

Article

Research on High-Quality Development Efficiency and Total Factor Productivity of Regional Economies in China

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Abstract: Different from the developmental mode of western developed countries, China's economy has changed from a stage of high-speed growth to a stage of high-quality development, where the people's growing needs for better lives can be met, embodying this new concept of development. The aim of our study is to evaluate the high-quality development efficiency and total factor productivity (TFP) of regional economies in China, and to explore the characteristics of spatial-temporal pattern evolution and their influencing factors. By using the slacks-based measure of directional distance functions (SBM-DDF) model, based on the undesirable output perspective, the high-quality development efficiency and TFP of regional economies in China, from 2000 to 2018, are evaluated in this paper. The exploratory spatial data analysis (ESDA) and Tobit models are then used to identify the spatial-temporal correlation patterns and influencing factors of high-quality development efficiency and TFP. The key results show the following: (1) from 2001 to 2018, the greatest high-quality development efficiency and TFP belonged to China's eastern region and the least to its central region. (2) U and inverted-U trend lines show that high-quality development efficiency has significant regional difference in the east–west direction, presenting a significant feature of spatial imbalance. (3) Government, urbanization rate, and marketization level play a positive role in their impact of TFP, whereas financial development, infrastructure, foreign direct investment, and capital labor ratio play a negative one.

Keywords: high-quality development; total factor productivity; slacks-based measure of directional distance functions model; spatial-temporal pattern evolution; tobit model



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1. Introduction

Benefiting from reform and opening itself to the world, China has experienced extensive development and high economic growth (Figure 1), leading to remarkable achievements and significant contributions to the world's economic development in recent decades. However, its past mode of growth is unsustainable and relies heavily on the massive input of resources, which is not desirable for the long term and emits significant amounts of polluting emissions [1]. Being different from extensive development, high-quality development has become fundamentally requisite for the Chinese government in making determinations concerning development ideas, formulating economic policy, and implementing macro-control in the present and future [2,3]. It is necessary to accelerate the formation of index, policy, standard, and statistical systems, performance evaluations, and performance appraisals to promote high-quality development. High-quality development alone can meet China's growing lifestyle demands; additionally, it embodies China's new conceptualization of development (with reference to the “five development concepts” of

China, which includes innovative development, coordinated development, green development, open development, and shared development), in which it aims to promote efficient, dynamic change to achieve development that is fairer, safer, higher quality, and more efficient and sustainable. We note that high-quality development in China is defined as that where innovation becomes the primary driver, coordination becomes the intrinsic characteristic, green becomes the universal form, open becomes the necessary way, and sharing becomes the fundamental goal [4,5].

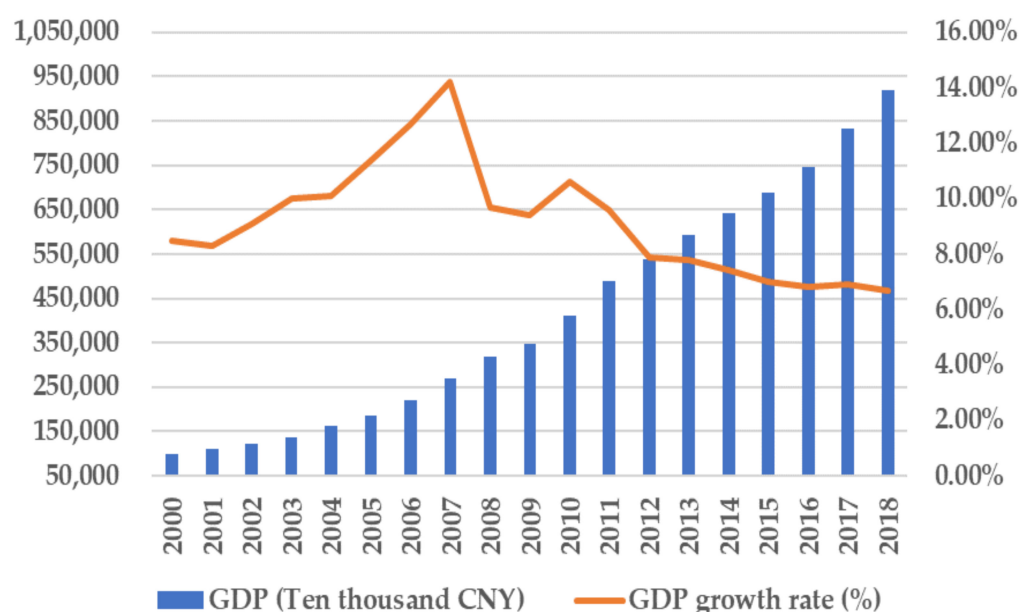


Figure 1. The scale and growth of China's economy from 2000 to 2018.

It is obvious that improving efficiency and TFP is key to high-quality development, as they are indeed the implicit requirements of it. In our study, we assume the following definition for high-quality development efficiency: that in which an economy can not only maximize GDP and minimize environmental consequences (nongreen development) under specific input conditions for labor, capital, energy, and other factors, but also optimize innovation, coordination, open, and sharing developments, this to be ideal, and expandable, in general, to economic development efficiency and, in particular, green economic development efficiency. Therefore, we seek to understand how to better evaluate high-quality development efficiency and TFP for regional economies in China. What are the characteristics of spatial trends and spatial-temporal correlation pattern of the high-quality development efficiency and TFP of regional economies in China? What are the factors influencing the high-quality development efficiency and TFP of regional economies in China? It has the important theoretical and practical significance to clarify and solve these problems.

The purpose of our study is to evaluate the high-quality development efficiency and TFP of regional economies in China from 2000 to 2018 and to explore the characteristics of spatial-temporal pattern evolution and its influencing factors. To the best of our knowledge, this is the first paper to study China's high-quality development efficiency and TFP from the perspectives of the five development concepts. The main contributions of our study are as follows: First, the static high-quality development efficiency and dynamic high-quality development TFP of regional economies in China are evaluated by using the SBM-DDF model based on undesirable output, and our study expands the research perspective. Second, our study identifies the spatial trends and spatial-temporal correlation pattern of high-quality development efficiency and TFP by using the ESDA model, providing evidence for the spatial heterogeneity, imbalance, and correlation of high-quality development efficiency and TFP of regional economies in China. Third, our study utilizes

the Tobit model to explore the influencing factors of high-quality development efficiency and TFP, which is very beneficial in terms of policy implications. The inferences obtained from our study not only are helpful for government managers and policymakers concerned with high-quality development but also provide clearer pictures of different provinces in China and may assist in under the scenario from a broader and more inclusive regional angle. This study has important academic and practical application value for high-quality development research in China as well as other countries or regions.

The rest of this paper is organized as follows: Section 2 summarizes in detail the literature review about high-quality development efficiency at home and abroad. Section 3 briefly introduces some materials and methods. Section 4 presents the results, including the evaluation of high-quality development efficiency and TFP of regional economies in China, and spatial trends, spatial-temporal correlation patterns and the influential factors of high-quality development efficiency and TFP. Some discussions are given in Section 5. Some conclusions with summaries and policy recommendations, main contributions, limitations, and future research possibilities are drawn in Section 6.

2. Literature Review

At present, the research on high-quality development mostly focuses on the connotations [6], characteristics [7,8] and countermeasures of high-quality development [9,10]. Research on the definition of high-quality development can be summarized into the following three categories: the first category considers high-quality development to be high-efficiency, fair, green sustainable development aiming at meeting people's growing needs for a better life; the second category emphasizes the transformation from high speed to high quality in high-quality development; and the third category considers high-quality development to include the process of social reproduction and the all processes in social and economic life. However, in view of different scholars' different understandings of high-quality development, there is still a lack of consistency in evaluations of high-quality development in academic circles, and a unified evaluation index system has not yet been formed. The evaluation of high-quality development is still in its infancy and remains to be further explored, especially for high-quality development efficiency and TFP.

