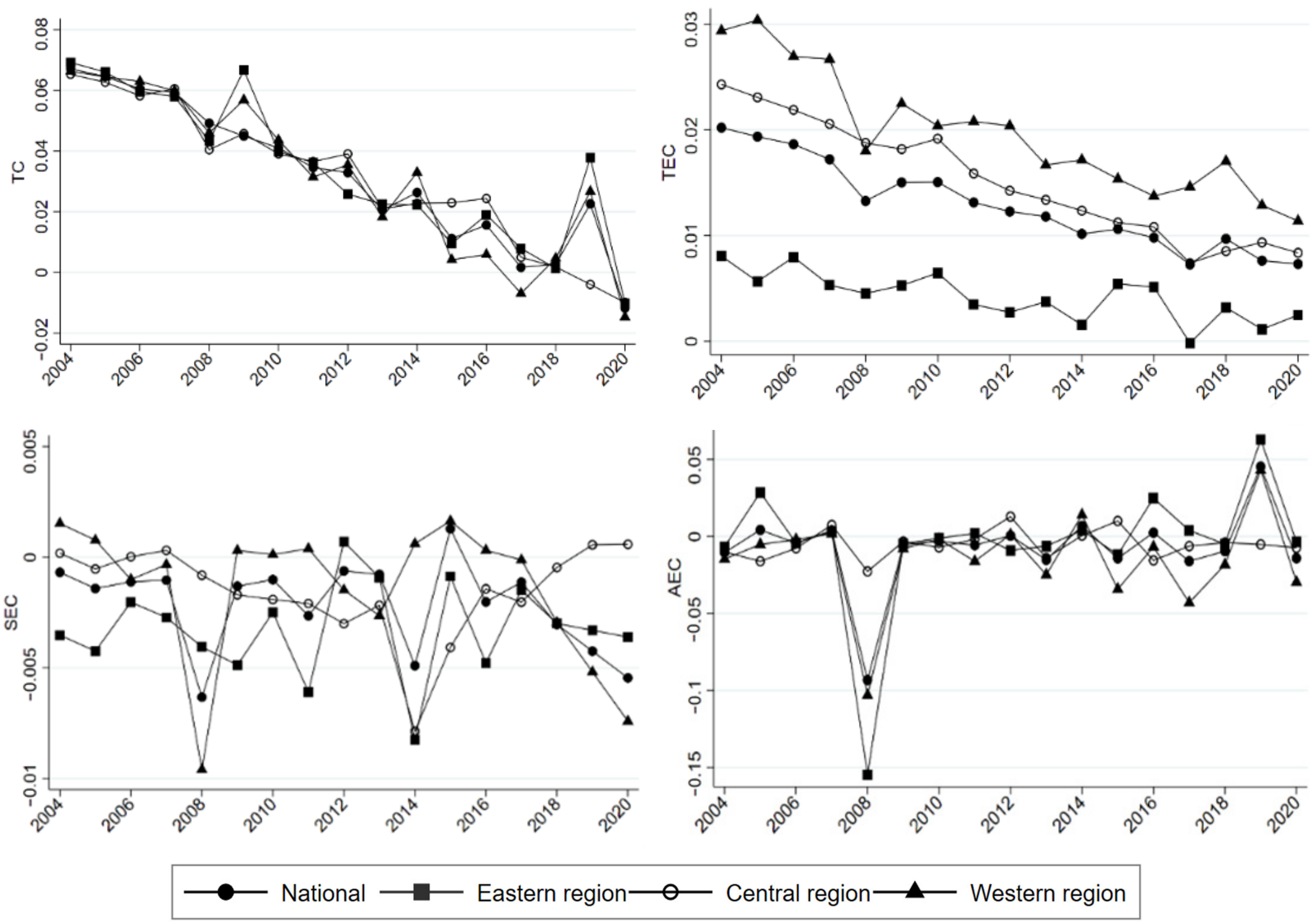

Figure 2. Changing trends of the four components of TFP growth in different regions of China (2004–2020).

5.3. Further Analysis of TFP Growth and Its Decomposition in Service-Oriented Manufacturing Sub-Sectors

As discussed in Section 5.2, TFP growth and its four components exhibit significant heterogeneity between different regions. To this end, some further interesting questions arise: what is the changing trend of TFP growth and its components in the sub-sectors of service-oriented manufacturing? How do they behave in different regions? What is the contribution of each factor to output growth? To answer these questions, we further calculated the TFP growth of each sub-sector and carried out a decomposition analysis.

