Hindawi
Mathematical Problems in Engineering
Volume 2020, Article ID 2768025, 11 pages
https://doi.org/10.1155/2020/2768025

Research Article

Does Economic Growth Driving Force Convert? Evidence from China

Zejun Li,[1] Zimei Huang,[2] and Tinghui Li[2]

[1]*School of Computer and Information Science, Hunan Institute of Technology, Hengyang 421002, China*
[2]*School of Economics and Statistics, Guangzhou University, Guangzhou 510006, China*

Correspondence should be addressed to Tinghui Li; lith@gzhu.edu.cn

Received 1 June 2020; Revised 28 August 2020; Accepted 28 September 2020; Published 16 October 2020

Academic Editor: Jie Yan

The conversion from conventional to new driving forces and their time-varying characteristics are of great importance to China's economic transformation. In this paper, we attempt to investigate the economic growth driving force conversion in China and the time-varying characteristics of driving forces by constructing a time-varying coefficient panel data model during the period of 1998–2015. The empirical results indicate that China's economy has undergone driving force conversion. Specifically, China's economic growth driving forces have been transformed from traditional ones (human capital and gross fixed capital formation) to new ones (innovation capacity and structural transformation). Furthermore, we find that the characteristics of the driving forces are time-varying and heterogeneous. Innovation capacity and structural transformation have a more crucial impact on economic growth. Finally, based on the conclusions of the quantitative analysis, some important policy implications can be pursued to foster economic growth. Chinese government ought to enact various policies that are conducive to enhancing innovation capacity and accelerating structural transformation.

1. Introduction

The driving force of economic growth is an ongoing topic that has lasted for a long time. The evolution of the world economy is a leap from relying mainly on simple labour to relying mainly on mental labour. With the improvement of the level of economic development, more and more simple labour will be replaced by intelligence. Knowledge, innovation [1, 2], technology [3], information, and other intangible elements are playing a crucial role in economic growth. Through economic transformation, stimulate the vitality of new production factors and promote the rational flow and effective agglomeration of new production factors such as knowledge, technology, information, and data. Therefore, sustainable economic growth requires economic growth driving force conversion. Economic growth driving force conversion is through the new model, forms, technology, materials, and energy to replace the old ones, to realize the industrial upgrading, and to transfer from quantity, epitaxial, and labour-intensive economic growth to quality, connotation, and knowledge-intensive economic growth.

As a developing country, China has paid much attention to economic growth driving force conversion. China's economy has experienced years of sustained and rapid growth since the reform and opening up [4]. It is well known that China's economic growth is mainly driven by huge investment and energy-intensive industry [5]. At present, China's economy is transitioning from a phase of rapid growth to a stage of high-quality development. However, the labour- and investment-driven and energy-intensive economic growth mode of China has increased energy consumption and entailed serious environmental, resource, ecological, and social problems, thereby undermining green productivity [6] and resulting in less sustainable economic growth. To maintain sustainable economic development, China is required to undergo an economic transformation. Hence, this is a pivotal stage for transforming the growth model, improving economic structure, and fostering new driving forces of economic growth. Therefore, to foster economic growth, an accurate understanding of economic growth driving force conversion and its time-varying characteristics is extremely crucial.

In the process of transforming China's economic growth driving forces, green total factor productivity (GTFP) can effectively reflect the sustainability of economic growth [7]. Broadly, GTFP, also called environmental total factor productivity (TFP), is most commonly defined as the TFP that takes environmental factors and energy consumption into consideration [8, 9]. GTFP is an important index for measuring economic vitality because it can reflect the engine and quality of economic development [10]. A review of the available literature manifests that several advancements have been made in the methodological development of the typical productivity index. The measurement method of GTFP mainly includes the Solow residual method [11], stochastic frontier analysis (SFA), and DEA. The Solow residual method and SFA are based on the production function and required large sample data, which are subject to the conditions of the functional form itself and are unsuitable not only for a situation involving multiple inputs and outputs but also for small sample problems, thus, resulting in a certain gap between assumptions and reality [12]. However, DEA is a linear programming-based technique for measuring the relative performance of organizational units. Compared with the Solow residual method and SFA, DEA is unnecessary for fitting the production function and estimating parameters and suitable for a situation involving multiple inputs and outputs. Moreover, our problem is a small sample problem and we employed three inputs and three outputs to measure GTFP. Therefore, in this paper, DEA is a more powerful tool to measure GTFP.