The common evaluation methods of high-quality development efficiency include single-index evaluation or multi-index weighted combination scoring evaluation. For example, some scholars use the investment efficiency, labor productivity growth, intermediate input-output rate of enterprises and other indicators to measure development efficiency. Although these single indicators have certain effects, they have greater one-sided and limitations, and cannot comprehensively reveal the whole picture of a high-quality development level in a certain region. Therefore, the comprehensive evaluation of high-quality development levels through the construction of measurement systems has become a research hotspot in recent years. The evaluation perspectives of these measurement systems are rich and diverse, and the measurement indicators have their own characteristics, which improves the limitations of using a single indicator to represent the high-quality development level [7,10]. For example, Wei et al. [7] constructed a measurement system of high-quality economic development level from the perspectives of economic structure optimization, innovation-driven development, efficient resource allocation, perfect market mechanism, stable economic growth, regional coordination and sharing, high-quality products and services, infrastructure improvement, ecological civilization construction and economic achievements benefiting the people and then used the entropy weight TOPSIS method to measure the high-quality development efficiency of 30 provinces in China. Ma et al. [11] constructed a high-quality development index system from the perspectives of high-quality supply, high-quality demand, development efficiency, economic operation and opening-up and measured China's high-quality development efficiency with the linear weighting method. Wang et al. [12] constructed a high-quality development evaluation system from the perspectives of the main elements, service and regulatory elements, incentives, safety assurance capability, urban credit system, innovation ability, satisfaction degree of

citizens, policy environment, economic development environment, legal environment and cultural environment. Wang et al. [13] measured the China's high-quality development efficiency based on economic vitality, development potential, urban and rural joint forces and ecological strength. Guided by the "five development concepts", Lv et al. [14] measured the high-quality development level of each province in China in each period and the regional gap between different regions by constructing a high-quality development index evaluation system based on economic vitality, innovation-driven, coordinated development, green development, open development and achievement sharing. Shi et al. [15] and Sun et al. [16] constructed a high-quality development evaluation system including innovation, coordination, green, open and sharing to measure high-quality development efficiency in China. It is worth noting that Chinese government officials and a growing number of scholars believe that high-quality development is based on the "five development concepts", that is, innovation, coordination, green, openness and sharing are indispensable, which has gradually become the mainstream of evaluating high-quality development.

The evaluation of TFP is one of the most effective calculation methods of high-quality development efficiency, considering that single-index evaluation or multi-index weighted combination scoring evaluation may ignore the internal logic of high-quality development. The data envelopment analysis (DEA) [17,18] model is the main method used for measuring economic development efficiency and TFP, which only requires inputs and outputs to be quantified with no hypothesis function form [19,20], including radial DEA [21,22], oriented DEA [23], original constant return to scale DEA (CCR-DEA) [24], network DEA [25], super-DEA [26], multistage DEA [27,28], SBM [29] and so on. In high-quality development, resources and the environment are not only endogenous variables of economic development but also rigid constraints on the scale and speed of economic development. In the past, GDP was the main evaluation performance of extensive and unsustainable development with massive input, which only considered good outputs, but not the constraint of inputs and bad outputs. It is obvious that even if the economic development level of a certain region is relatively high, if the input is relatively large, it is actually achieved by obtaining resources and sacrificing the development of other regions. From the perspective of the whole society, resources have not been reasonably allocated, and the input-output rate is not high, reducing the TFP of the whole society. The measurement of economic development efficiency can avoid the problem and reflect the input-output efficiency relatively accurately. However, traditional TFP only considers the input constraints of production factors, such as labor and capital, but does not consider the constraints of resources and the environment, which distorts the evaluation of social welfare changes and economic performance, thus misleading policy recommendations. Therefore, a large number of scholars focus on the efficiency of green development. For example, Gökgöz et al. [26] empirically confirmed the substitution effect of renewable energy for energy imports and benchmarked the performance of the selected European Union countries in renewable energy efficiency and productivity from 2004 to 2014 with the perspective of energy security using the superefficiency model of data envelopment analysis. They found that, while Sweden, Germany, Spain, Belgium and Romania were among the efficiency leaders, conventional energy producers limited renewable energy in France and the United Kingdom, and the average TFP of the group increased by 8.4% annually, where technological change (innovation) was the prime driver of productivity growth. Bigerna et al. [30] analyzed the relationship between energy efficiency and the stringency of the environment in 19 European Union countries from 2006 to 2014 with two-stages DEA, decomposing the environmental policy stringency index, OECD regulatory indicators and TFP growth. They found that the pure and scale efficiency indices are negatively affected by sectorial regulation that positively affected the shift of the technological frontier and that environmental policy negatively affects the shift of the efficient frontier but has a positive effect on the scale efficiency. Yu et al. [31] studied the impact of the spatial agglomeration of foreign direct investment on the green TFP of Chinese cities based on data from 285 Chinese cities from 2003 to 2017. They found that progress in green technology plays an important

role in improving urban green TFP and that foreign direct investment plays a positive role in promoting green TFP. Amri [32] examined the linkage between CO₂ emissions and TFP as a measure of income, information and communication technology, trade, financial development and energy consumption in Tunisia from 1975 to 2014. They found that trade, financial development and energy consumption negatively affect the environmental quality. Adnan et al. [33] summarized the socioeconomic effects of COVID-19 on various aspects of the world economy and noted that the COVID-19 epidemic checked the resilience of the agricultural sector in Malaysia, especially the paddy industry. The above studies have important reference value, but the measurement of high-quality development efficiency and TFP from the perspective of five development concepts needs to be further studied.

3. Materials and Methods

First, to evaluate the high-quality development efficiency and TFP, the SBM-DDF model combined with high quality development is introduced in detail in Section 3.1. In addition, the spatial autocorrelation model, including the trend surface model, the global Moran's I index the local Moran's I index, are given in Section 3.2. Furthermore, the Tobit model for influencing factors of high-quality development efficiency and TFP is constructed in Section 3.3. Finally, the indicators for evaluation and data sources are discussed in Sections 3.4 and 3.5, respectively.

3.1. The Evaluation with SBM-DDF Model

When there are excessive inputs or insufficient outputs, that is, the nonzero relaxation of inputs or outputs, the radial DEA will overestimate the efficiency of the evaluation object, and the oriented DEA may not be accurate due to neglecting a certain aspect of inputs or outputs. Traditional DEA assumes that all the outputs should be maximized for the given input level. However, when undesirable outputs are generated as byproducts of desirable outputs, the assumption is no longer appropriate [34]. It should be noted that network DEA and multistage DEA may not be suitable for the evaluation of high-quality development efficiency proposed in our study, considering that the five developments are synchronous and equally important. In the different deformations of DEA, the direction distance function (DDF) is one of the most popular models, which considers the effects of desirable and undesirable outputs separately and can help increase the desirable output and reduce the undesirable output simultaneously [35]. The slacks-based measure (SBM) model contains slacks variables of input and output, which can prevent DDF models' radial character and directivity from being effectively avoided. To overcome these defects, the slacks-based measure of directional distance functions (SBM-DDF) model is developed by minimizing the ratio of the average undesirable output reduction to the average desirable output increment [36,37]. The nonradial model is generally treated as a composite index for modeling economic environmental performance. The SBM-DDF model has been widely used in the evaluation of TFP because it decreases undesirable outputs while increasing the desirable outputs at the same time [38–40]. The essence of high-quality development efficiency is to investigate how to produce better outputs and fewer bad outputs under some inputs, which needs to be measured and decomposed under the framework of TFP. In other words, the SBM-DDF model can achieve more accurate measurements of high-quality development efficiency and TFP compared with other methods.

Many studies show that the SBM-DDF method based on the slacks variable and Luenberger productivity indicator best fits the context of the regional economy in terms of measuring TFP [38], which has gained popularity in academia both at home and abroad. A province P is represented as DMU_P with N inputs $x = (x_1, \dots, x_n) \in R_N^+$, M desirable outputs $y = (y_1, \dots, y_m) \in R_M^+$ and I undesirable outputs $b = (b_1, \dots, b_i) \in R_I^+$. The

global production possibilities set $HQP^t(x^t)$ of high-quality development, emphasizing the consistency and comparability of the production frontier [38]:

$$HQP^t(x^t) = \left\{ (y^t, b^t) : \sum_{k=1}^K z_k^t y_{km}^t \geq y_{km}^t, \forall m; \sum_{k=1}^K z_k^t b_{ki}^t = b_{ki}^t, \forall i; \sum_{k=1}^K z_k^t x_{kn}^t \leq x_{kn}^t, \forall n; \sum_{t=1}^T z_k^t = 1, z_k^t \geq 0, \forall k \right\} \quad (1)$$

where z_k^t denotes the weight of each cross section, the two constraints are that the sum of the weight variables is 1 and that nonnegative weight variables represent production technology as the variable return to scale (VRS) [41]; if the constraint that the sum of weight variables is 1 is removed, it means constant return to scale (CRS) [42]. In this paper, the high-quality development efficiency calculated under the CRS condition is recorded as HQE(CRS), and the high-quality development efficiency calculated under the VRS condition is recorded as HQE(VRS).

Drawing on the experience of Fukuyama and Weber [38,39,43,44], we define the SBM-DDF that covers undesirable outputs considering high-quality development as follows:

$$\begin{aligned} \overrightarrow{HQS}_V^t(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b) = \max_{s^x, s^y, s^b} & \frac{\frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{g_n^x} + \frac{1}{M+1} \left[\sum_{m=1}^M \frac{s_m^y}{g_m^y} + \sum_{i=1}^I \frac{s_i^b}{g_i^b} \right]}{2} \\ \text{s.t. } & \sum_{k=1}^K z_k^t x_{km}^t + s_n^x = x_{k'n}^t, \forall n; \\ & \sum_{k=1}^K z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m; \\ & \sum_{k=1}^K z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i; \\ & \sum_{k=1}^K z_k^t = 1, z_k^t \geq 0, \forall k; \\ & s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i \end{aligned} \quad (2)$$

where $(x^{t,k'}, y^{t,k'}, b^{t,k'})$ denote the vectors of inputs, desirable outputs and undesirable outputs, respectively. (g^x, g^y, g^b) denote the direction vectors for decreasing inputs, increasing desirable outputs and decreasing undesirable outputs, respectively. (s_n^x, s_m^y, s_i^b) denote the slacks vectors for redundant inputs, inadequate desirable outputs and redundant undesirable outputs, respectively.