Figure 3 displays the changing trend of TFP growth in certain sub-sectors. It shows that the TFP growth of China's service-oriented manufacturing shows significant differences between sub-sectors, varying across industries at each time point, but generally exhibiting the common characteristic of gradual decline over time. Hit by the financial crisis in 2008, the TFP growth of each sub-sector showed a significant downward trend to some extent. Among the sub-sectors, the I_7 industry experienced the largest decline, from 0.2097 to 0.0662. After 2014, I_1, I_2, and I_6 showed significant fluctuations, while I_4 showed the most obvious downward trend, decreasing from the maximum value (0.2295) to the minimum value (−0.0216) during the sample period; additionally, the I_5 industry showed the most stable change. During the whole sample period, the I_7 industry exhibited the highest TFP growth, with an average of 0.1667, and the I_3 industry showed the lowest (0.0696).

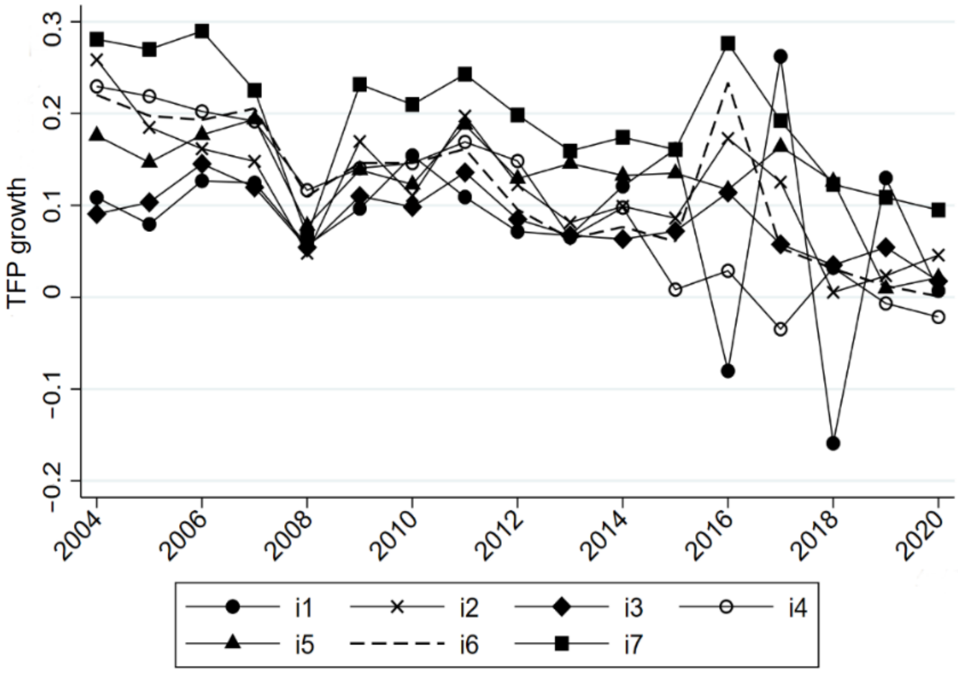

Figure 3. Changing trend of TFP growth in service-oriented manufacturing sub-sectors.

From a regional perspective, Figure 4 depicts the differences in the TFP growth of service-oriented manufacturing sub-sectors in different regions. As Figure 4 shows, the TFP growth rate of each sub-industry exhibits significant regional heterogeneity. Specifically, in the eastern region, the I_3, I_6, and I_7 industries had higher TFP growth than in other regions; meanwhile, in the central region, the I_3 industry exhibited the highest TFP growth. Additionally, the I_1, I_2, and I_5 industries showed higher TFP growth in the western region than in the central and eastern regions. Notably, the TFP growth of I_7 was higher than that of other industries in all the three regions.