Since the seminal studies of Caves et al. [13], there has been an explosion of work exploring the productivity index by employing the DEA method. The methods include Malmquist (M) productivity index [13], Luenberger (L) productivity index [14], Malmquist–Luenberger (ML) productivity index [15], global Malmquist (GM) productivity index [16], GML index [17], and GML index based on the SBM-DDF [10]. Specifically, M productivity index is not circular and does not account for the effect of environmentally harmful byproducts. GML productivity index is not only circular and immune to linear programming infeasibility, but also it considers undesirable output. To account for the potential of slack in technological constraints, Fukuyama and Weber [18] propose a directional SBM of technical inefficiency. To more accurately measure the GTFP, combining the advantages of the above method, Liu and Xin [10] construct a GML index based on the SBM-DDF. Compared with the above methods, this method can not only effectively deal with radial and oriented problems and achieve global comparability in the production frontier, but also take undesirable output into consideration. The GML index based on the SBM-DDF is extensively adopted to calculate the GTFP [19]. Therefore, in this paper, a GML index based on the SBM-DDF is employed to measure the GTFP.

According to the above, determinants of GTFP can be regarded as driving forces of economic growth. Various mainstream research studies have examined the influential factors of GTFP and have been studied from different perspectives [20]. For instance, Chen et al. [21] revealed that environmental regulation, technological innovation, independent research and development, and endowment and property right structure are the determinants of GTFP. Besides that, some scholars conducted empirical analyses to find that technological change [22], environmental governance [23], degree of openness, financial development [24–26], and monetary policy [27] are the main influencing factors of GTFP and economic growth.

The aim of this paper is to shed light on the economic growth driving force conversion in China. In this paper, we expand and supplement the existing literature in the following three regards. The first of this article's contributions is that we provide evidence on economic growth from the GTFP perspective. The main contribution of this perspective is that we can gain insight into the sustainability of economic growth by observing GTFP.

The second important contribution of our studies is that we attempt to further explore the economic growth driving force conversation by dividing the driving forces into conventional and new driving forces. In the past few years, China's rapid economic growth has been through labour and investment-driven modes, which we regarded as the main traditional economic growth driving forces. However, this mode promotes growth but entails serious environmental, resource, ecological, and social problems, resulting in less sustainable economic growth. Thus, it is urgent to foster new economic growth driving forces. Improving innovation capacity can accelerate technological progress, thereby promoting economic development. At the same time, optimizing and updating industrial structure will reduce environmental equality as well as improve resource allocation efficiency, thus enhancing GTFP. Hence, we consider innovation capacity and industrial structural transformation as new economic growth driving forces.

The third contribution of our work is to find empirical evidence for the time-varying characteristics of the conventional and new driving forces that contribute to GTFP. These time-varying characteristics are crucial for China to enact corresponding policies to foster economic growth. However, the vast majority of literature has focused on the theoretical research of economic growth driving force conversion. There is little empirical evidence on the time-varying characteristics of economic growth driving force conversion. In this article, we construct such an empirical analysis. Employing a sample of 30 Chinese provinces for the 1998–2015 periods, we construct a time-varying coefficient panel data model to exploit the characteristics of economic growth driving force conversion.

The paper proceeds as follows: Section 2 introduces the methods employed in this paper. In Section 3, we introduce the variables selection and data source. In Section 4, we perform a case study. Section 5 includes the conclusion.

2. Methods

In this section, we mainly focus on the methods that we employ in this paper. First, in Section 2.1, we introduce the global Malmquist–Luenberger (GML) index based on the slacks-based measure (SBM) directional distance function (DDF) to measure the GTFP. Section 2.2 introduces the panel regression model, which is adapted to investigate economic growth driving forces conversion. In Section 2.3, we briefly introduce the time-varying coefficient panel data model, which is employed to further investigate the time-

varying characteristics of the conventional and new driving forces' contributions to the GTFP.

2.1. GML Based on SBM. Each province in China is regarded as a decision-making unit (DMU). First, following the contribution of Oh [17], we produce a global production possibility set (PPS), including M desirable outputs (real GDP), $y = (y_1, \cdots, y_n) \in R_M^+$, and I undesirable outputs (waste water and waste gas), $b = (b_1, \cdots, b_n) \in R_I^+$, and N inputs (i.e., labour input, capital input, energy input), $x = (x_1, \cdots, x_n) \in R_N^+$. The global PPS is defined as follows:

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

where z_k^t denotes the weight of each province. If $z_k^t \geq 0$, it indicates the constant returns to scale (CRS). If $\sum_{k=1}^{K} z_k^t = 1$, $z_k^t \geq 0$, it indicates the variable returns to scale (VRS). In this paper, CRS are assumed.

Second, drawing on the research of Fukuyama and Weber [10, 18], we construct a global SBM-DDF that covers undesired output, as follows:

$$\overrightarrow{S}^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x, s^y, s^b} \frac{(1/N)\sum_{n=1}^{N}\left(\left(s_n^x/g_n^x\right) + (1/(M+I))\right)\left(\sum_{m=1}^{M} s\left(s_m^y/g_m^y\right) + \sum_{i=1}^{I}\left(s_i^b/g_i^b\right)\right)}{2},$$

$$\text{s.t.} \begin{cases} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \quad \forall n, \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t + s_m^y = y_{k'm}^t, \quad \forall m, \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b \\ = b_{k'i}^t, \quad \forall i, \\ z_k^t \geq 0, \quad \forall k, \\ s_m^y \geq 0, \quad \forall m, \\ s_i^b \geq 0, \quad \forall i, \end{cases} \tag{2}$$

where (g^x, g^y, g^b) represents the direction vectors for decreasing labour, capital, and energy inputs, increasing real GDP, and decreasing waste water and gas, respectively, and (s_n^x, s_m^y, s_i^b) denotes the slack vectors for redundant labour, capital and energy inputs, inadequate real GDP, and redundant waste water and gas, respectively. If the value is greater than 0, the actual labour, capital, and energy inputs and the waste water and gas are greater than the boundary labour, capital, and energy inputs and waste water and gas, while the actual real GDP are less than the boundary real GDP.