The Luenberger productivity indicator is more suitable for measuring the TFP, which considers the decrease in inputs and increase in outputs simultaneously, avoiding different perspectives and the rate variable [45,46]. The Luenberger productivity indicator between period t and period $t+1$ is calculated as follows [38]:

$$\begin{aligned} HQTFP_t^{t+1} = \frac{1}{2} \left\{ \left[\overrightarrow{S}_C^t(x^t, y^t, b^t; g) - \overrightarrow{S}_C^t(x^{t+1}, y^{t+1}, b^{t+1}; g) \right] \right. \\ \left. + \left[\overrightarrow{S}_C^{t+1}(x^t, y^t, b^t; g) - \overrightarrow{S}_C^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g) \right] \right\} \end{aligned} \quad (3)$$

In addition, the Luenberger productivity index can be divided into HQPEC, HQPTP, HQSEC, and HQTPSC [38,39].

$$HQTFP = HQPEC + HQPTP + HQSEC + HQTPSC \quad (4)$$

$$HQPEC_t^{t+1} = \overrightarrow{S}_V^t(x^t, y^t, b^t; g) - \overrightarrow{S}_V^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g) \quad (5)$$

$$\begin{aligned} HQPTP_t^{t+1} = \frac{1}{2} \left\{ \left[\overrightarrow{S}_V^{t+1}(x^t, y^t, b^t; g) - \overrightarrow{S}_V^t(x^t, y^t, b^t; g) \right] \right. \\ \left. + \left[\overrightarrow{S}_V^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g) - \overrightarrow{S}_V^t(x^{t+1}, y^{t+1}, b^{t+1}; g) \right] \right\} \end{aligned} \quad (6)$$

$$HQSEC_t^{t+1} = [\bar{S}_C(x^t, y^t, b^t; g) - \bar{S}_V(x^t, y^t, b^t; g)] - [\bar{S}_C(x^{t+1}, y^{t+1}, b^{t+1}; g) - \bar{S}_V(x^{t+1}, y^{t+1}, b^{t+1}; g)] \quad (7)$$

$$HQTPSC_t^{t+1} = \frac{1}{2} \{ [\bar{S}_C(x^t, y^t, b^t; g) - \bar{S}_V(x^t, y^t, b^t; g)] - [\bar{S}_C(x^{t+1}, y^{t+1}, b^{t+1}; g) - \bar{S}_V(x^{t+1}, y^{t+1}, b^{t+1}; g)] + [\bar{S}_C(x^{t+1}, y^{t+1}, b^{t+1}; g) - \bar{S}_V(x^{t+1}, y^{t+1}, b^{t+1}; g)] - [\bar{S}_C(x^{t+1}, y^{t+1}, b^{t+1}; g) - \bar{S}_V(x^{t+1}, y^{t+1}, b^{t+1}; g)] \} \quad (8)$$

where HQPEC represents the catching-up effect, which measures the maximum closeness degree of the practical production of a DMU to the production frontier; HQTP represents the progress or retrogress of technology, which measures the movement of the production frontier from period t to $t + 1$; HQSEC represents the scale effect caused by the change of efficiency value, which measures the change of scale efficiency; and HQTPSC represents the scale effect of technology development [47,48].

3.2. Spatial Autocorrelation Model

The trend surface is the nearsighted value of the actual surface. By abstracting the mathematical surface and filtering out the influence of local random factors, it can accurately simulate the spatial distribution law of geographical elements, show the change trend of geographical elements in the regional space and be used to explore the overall spatial layout characteristics of high-quality development efficiency and TFP of regional economies in China [48,49]. It is assumed that $Z_i(X_i, Y_i)$ is the actual level of high-quality development efficiency or TFP, which represents the spatial plane coordinates. The trend surface model is defined as follows [50]:

$$Z_i(X_i, Y_i) = T_i(X_i, Y_i) + \varepsilon_i \quad (9)$$

where $T_i(X_i, Y_i)$ is the trend function, which represents the fitting value of the high-quality development efficiency or TFP trend surface in the region, reflecting the macro distribution law of HQE or HQTFP; ε_i is the autocorrelation random error, which represents the error between the real value and trend value of HQE or HQTFP in the region i , namely the influence of random factors. Based on previous research experience, this paper uses common second-order polynomials to measure the trend value of HQE or HQTFP of regional economies in China. The trend function can be expressed as [51]:

$$T_i(X_i, Y_i) = \alpha_0 + \alpha_1 x + \alpha_2 y + \alpha_3 x^2 + \alpha_4 y^2 + \alpha_5 xy \quad (10)$$

where $\alpha_0, \dots, \alpha_5$ are regression fitting coefficients of trend function, respectively.

The theory of spatial econometrics holds that the observation value of an attribute on a geospatial unit is closely related to the observation value on the adjacent space unit, and there is a spatial autocorrelation characteristic. The exploratory spatial data analysis (ESDA) model can reveal spatial autocorrelation characteristics and spatial interactions by calculating the global and local Moran's I indices of different attribute values of different spatial units. The global Moran's I index of high-quality development efficiency and TFP is calculated as follows [52,53]:

$$I = \frac{\sum_{i=1}^m \sum_{j=1}^m W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^m \sum_{j=1}^m W_{ij}} \quad (11)$$

$$S^2 = \frac{1}{m} \sum_{i=1}^m (X_i - \bar{X})^2 \quad (12)$$

$$\bar{X} = \frac{1}{m} \sum_{i=1}^m X_i \quad (13)$$

where X represents the HQE or HQTFP and W_{ij} represents the normalized spatial weight matrix; Moran's I index ranges from $[-1, 1]$; if the value of Moran's I index is less than 0, the HQE or HQTFP is negatively correlated; if the value of Moran's I index is greater than 0, the HQE or HQTFP is positively correlated; if the value of Moran's I index equals 0, the HQE or HQTFP is irrelevant. Standardized statistics are usually used to test the significance of the global Moran's I index. The formulas are shown as follows [53,54]:

$$Z = \frac{I - E(I)}{\sqrt{\text{VAR}(I)}} \quad (14)$$

$$E(I) = -\frac{1}{m-1} \quad (15)$$

If the value of Z is significant and positive, it indicates that there is a positive spatial autocorrelation between the HQE or HQTFP. If the value of Z is significant and negative, it indicates that there is a negative spatial autocorrelation between the HQE or HQTFP. If the value of Z equals 0, it indicates that the HQE or HQTFP presents a random distribution state.

The local distribution of the spatial correlation of high-quality development efficiency and TFP among regions may appear "atypical", which cannot be reflected by the global indicators. Therefore, it is necessary to use the local indicator of spatial correlation (LISA), i.e., local Moran's I index, to analyze the local characteristics of HQE or HQTFP correlations among regions. The calculation formula is as follows [55]:

$$I_i = (X_i - \bar{X}) \sum_{j=1}^m W_{ij} (X_j - \bar{X}) \quad (16)$$

The index measures the degree of correlation between the regions and their surrounding regions: if the value of I_i is positive, it indicates the High–High (H-H) or Low–Low (L-L) of the HQE or HQTFP autocorrelation type. If the value of I_i is negative, it means Low–High (L-H) or High–Low (H-L) of the HQE or HQTFP autocorrelation type. High–High (H-H) type indicates that the HQE or HQTFP of the current region and the surrounding regions are similar and relatively high, and there is a smaller difference in spatial difference. The Low–High (L-H) type means that the HQE or HQTFP of the current region is relatively low, but HQE or HQTFP of its surrounding regions are generally higher, there is a relatively large difference in spatial difference. The Low–Low (L-L) type indicates that the HQE or HQTFP of the current region and its surrounding regions are similar and relatively low; there is a small difference in spatial difference. The High–Low (H-L) type means that the HQE or HQTFP of the current region is relatively high, and the HQE or HQTFP of its surrounding regions are generally lower; there is a larger difference in spatial difference [56].

3.3. Tobit Model for Influencing Factors

Considering the data structure and attributes of HQE and HQTFP, using the ordinary least squares (OLS) model may cause bias and inappropriate parameter estimation. Based on previous research experience, the Tobit model is used to estimate the influencing factors of high-quality development efficiency and TFP in this paper. We set up the Tobit model as follows [57,58]:

$$Y_i^* = \begin{cases} \alpha + \beta X_i + \varepsilon, & Y_i^* > 0 \\ 0, & Y_i^* \leq 0 \end{cases} \quad (17)$$

where Y_i^* represents the HQE(CRS), HQE(VRS), HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC, respectively. X_i is the independent variable vector; α is the intercept term vector; β is the correlation coefficient vector, and ε is the random error term. Based on previous

research experience, in this paper, the independent variables include the role of government (GOV), marketization level (MAR), urbanization rate (URB), financial development (FIN), infrastructure (INF), endowment structure (END), and foreign direct investment (FDI).