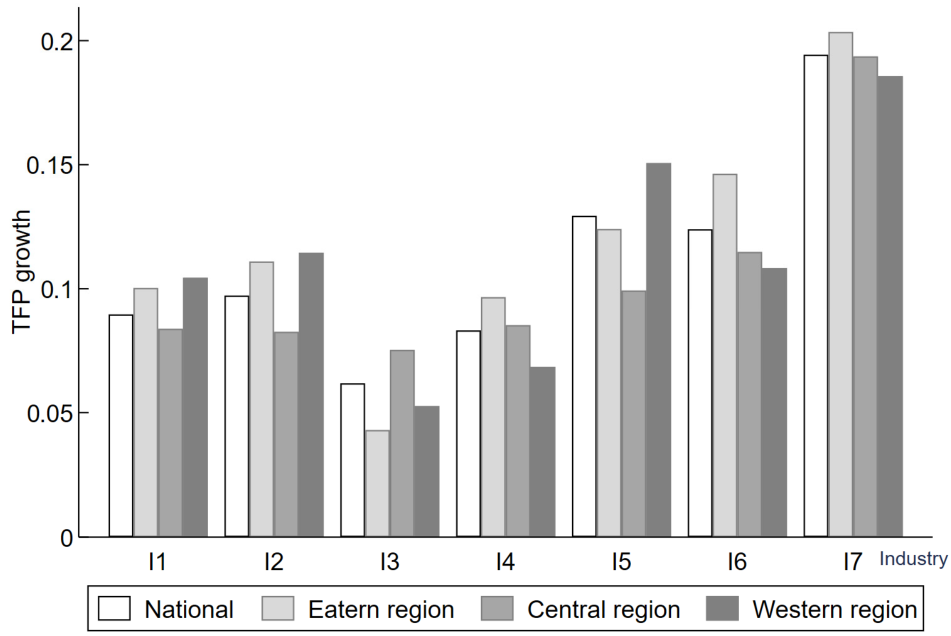

Figure 4. TFP growth of service-oriented manufacturing sub-sectors in different regions.

Furthermore, we also decomposed the TFP growth of service-oriented manufacturing sub-sectors into four components (i.e., TC, TEC, SEC, and AEC) and carried out growth accounting analysis. Table 6 shows the corresponding results, and demonstrates that the performance of the four decomposition terms varies among the different sub-sectors. First, the technical progress (TC) of each sub-industry made the largest contribution to the growth of TFP, which again supports the finding that TC is the main driver of TFP growth. In terms of the technical efficiency change (TEC), the I_1, I_5, and I_7 industries showed negative values, which implies deterioration in technical efficiency in these sub-industries during the sample period. Meanwhile, the I_2, I_4, and I_6 industries showed positive values, indicating a significant improvement in technical efficiency in these industries. However, the scale efficiency change (SEC) and allocation efficiency change (AEC) are heterogeneous among the different sub-industries. Except for the I_1, I_5, and I_6 industries, which are positive, all other sub-industries are negative; among them, the change in the scale efficiency in I_4 and allocative efficiency in I_7 deteriorated most seriously. Additionally, it is noteworthy that the contribution of the four decomposition terms to the TFP growth in each industry shows the order of TC > TEC > SEC > AEC, which again supports the conclusion that technological progress and technical efficiency are the main drivers of the TFP growth. From the accounting results of output growth, we can see that the comprehensive contributions of capital and labor factors in each sub-sector are greater than the contribution of TFP growth. What is more, the contribution of capital input represents a high proportion of the input factors, which indicates that China's service-oriented manufacturing is still in an extensive growth mode, and the industrial growth is mainly driven by capital input factors.

Table 6. Decomposition of TFP growth in service-oriented manufacturing sub-sectors and growth accounting.

Sectors	TFP Growth Decomposition				Output Growth Rate	Capital Growth Rate and Contribution	Labor Growth Rate and Contribution	TFP Growth Rate and Contribution
	TC	TEC	SEC	AEC				
I_1	0.0797 (0.944)	−0.0042 (−0.050)	0.0042 (0.050)	0.0047 (0.056)	0.1663	0.1403 (0.844)	0.0921 (0.554)	0.0845 (0.508)
I_2	0.0670 (0.811)	0.0213 (0.258)	−0.0014 (−0.017)	−0.0042 (−0.051)	0.1808	0.1283 (0.709)	0.0436 (0.241)	0.0826 (0.457)
I_3	0.0710 (1.021)	0.0023 (0.034)	−0.0006 (−0.008)	−0.0032 (−0.046)	0.1118	0.0824 (0.737)	0.0093 (0.083)	0.0696 (0.622)
I_4	0.0768 (0.754)	0.0406 (0.399)	−0.0063 (−0.062)	−0.0093 (−0.091)	0.1698	0.1161 (0.684)	0.0233 (0.137)	0.1018 (0.560)
I_5	0.1268 (0.980)	−0.0146 (−0.113)	0.0016 (0.012)	0.0156 (0.121)	0.1526	0.1137 (0.745)	0.0348 (0.228)	0.1294 (0.848)
I_6	0.0863 (0.696)	0.0249 (0.201)	0.0126 (0.102)	0.0001 (0.001)	0.1733	0.1297 (0.748)	0.0264 (0.153)	0.1240 (0.716)
I_7	0.1933 (1.160)	−0.0081 (−0.049)	−0.0047 (−0.028)	−0.0138 (−0.083)	0.1714	0.1285 (0.749)	0.0589 (0.343)	0.1667 (0.972)

Note: In brackets are the contributions of each variable, of which the last three columns are the contributions of capital, labor, and TFP growth to output growth and the first four columns are the contributions of TFP decomposition terms to TFP growth rate.