3.4. Indicators for Evaluation

Based on the connotation of high-quality development and “five development concepts”, this paper measures high-quality development efficiency and TFP based on the SBM-DDF model including input indicators (labor, financial capital, human capital, and energy), desirable outputs (economic development, innovation development, coordinated development, shared development, and open development), and undesirable outputs (non-green development). Based on the principle of availability, comparability, and continuity of statistical data, learning from predecessors’ experience [59–61], the evaluation indicator system and influencing variables of high-quality development efficiency and TFP in this paper are shown in Table 1.

Table 1. The evaluation indicators system and influencing variables of high-quality development efficiency and TFP.

Type	Indicator	Definition	Unit
Input indicators	Labor	Number of employees in the whole society	Ten thousand people
	Financial capital	Capital stock	Hundred million CNY
	Human capital	Average years of Education	Year
	Energy	Total electricity consumption	Ten thousand kWh
Desirable outputs	Economic development	Per capita GDP	CNY per person
	Innovation development	Patent authorization	Piece
	Coordinated development	Income level ratio of urban and rural residents	%
	Shared development	Number of beds per capita in health care institutions	Piece per person
	Open development	Total import and export volume	Ten thousand USD
Undesirable outputs	Nongreen development	Sulphur dioxide emissions	Ten thousand tons
Influencing Variables	The role of government	The proportion of fiscal expenditure to GDP	%
	Marketization level	The proportion of non-state-owned fixed assets investment in all regions	Point
	Urbanization rate	The proportion of urban population in the total population	%
	Financial development	Loan balance of financial institutions	Hundred million CNY
	Infrastructure	Per capita road construction area	Square meter per person
	Endowment structure	The proportion of capital in labor	%
	Foreign direct investment	The proportion of foreign direct investment in GDP	%

3.5. Data Sources

The current research objective does not include the empirical analysis of Hong Kong, Macao, or Taiwan because of the special endowment and data availability. The 31 areas are divided into four regions, eastern, central, western, and northeast, according to the distribution of natural resources and the level of economic and social development of China’s provincial administrative regions. The specific division results are shown in Table 2.

Relevant data from 2000 to 2018 are selected using the China Statistical Yearbook, China Environmental Yearbook, China Energy Statistics Yearbook and Statistical Yearbooks of Provinces. Considering that the data of the capital stock of provinces in China cannot be obtained from the statistical yearbook, most existing literature uses the formula $K_t = K_{t-1}(1 - \delta_t) + I_t$ to calculate capital stock. K_t and K_{t-1} are the capital stock at periods

t and $t - 1$, respectively. I_t denotes investment and δ_t is the depreciation rate at period t . In this paper, the indices of currency value are used to eliminate the effect of price fluctuation through the relevant price indices. Table 3 summarizes the descriptive statistics of the raw data of each variable observed for 31 DMUs.

Table 2. Division of China's four economic regions.

Region	Province
Eastern China	Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan
Central China	Shangxi, Henan, Hubei, Hunan, Jiangxi, Anhui
Western China	Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Neimenggu, Qinghai, Ningxia, Xinjiang, Tibet
Northeast China	Heilongjiang, Jilin, Liaoning

Table 3. Descriptive statistics of the raw data of each variable observed for 31 DMUs.

Variable	Number	Minimum	Maximum	Average	Standard Deviation
Labor	589	124.18	6766.86	2452.12	1705.464
Financial capital	589	38.26	42,498.7	7123.558	7456.79
Human capital	589	2.948	12.826	8.373385	1.298329
Energy	589	2.11	6323.354	1253.316	1151.42
Economic development	589	2759	140,211	32,394.98	25,580.09
Innovation development	589	7	478,082	24,381.71	50,299.46
Coordinated development	589	0.035871	0.541962	0.355785	0.071937
Shared development	589	0.001527	0.007213	0.003817	0.00132
Open development	589	10,594	128,119,159	8,327,484	17,809,179
Non-green development	589	734	2,002,000	611,413.5	434,610.5
The role of government	589	0.046791	1.379161	0.227471	0.177298
Marketization level	589	0.01	12.06778	6.064838	2.157696
Urbanization rate	589	9.235315	95.3221	50.82968	16.4596
Financial development	589	80.62	145,169.4	16,578.8	20,183.24
Infrastructure	589	0.421739	11.08042	3.863139	2.181689
Endowment structure	589	0.227729	12.92507	3.167673	2.523579
Foreign direct investment	589	0.655474	75.0313	5.871033	7.040357

4. Results

First, the high-quality development efficiency and TFP of regional economies in China are evaluated in Section 4.1. In addition, to further explore the spatial-temporal pattern evolution characteristics, the spatial trends and spatial correlation pattern of high-quality development efficiency and TFP are studied in Sections 4.2 and 4.3 from the spatial perspective of economic geography, respectively. Furthermore, the influential factors of high-quality development efficiency and TFP are discussed in Section 4.4.

4.1. The Evaluation on High-Quality Development Efficiency and TFP

In this subsection, the high-quality development efficiency and TFP are measured based on the SBM-DDF model with Maxdea software from 2000 to 2018, and the average values of the results are shown in Table 4. Table 4 contains seven headings: HQE(CRS), HQE(VRS), HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC, which are employed to analyze the high-quality development efficiency and TFP of regional economies in China from different angles.

Table 4. The average values of regional HQE, HQTTP and their decomposition in China.

Regions	HQE(CRS)	HQE(VRS)	HQTTP	HQPEC	HQTTP	HQSEC	HQTTPSC
Beijing	0.9675	0.9721	0.0723	0.0020	0.0470	0.0000	0.0313
Tianjin	0.9339	0.9656	0.0767	0.0007	0.0178	0.0117	0.0523
Hebei	0.2360	0.2971	0.0047	0.0011	−0.0167	0.0006	0.0334
Shanxi	0.1773	0.2296	0.0058	0.0240	−0.0067	0.0044	0.0171
Inner Mongolia	0.2315	0.3434	0.0520	−0.0081	0.0913	0.0015	−0.0325
Liaoning	0.3773	0.7767	0.0103	0.0010	0.0551	−0.0070	−0.0417
Jilin	0.2702	0.6653	0.0065	0.0337	0.0366	−0.0378	−0.0300
Heilongjiang	0.2801	0.8142	0.0083	0.0324	0.0112	−0.0354	−0.0043
Shanghai	0.9641	1.0000	0.0456	0.0000	0.0513	−0.0004	−0.0095
Jiangsu	0.9290	1.0000	0.0539	0.0000	0.0565	−0.0298	0.0145
Zhejiang	0.9546	0.9571	0.0573	0.0006	0.0308	0.0000	0.0283
Anhui	0.2741	0.2841	−0.0076	0.0034	−0.0344	0.0011	0.0206
Fujian	0.5031	0.5830	−0.0075	−0.0223	0.0289	−0.0005	0.0022
Jiangxi	0.2131	0.3292	−0.0323	−0.0267	0.0121	0.0333	−0.0260
Shandong	0.4563	0.4896	0.0888	0.0013	0.1200	−0.0360	−0.0063
Henan	0.1755	0.2388	0.0370	0.0125	0.0289	−0.0032	−0.0299
Hubei	0.2198	0.4148	0.0148	0.0165	0.0763	−0.0109	−0.0542
Hunan	0.2247	0.2750	0.0146	−0.0148	0.0824	0.0189	−0.0702
Guangdong	1.0000	1.0000	0.0543	0.0000	0.0554	−0.0008	−0.0169
Guangxi	0.1918	0.1993	0.0106	0.0044	0.0069	−0.0042	−0.0214
Hainan	0.4478	0.9558	−0.0528	0.0016	0.0165	−0.0029	−0.0674
Chongqing	0.2927	0.4462	0.0475	0.0461	0.0481	−0.0188	−0.0174
Sichuan	0.3230	0.4498	0.1128	0.0471	0.0741	0.0348	−0.0489
Guizhou	0.1608	0.2631	0.0266	0.0488	0.0311	−0.0005	−0.0529
Yunnan	0.1564	0.2158	0.0099	0.0048	0.0249	−0.0027	−0.0048
Tibet	1.0000	1.0000	−0.0076	0.0000	−0.0623	−0.0005	0.0512
Shaanxi	0.2375	0.2702	0.0206	0.0151	0.0572	−0.0079	−0.0447
Gansu	0.1922	0.2465	0.0052	0.0401	0.0057	−0.0387	−0.0037
Qinghai	0.3907	0.9617	0.0820	−0.0001	0.0033	0.0455	0.0235
Ningxia	0.2518	0.9729	0.0363	−0.0022	0.0325	−0.0029	0.0087
Xinjiang	0.3578	0.8919	0.0322	0.0001	−0.0322	−0.0003	0.0548
Eastern	0.7392	0.8220	0.0393	−0.0015	0.0407	−0.0058	0.0062
Central	0.2141	0.2952	0.0054	0.0025	0.0264	0.0073	−0.0238
Western	0.3155	0.5217	0.0357	0.0163	0.0234	0.0005	−0.0073
Northeast	0.3092	0.7521	0.0084	0.0224	0.0343	−0.0268	−0.0253
Nationwide	0.4320	0.5971	0.0283	0.0085	0.0306	−0.0029	−0.0079

High-quality development efficiency (HQE) measures the relative relationship between provinces and production boundaries in a given period, and is a static analysis. From Table 4, we can find that the average value of the nationwide high-quality development efficiency under CRS from 2001 to 2018 is 0.4320, and the average value of the nationwide high-quality development efficiency under VRS is 0.5971. The average values of HQE(VRS) are slightly higher than those of HQE(CRS). From the perspective of different regions, the high-quality development efficiency under CRS of the eastern region (0.7392) is the highest, while the high-quality development efficiency under CRS is the lowest in the central region (0.2141). The high-quality development efficiency under VRS of the eastern region (0.8220) is also the highest, followed by the northeast region (0.7521), the western region (0.5217), and the central region (0.2952). From the perspective of various provinces, only Guangdong, Shanghai, Jiangsu, and Tibet are on the production boundary of high-quality development efficiency, and other provinces are not. The provinces with higher efficiency are concentrated in the eastern region. The provinces with lower high-quality development efficiency are Yunnan, Guizhou, Guangxi, Henan, Shanxi, and Gansu. It is worth noting that Tibet's high-quality development efficiency benefits from its lower inputs, which produces a moderate amount of good outputs and a small amount of bad outputs. It shows that high-quality development is not “more input and more output”, but “less input and better output” from the side.

High-quality development TFP (HQTFP) analysis is a dynamic method that can analyze the relative position change (efficiency change) of each province and the production boundary, and the movement of the production boundary (technical progress). The average growth rate of the HQTFP nationwide in regional economies in China from 2001 to 2018 is 2.83%. From the perspective of decomposition of HQTFP, the average growth rate of the HQPTP nationwide is the largest at 3.06%, followed by HQPEC at 0.85%. However, the average growth rates of HQSEC and HQTPSC nationwide are negative, at -0.29% and -0.79% , respectively. From the perspective of different regions, the average growth rate of the HQTFP in the eastern region is the largest at 3.93% , which is determined by the HQPTP (4.07%) and HQTPSC (0.62%). The average growth rate of the HQTFP in the central region is lowest at 0.54% , which is determined by the HQPTP (2.64%) and HQSEC (0.73%). From the perspective of various provinces, in addition to Anhui, Fujian, Jiangxi, Hainan, and Tibet, the HQTFP of other provinces shows positive growth. The top three fastest growth rates of HQTFP are Sichuan (11.28%), Shandong (8.88%), and Qinghai (8.20%). The last three slowest growth rates of HQTFP are Hainan (-5.28%), Jiangxi (-3.23%), and Tibet (-0.76%). Only Beijing, Tianjin, and Zhejiang have positive HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC, where the TFP of high-quality development is driven by pure efficiency change, pure technological progress, scale efficiency change, and technological scale change at the same time.

The trend of HQTFP and its decomposition of regional economies in China with regard to time from 2001 to 2018 are shown in Figure 2, wherein the horizontal axis represents the year and the vertical axis represents the efficiency value. Figure 2 shows that from 2001 to 2018, HQTFP shows a fluctuating rising trend overall. In 2010, there was a significant increase led by the HQPTP and HQPEC. It is not difficult to determine that the HQPTP has increased at a similar pace as the HQTFP in the past twenty years. The contribution rates of HQPEC and HQSEC fluctuate irregularly. The contribution of HQTPSC shows a downward trend, which deserves our attention, and the trend has become more severe in the last five years. HQTPSC has become the largest obstacle of HQTFP, which shows the urgency and great potential of improving the high-quality development TFP of regional economies in China by upgrading technology.

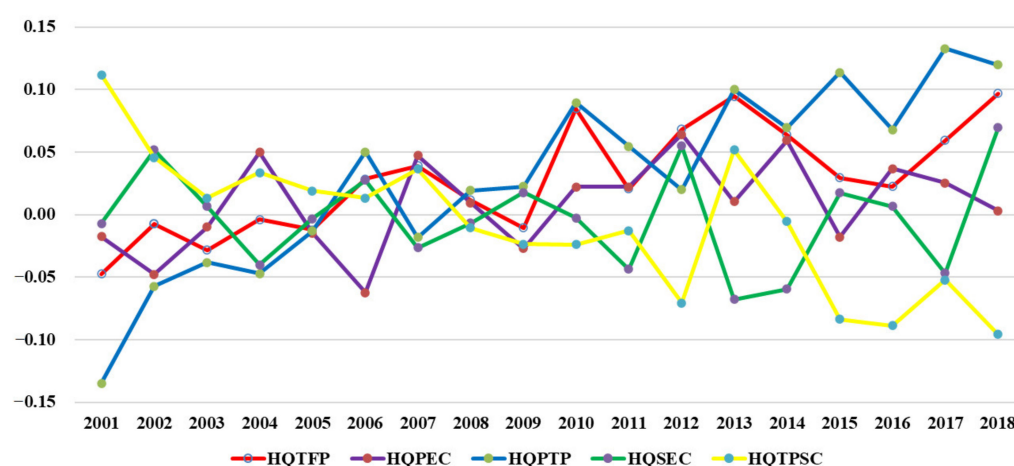


Figure 2. The trend of the regional HQTFP and its decomposition in China.

4.2. The Spatial Trends of High-Quality Development Efficiency and TFP

The high-quality development efficiencies among the eastern, central, western, and northeast regions are significantly different from those in Table 4. To further understand the differences, the spatial distribution tendency of the high-quality development efficiency of regional economies in China in 2001 and 2018 is visually described by using the tendency analysis tool of ArcGIS 10.6 software (ESRI, Redlands, CA, USA) from the American ESRI Company. As shown in Figures 3–5, the Z axis represents the value of regional high-

quality development efficiency, the X axis is the west–east direction, and the Y axis is the south–north direction. For high-quality development efficiency, the U and inverted-U trend lines show that HQE(CRS) and HQE(VRS) have significant regional differences in the east–west direction, presenting a significant feature of spatial imbalance. The high-quality development efficiency of the eastern region is higher than that of the western region. In the south–north direction, there is little difference among the HQE(CRS), and the HQE(VRS) of the southern region is higher than that of the northern region in 2001; the result is opposite in 2018. For the high-quality development TFP, the eastern region is slightly higher than that of the western region, and the northern region is slightly higher than that of the southern region in 2018.

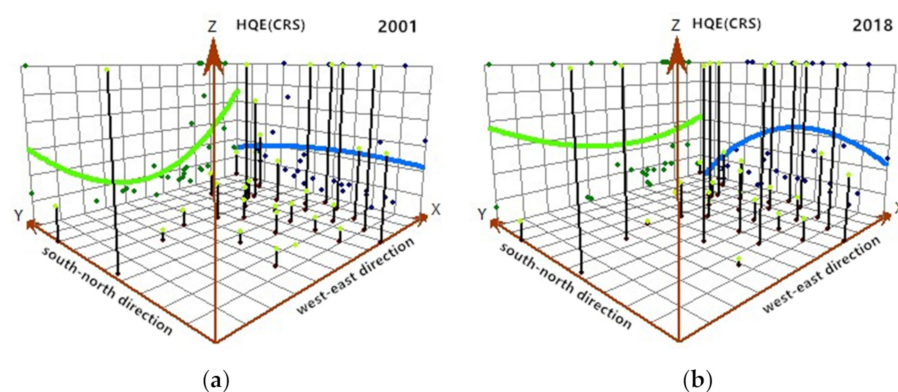


Figure 3. Spatial evolution tendency of regional HQE(CRS) in China with (a) 2001 and (b) 2018.

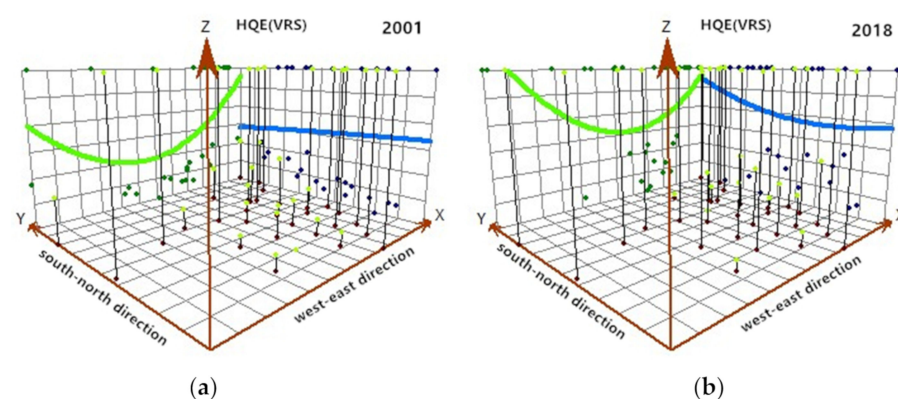


Figure 4. Spatial evolution tendency of regional HQE(VRS) in China with (a) 2001 and (b) 2018.