6. Conclusions and Policy Implications

By constructing a translogarithmic stochastic frontier production model, this study explored the TFP performance of China's service-oriented manufacturing industry and its sub-sectors from 2004–2020. To better understand the reasons behind the changes in TFP, we further decomposed TFP growth into four components (i.e., TC, TEC, SEC, and AEC) and analyzed the dynamic impacts of each component on TFP growth from national, regional, and sectoral perspectives. The main conclusions are as follows.

First, the TFP of China's service-oriented manufacturing improved to some extent in the sample period, but the contribution of TFP growth to the output growth of the industry is still low, at only 4.47%. Industrial growth is mainly driven by factor inputs (capital input, to be exact) and has not realized the transformation of the growth mode from extensive to intensive.

Second, technological progress and technical efficiency change are the main drivers of TFP growth. However, the rate of technological progress is gradually declining and its driving effect on TFP growth is weakening, while the change of technical efficiency is gradually tending towards stability. Furthermore, the deterioration of both scale efficiency and allocation efficiency has hindered the improvement of the TFP; there is still room for the service-oriented manufacturing to promote its TFP growth by improving in these areas.

Third, there exists significant heterogeneity in TFP growth between different regions and sub-sectors. Specifically, the growth rates of TFP in the central and western regions are relatively close and higher than that in the eastern region; this is mainly driven by technological progress and technical efficiency change. However, the serious deterioration of allocation efficiency and scale efficiency in the eastern region prevents the growth of its TFP. From the sub-industry perspective, the TFP growth varied across sub-industries over the years, but, over time, the overall trend shows a decrease. The electrical machinery and equipment manufacturing industry reached the highest average TFP growth of 0.1667 during the sample period, while the lowest value was obtained by the food manufacturing industry, at 0.0696. Regarding the decomposition of TFP growth, the heterogeneity of each industry segment is also obvious. In addition to the positive effects of technological progress in all the sub-industries, the changes of technical efficiency, scale efficiency, and allocation efficiency were positive only in three industries, while the other four industries showed different degrees of deterioration.

Based on the above research results, this study highlights several policy implications as follows:

First, it is important for service-oriented manufacturing to accelerate the transformation of the growth mode from extensive to intensive. In particular, efforts should be made to break away from excessive dependence on capital input and gradually shift from being driven by factor inputs to the continuous improvement of the TFP. Manufacturing enterprises should enhance the allocation efficiency of production factors, increase investment in high-end manufacturing technologies, and strengthen cooperation with advanced enterprises to enhance the exchange of development experience and technology introduction. At the same time, local governments should encourage enterprises to increase investment in TFP improvement through tax incentives, subsidies, and special funds.

Second, as technological progress and technical efficiency are the main sources of TFP growth, it is of great significance for service-oriented manufacturing to innovate the path of technological progress and improve technical efficiency. It is also necessary to accelerate the transition of the technological innovation route from relying on external acquisition modes, such as technology introduction and technology transformation, to internal modes, such as independent research and development (R&D). An open cooperative network and innovation system based on patent licensing, collaborative R&D, and technical standard cooperation should be established to improve the level of innovation in service-oriented manufacturing. On the one hand, it is necessary to strengthen the construction of innovation carriers such as enterprise technology centers and industrial technology innovation platforms, while improving the technical innovation service system for small and medium-sized enterprises, enhancing the rate of technology industrialization, and accelerating the speed of technology transformation; On the other hand, it is necessary to innovate the investment and financing mode of the service-oriented manufacturing industry, formulate a sound talent gathering policy, and improve the technological level of service-oriented manufacturing industry.

Third, according to the decomposition results of TFP, both the scale efficiency and allocation efficiency of service-oriented manufacturing have deteriorated to some extent; therefore, it is necessary to take effective measures to improve in these areas. Manufacturers should pay attention to the reasonable adjustment of the industrial scale and should also improve the efficiency of factor allocation through various approaches, such as upgrading the total quality of human capital, accelerating financial reforms, and improving the level of technological innovation.

Fourth, in view of the obvious regional and sub-sectoral heterogeneity of TFP growth among different regions and sub-industries, differentiated policy combinations should be adopted. On one hand, increasing policy support should be given to the industries with low TFP growth, especially those in the central and western regions. At the national level, special funds should be given to the less-developed central and western regions to carry out independent research and development. At the same time, these regions should actively introduce advanced technologies and make use of the penetration and integration of information technologies to carry out management innovation and business model innovation, improving scale efficiency and factor allocation efficiency and thereby improving the TFP level of the whole industry. On the other hand, industries with high TFP growth should further enhance technological progress and innovation capacity to strengthen their leading role and promote the optimization and adjustment of industrial structures to further improve their TFP level.

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