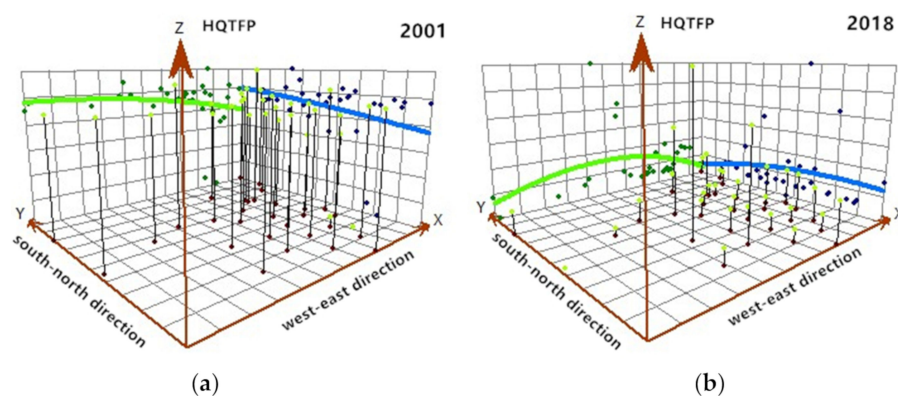


Figure 5. Spatial evolution tendency of regional HQTFF in China with (a) 2001 and (b) 2018.

4.3. The Spatial Correlation Pattern of High-Quality Development Efficiency and TFP

“The first law of geography” holds that everything is related to each other, and there is a certain spatial correlation between them. The global spatial correlation of the high-quality development efficiency and high-quality development TFP in regional economies in China from 2001 to 2018 are calculated using ArcGIS 10.6 software. The results of the global Moran’s I index are shown in Table 5. The Moran’s I indices of HQE(CRS) and HQE(VRS) show that there is significant positive spatial autocorrelation in regional economies in China, indicating that the high-quality development efficiency is not completely random, but is the result of positive spatial correlation of high-quality development efficiency. The spatial agglomeration of the high-quality development efficiency in regional economies in China shows a significant spatial dependence. There is only significant positive spatial autocorrelation of HQTFF in regional economies in China in 2001, 2007, 2016, and 2017, indicating that the high-quality development TFP is partially randomly distributed, and the spatial correlation needs to be increased with ongoing high-quality development.

Table 5. The calculated results of global Moran’s I of regional HQE and HQTFF in China.

Year	HQE(CRS)			HQE(VRS)			HQTFF		
	Moran’s I	Z-Value	p-Value	Moran’s I	Z-Value	p-Value	Moran’s I	Z-Value	p-Value
2001	0.2729	2.8165	0.0048 ***	0.3372	3.3346	0.0008 ***	0.2305	2.7953	0.0051 ***
2002	0.3254	3.2813	0.0010 ***	0.2753	2.7806	0.0054 ***	−0.0866	−0.5159	0.6058
2003	0.3299	3.3193	0.0009 ***	0.3532	3.4823	0.0004 ***	0.1080	1.3631	0.1728
2004	0.3139	3.1729	0.0015 ***	0.3135	3.1161	0.0018 ***	−0.0227	0.1395	0.8890
2005	0.2919	2.9873	0.0028 ***	0.3123	3.1091	0.0018 ***	−0.0025	0.4316	0.6659
2006	0.2241	2.3860	0.0170 **	0.3170	3.1632	0.0015 ***	0.0857	1.1524	0.2491
2007	0.2761	2.8488	0.0043 ***	0.2531	2.5766	0.0099 ***	0.1798	2.0612	0.0392 **
2008	0.2719	2.8113	0.0049 ***	0.2552	2.5957	0.0094 ***	0.0020	0.4901	0.6239
2009	0.2757	2.8452	0.0044 ***	0.2857	2.8743	0.0040 ***	0.0548	0.8186	0.4129
2010	0.2722	2.7933	0.0052 ***	0.3076	3.0674	0.0021 ***	−0.0892	−0.6154	0.5382
2011	0.2574	2.6781	0.0074 ***	0.2940	2.9419	0.0032 ***	0.0446	1.0652	0.2867
2012	0.2917	2.9428	0.0032 ***	0.2301	2.3701	0.0177 **	−0.0437	−0.1200	0.9044
2013	0.0779	1.0158	0.3096	0.1743	1.8710	0.0613 *	0.0139	0.5273	0.5979
2014	0.2512	2.6008	0.0093 ***	0.0524	0.7741	0.4388	0.0201	0.7599	0.4472
2015	0.2322	2.4253	0.0152 **	0.0826	1.0455	0.2957	−0.1539	−1.3900	0.1645
2016	0.2339	2.4286	0.0151 **	0.0580	0.8261	0.4087	−0.1878	−1.9330	0.0532 *
2017	−0.1686	−1.2363	0.2163	−0.0701	−0.3326	0.7394	0.1358	1.7874	0.0738 *
2018	0.2081	2.1864	0.0287 **	0.2067	2.1692	0.0300 **	−0.0142	0.2009	0.8407

Note: ***, **, * indicate that the statistical test with significance level of 1%, 5%, 10% can be passed, separately.

Whereas the global Moran’s I index cannot reveal local spatial correlation and heterogeneity, this paper further tests whether there is local spatial agglomeration of high-quality development efficiency and high-quality development TFP in regional economies in China through the local indicators of spatial association (LISA). The local spatial autocorrelation LISA agglomeration map reflects the local spatial interdependence and spatial heterogeneity of high-quality development efficiency and TFP in regional economies in China. The LISA graphs for 2001, 2009, and 2018 are shown in Figures 6–8, which show the clustered points of high-quality development efficiency and TFP, respectively, in regional economies in China, in terms of the four types of spatial correlations: High-High, Low-Low, High-Low, and Low-High.

The Chinese regional HQE(CRS) is characterized by the L-L type, as shown in Figure 6. In 2001, only Shanghai belonged to the H-H type, showing a significant positive spatial correlation. The provinces belonging to the L-L type were mainly located in Shannxi, Hubei, Chongqing, and Guizhou. Furthermore, there was no province that belongs to the H-L and L-H types. In 2009, the provinces of the H-H type extended to Shanghai and Jiangsu, and the provinces of the L-L type expanded northward to Ningxia, Shanxi, Gansu, and Inner Mongolia, including Shannxi, Hubei, Chongqing, and Guizhou. In 2018, the

provinces of the L-L type adjusted northeastward to Hubei, Henan, Shanxi, Ningxia, Inner Mongolia, Liaoning, and Heilongjiang. The main reason may be that these provinces tend to use larger amounts of material inputs to obtain greater economic benefits. Such extensive development led to higher bad outputs and imbalance. It was worth noting that Hainan evolved into the L-H type. The Chinese regional HQE(VRS) was also characterized by the L-L type, mainly shown in Figure 7. In 2001, only Zhejiang belonged to the H-H type, and there were six provinces belonging to the L-L type, including Shanxi, Shannxi, Henan, Hubei, Chongqing, and Guizhou. Similarly, there was also no province that belonged to the H-L and L-H types. In 2009, Ningxia evolved into H-L type. In 2018, the provinces of the L-L type reduced to Hubei, Henan, and Shanxi. Compared with HQE(CRS) and HQE(VRS), the type of HQTFP was obviously different from Figure 8. In 2001, only Zhejiang, Jiangxi, and Fujian belonged to the L-L type, and Guangdong and Anhui belonged to the H-L type. There was no province that belonged to the H-H and L-H types. In 2009, Shanghai and Jiangsu evolved into the H-H type, Shannxi evolved into the L-L type, and Inner Mongolia evolved into the H-L type. In 2018, Chongqing and Yunnan evolved into the L-H type, whereas provinces with low scores more easily accepted efficient production models. Henan and Xinjiang evolved into the L-L type. Overall, there is a long way to go from extensive development to high-quality development, so different types of local agglomerations will coexist in the future.

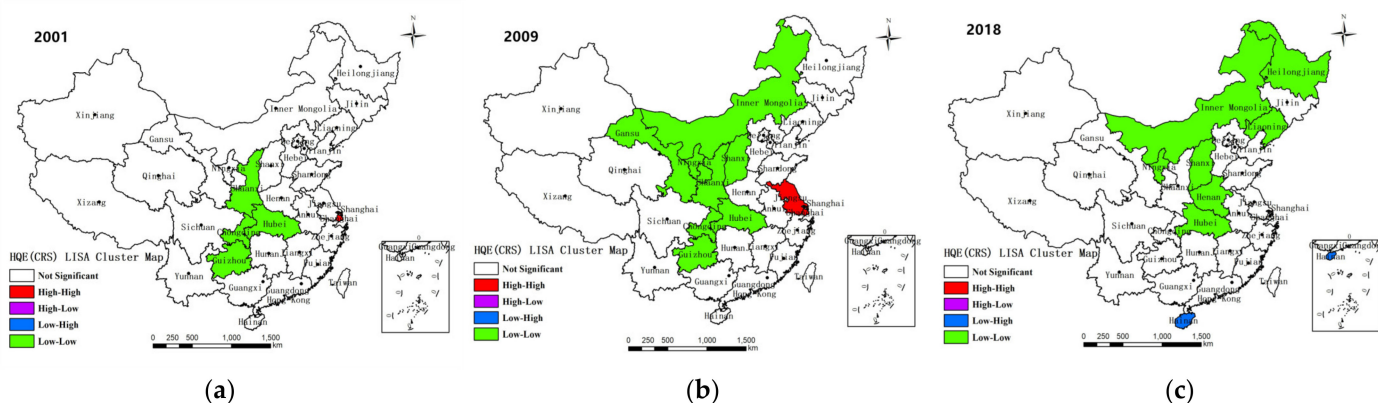


Figure 6. The LISA spatial distribution map of regional HQE(CRS) in China with (a) 2001, (b) 2009, and (c) 2018.

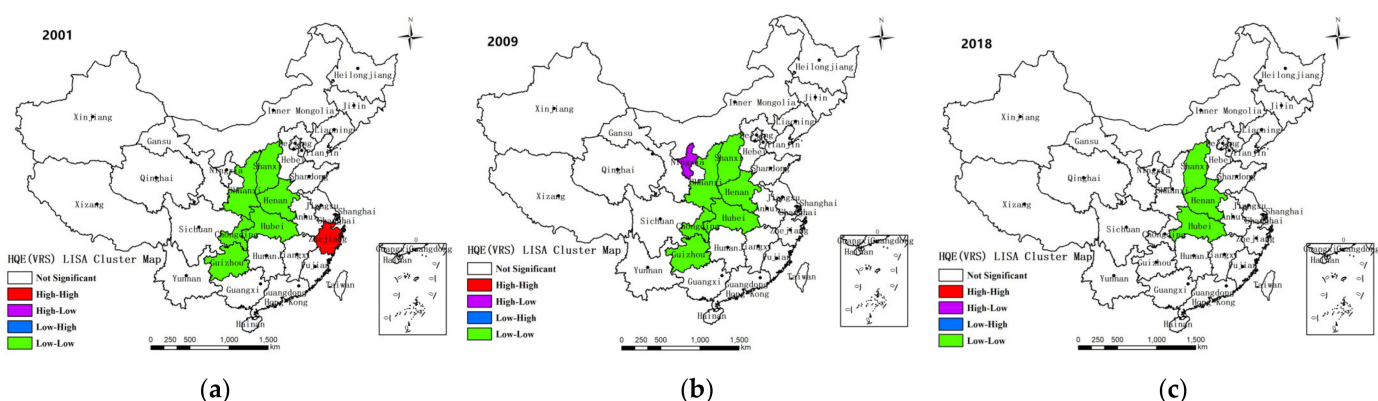


Figure 7. The LISA spatial distribution map of regional HQE(VRS) in China with (a) 2001, (b) 2009, and (c) 2018.

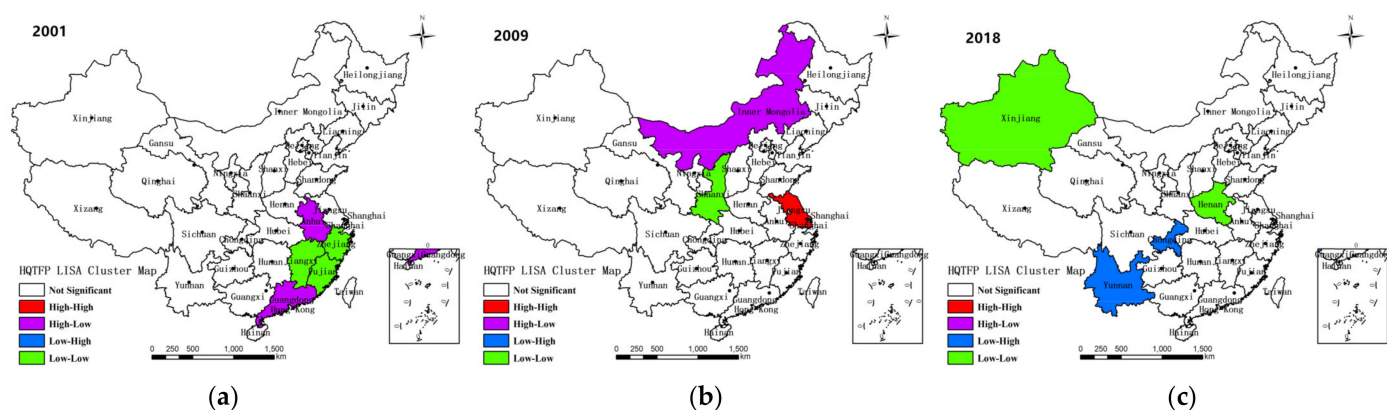


Figure 8. The LISA spatial distribution map of regional HQTFP in China with (a) 2001, (b) 2009, and (c) 2018.

4.4. Influential Factors of High-Quality Development Efficiency and TFP

In this subsection, first, Phillips–Perron (PP) and augmented Dickey–Fuller (ADF) unit root test results show that the series are not order-one integrated. After the first-order difference processing, all the sequences in this study meet the 10% significance level of rejection of the original hypothesis, and the panel data are stationary series, so further cointegration tests are needed. Both Pedroni and Kao cointegration tests meet the 10% level, and there is a significant cointegration relationship between the data, meaning that the data are suitable for empirical analysis. Furthermore, the Hausman test shows that the fixed effect model should be selected for the regression analysis. Calculations are carried out in Tobit with Eviews 8 software, and Table 6 shows the regression analysis results. Under the two hypotheses of CRS and VRS, the influence direction of each factor on high-quality development efficiency is basically the same. The influence direction of each factor on high-quality development TFP is also basically the same.

Table 6. The regression results of regional HQE and HQTFP in China.

	HQE(CRS)	HQE(VRS)	HQTFP	HQPEC	HQPTP	HQSEC	HQTPSC
Variables	Coe. Sig.	Coe. Sig.	Coe. Sig.	Coe. Sig.	Coe. Sig.	Coe. Sig.	Coe. Sig.
GOV	0.5064 0.0000 ***	0.6300 0.0000 ***	0.6676 0.0000 ***	0.6845 0.0000 ***	0.6388 0.0000 ***	0.6803 0.0000 ***	0.6891 0.0000 ***
MAR	1.3911 0.0035 ***	−0.7158 0.1947	2.6943 0.0000 ***	2.4503 0.0000 ***	2.7191 0.0000 ***	2.4576 0.0000 ***	2.4076 0.0000 ***
URB	0.0020 0.0051 ***	0.0034 0.0000 ***	0.0118 0.0000 ***	0.0122 0.0000 ***	0.0115 0.0000 ***	0.0121 0.0000 ***	0.0123 0.0000 ***
FIN	0.0000 0.0000 ***	0.0000 0.9999	−0.0000 0.0000 ***	−0.0000 0.0000 ***	−0.0000 0.0000 ***	−0.0000 0.0000 ***	−0.0001 0.0000 ***
INF	0.0193 0.0298 **	0.0638 0.0000 ***	−0.0158 0.0011 ***	−0.0178 0.0009 ***	−0.0145 0.0049 ***	−0.0193 0.0011 ***	−0.0138 0.1238
END	−0.0109 0.1055	−0.0124 0.1136	−0.0129 0.0005 **	−0.0180 0.0000 ***	−0.0088 0.0251 **	−0.0187 0.0000 ***	−0.0266 0.0000 ***
FDI	0.0155 0.0000 ***	0.0139 0.0000 ***	−0.0067 0.0000 ***	−0.0065 0.0000 ***	−0.0063 0.0000 ***	−0.0055 0.0000 ***	−0.0061 0.0000 ***
Sigma	−33.7830	−33.4591	−51.7177	−3.9043	−17.8377	−85.6390	−1.2518
R ²	0.9990	0.9989	0.9885	0.9930	0.9928	0.9952	0.9936

Note: ***, ** indicate that the statistical test with significance level of 1%, 5% can be passed, separately.

The empirical results show that GOV and URB have a positive and significant impact on HQE(CRS), HQE(VRS), HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC with a significance level of 1%, indicating that the role of government and urbanization rate can improve the high-quality development efficiency and TFP. In other words, the higher the

proportion of fiscal expenditure to GDP and the proportion of urban population in the total population, the higher the value of the high-quality development efficiency and TFP. The coefficients of MAR are positive and significant on HQE(CRS), HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC with a significance level of 1%, except for HQE(VRS) with a negative but nonsignificant coefficient. It is not difficult to determine that the marketization level has the largest impact on the high-quality development efficiency and TFP, implying that the increase in the efficiency and productivity depends largely on the improvement of the marketization level; that is to say, the proportion of nonstate-owned fixed assets investment makes the most important contribution to the high-quality development efficiency and TFP. Concerning the impact of the other control variables, FIN, INF, and FDI have a positive and significant impact on HQE(CRS) and HQE(VRS) and a negative and significant impact on HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC, indicating that financial development, infrastructure, and foreign direct investment can improve high-quality development efficiency, but can also reduce high-quality development TFP. The main reason can be explained as follows: the improvement of financial efficiency is conducive to the improvement of high-quality development efficiency, but the rapid expansion of financial scale reduces the high-quality development TFP. Furthermore, with the continuous improvement of infrastructure, the outflow of regional factors may be accelerated, which is not conducive to the improvement of high-quality development TFP. It is worth noting that FDI can bring advanced enterprise management experience and cutting-edge technology, which promotes the improvement of high-quality development efficiency. However, the “pollution paradise” hypothesis holds that the level of environmental regulation in developed countries is higher than that in developing countries. Therefore, there must be a large amount of FDI flowing into the pollution intensive sectors of developing countries. Considering that foreign-funded enterprises tend to migrate polluting enterprises to developing countries, it is not conducive to the promotion of high-quality development TFP, in contrary, it will have a certain inhibitory effect on high-quality development TFP. It is worth noting that END has a negative and significant impact on HQE(CRS), HQE(VRS), HQTFP, HQPEC, HQPTP, HQSEC, and HQTPSC, which is consistent with our expectation. If the capital labor ratio increases, it shows that the economic structure is transforming from labor-intensive to capital-intensive. Capital-intensive industries and labor-intensive industries tend to be heavy-pollution industries and light-pollution industries, respectively.

5. Discussion

In this section, a discussion comparing these findings with those of previous studies is presented in two parts. The first part relates to the indicators of high-quality development, and the second part describes the evaluation of high-quality development TFP.

5.1. Indicators of High-Quality Development

The classification of a high-quality development index system is mainly based on the connotation of high-quality development. Different understandings of the connotation lead to different measurement index systems. Generally, the measurement of high-quality development mainly focuses on the following three aspects: (i) from the five development concepts guiding high-quality development, that is, to build the high-quality development evaluation index system from the five fields of innovation, coordination, green, open, and sharing [14,15]; (ii) from the characteristics of high-quality development, that is, from the five areas of high-quality supply, high-quality demand, high-quality input-output, high-quality income distribution, and high-quality economic cycle to build the high-quality development evaluation index system [7,11]; and (iii) from the requirements of high-quality development, that is, to build the high-quality development evaluation index system from the three areas of quality change, efficiency change, and dynamic change [12,13]. The results of different index measurement systems are slightly different. Of course, the above three measurement index systems of high-quality development are also suitable for other countries or regions. Considering the internal or external factors of different countries or

regions, the index systems may be slightly different. For the new concept of high-quality development, scholars at home and abroad need to make efforts to further explore and improve in the future.

5.2. Evaluation on High-Quality Development TFP

Generally, from the perspective of the evaluation index system, high-quality development TFP includes green economic development TFP, to a certain extent. For the evaluation of green economic development TFP, scholars consider not only the good output GDP but also the bad output pollution emissions. For the evaluation of high-quality development TFP, on the one hand, it considers the good output of GDP and the bad output of pollution emissions (nongreen development); on the other hand, it also considers the good outputs innovative development, coordinated development, open development, and shared development. Currently, for the evaluation of economic high-quality development TFP, most scholars focus on the evaluation of green economic development TFP. Li et al. [62] measured the green TFP of the Pearl River Delta urban agglomeration from 2005 to 2018 and analyzed its changes from time and space dimensions by using the SBM Malmquist–Luenberger model. Hou et al. [63] studied the spatial effect and transmission mechanism of market integration on regional green TFP by calculating the Malmquist–Luenberger model based on panel data of 30 provinces in China from 2008 to 2017. Elsadig [64] assessed the impact of green TFP intensity on sustainable productivity growth in Malaysia, Indonesia, the Philippines, Singapore, Thailand, China, Japan, and South Korea. From the perspective of the TFP evaluation method, they have the same usability, but the difference lies in how the index system and model are built from the theoretical level. It should be pointed out that the TFP obtained by different evaluation methods may be different. The focus of this study is not on the innovation of methods but creatively combines the connotation of high-quality development theory with the general SBM model for quantitative analysis. It should be noted that the combination of a high-quality development assessment system with different measurement methods of TFP is also applicable to other countries and regions.

6. Conclusions

6.1. Summaries and Policy Recommendations

In this paper, we first analyze the static high-quality development efficiency and dynamic high-quality development TFP of regional economies in China from 2000 to 2018 with the Malmquist productivity index and the SBM-DDF model based on an undesirable output perspective with slacks-based methods. Then, the spatial trends and spatial correlation pattern of high-quality development efficiency and TFP of regional economies in China are identified. In addition, we explore the influencing factors of high-quality development efficiency and TFP of regional economies in China with the Tobit model. The main research results are as follows:

- (1) The high-quality development efficiency of the eastern region is the highest, followed by the northeast region, the western region, and the central region. Only Guangdong, Shanghai, Jiangsu, and Tibet are on the production boundary of high-quality development efficiency. Yunnan, Guizhou, and Guangxi have lower high-quality development efficiency. The average growth rate of the high-quality development TFP in the eastern region is the largest, and that in the central region is the lowest. Only Beijing, Tianjin, and Zhejiang have positive TFP, pure efficiency change, pure technological progress, scale efficiency change, and technological scale change at the same time.
- (2) From 2001 to 2018, the high-quality development TFP shows a fluctuating rising trend overall. The U and inverted-U trend lines show that the high-quality development efficiency has significant regional differences in the east–west direction, presenting a significant feature of spatial imbalance. The high-quality development TFP of the eastern regions is slightly higher than that of the western regions, and that of the northern regions is slightly higher than that of the southern regions. There is

significant positive spatial autocorrelation in the high-quality development efficiency, which is mainly characterized by the L-L type.

- (3) The role of government, urbanization rate, and marketization levels have a positive and significant impact on high-quality development efficiency and TFP. Financial development, infrastructure, and foreign direct investment can improve the high-quality development efficiency but can also reduce high-quality development TFP. The capital–labor ratio has a negative and significant impact on high-quality development efficiency and TFP.

Based on the above research conclusions, we offer some suggestions and advice to government managers and policymakers for improving the high-quality development efficiency and TFP of regional economies in China. First, government managers and policymakers should improve the role of government, urbanization rate, and marketization levels and reduce energy conservation. Second, relying on the spatial characteristics of high-quality development efficiency and TFP, government managers and policymakers should optimize the spatial layout of high-quality development elements to form multilevel, multigradient, dislocation competition, cooperation and win–win high-quality development spatial support systems. Finally, government managers and policymakers also need to take responsibility for adopting a high-quality development path, avoiding extensive development.

6.2. Main Contributions

The main contributions of this paper are as follows: (i) Based on the five development concepts, this paper creatively combines the measurement of TFP of high-quality development with the SBM-DDF model, which not only enriches the theoretical connotation of high-quality development, but also finds one of the effective methods of high-quality development performance evaluation, which is the greatest contribution of this paper. (ii) The results of this paper are helpful to enrich the content of high-quality development research systems from the perspective of spatial economics, and provide an important decision-making reference for the relevant government departments in China to optimize the spatial layout of high-quality development elements and promote the formation of regional spatial patterns with complementary advantages and high-quality development.

6.3. Limitations and Future Research

It needs to be pointed out that the research on high-quality development is still in its infancy; many problems have not been addressed by the academic community, and there are several limitations and future directions of the study presented here. First, we only study one of the three aspects of high-quality development evaluation listed in this paper. The other two different evaluation methods or new evaluation methods will be taken as in-depth theoretical research with technical analysis in the future. Second, due to the lack of data, especially at the micro level, this paper does not include cities or counties in China in the research system. In future work, it will be worth considering the comprehensive measurement of other high-quality development indicators, especially those based on big data from online and offline from different research countries, regions, and geographical levels. Third, in this paper, we carefully use the most common SBM-DDF method to measure the high-quality development efficiency and TFP. There is a need for an improved evaluation system using advanced algorithms, such as SBM-NDEA [65], DNSBM [66], NDDF [67], SFA [68], and panel SFA [69], and the comparison of different methods is worthy of further investigation. Fourth, there may also be more driving paths in the Tobit model as well as potential interactions between them, and further research with more influencing factors, especially the effects of COVID-19, will continue to be interest in the future.

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