Finally, we construct the GML index as follows:

$$\mathrm{GML}^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + \overrightarrow{S}^G\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1 + \overrightarrow{S}^G\left(x^{t+1}, y^{t+1}, b^{t+1}, g^x, g^y, g^b\right)}, \tag{3}$$

where $\overrightarrow{S}^G(x^t, y^t, b^t; g^x, g^y, g^b)$ represents the global SBM-DDFs based on nonradial and nonoriented measurements. The GML index denotes the change from period t to period $t+1$. If the GML is greater than 1, it indicates that GTFP increases. If the GML is equal to 1, the GTFP is in a stable state. Otherwise, the GTFP decreases.

However, the GML index is not the GTFP, but rather its change rate. Thus, regression treatment is needed. Following the work of Liu and Xin [10], we suppose that the GTFP of each province in 1997 is 1. Then, the GTFP in 1998 would be the GTFP in 1997 multiplied by the GML index: $\mathrm{GTFP}_{1998} = \mathrm{GTFP}_{1997} * \mathrm{GML}_{1997-1998}$. The GTFP of other years can be calculated similarly.

2.2. Panel Regression Model. Economic growth driving forces convert in China. Since the reform and opening up, China has made full use of the advantages of resource endowment and demographic dividend to form comparative advantages in product production, processing, and manufacturing, to promote economic growth. With China joining the World Trade Organization, the investment-driven development mode has become more important. However, since 2010, the

contradictions in economic development gradually appeared: the economic structure was unbalanced, the investment efficiency was reduced, the environmental carrying capacity continues to decline, and the economic constraints of resources and environment are gradually strengthened. China's economic growth rate has decreased to some extent [5]. With the rising labour cost, the advantages of conventional driving force are gradually weakened. The traditional growth pattern is no longer adapted to the new situation, and conventional driving forces of economic growth are being replaced by new ones. In other words, China converts economic growth driving forces.

To investigate the economic growth driving forces conversion, we specify the panel regression model. Over the past decade, the use of panel data in the econometric investigation has become popular [28]. The panel data approach encompasses data across cross sections and over time series, thus providing a comprehensive analysis to examine the influencing factors of economic growth driving force conversion [14]. The panel regression model typically assumes heterogeneity in the data, which allows us to completely capture by means of individual and time effects. The panel data model should be tested before estimating the model parameters, in order to facilitate the correct setting of the model in [29]. Panel regression models are estimated using recently developed techniques such as mean group estimators, which allow for heterogeneity in the estimation of the slope coefficients. Therefore, it can provide a more efficient estimation and information to discover the influencing factors of economic growth driving force conversion. To explore the conventional and new driving forces that affect economic growth, we perform the following panel regression model:

$$\mathrm{GTFP}_{it} = \alpha_i + \beta_1 * hc_{it} + \beta_2 * gf_{it} + \beta_3 * \mathrm{inno}_{it} + \beta_4 * st_{it}, \tag{4}$$

where i and t represent province i and time t, respectively, and α_i denotes the province effect, which captures the unobserved heterogeneity across provinces. GTFP is green total factor productivity, hc denotes human capital, gf stands for gross fixed capital formation, inno represents innovation capacity, and st refers to structural transformation.

2.3. Time-Varying Coefficient Panel Data Model. The impact of economic growth driving forces on economic growth is time-varying. Economic growth driving forces conversion is a dynamic and continuous process, and the transformation process takes some time. Since the reform and opening up, China mainly relied on land, capital, and low-cost labour to promote economic development. Labour and capital have an important impact on economic growth. However, in recent years, China's economic development reached a certain extent and elements-driven economic growth gradually weakened, which cannot keep continuous high growth. At the same time, land tension, resource shortages, ecological environment deterioration, and other negative problems gradually appear [20]. In order to maintain sustained economic growth, it is necessary to improve the GTFP by improving the innovation capacity and structural transformation. That is to say, innovation capacity and structural transformation exert a more crucial role in economic growth at present. In a word, various stages of economic development have different economic growth driving forces. Therefore, it is crucial for China to understand the time-varying characteristic of the conventional and new driving forces' contribution to economic growth.

Varying coefficient models were developed by Hastie and Tibshirani [30] and are an extension of classical linear regression models in the sense that the regression coefficients are replaced by functions in certain variables (often time t). Varying coefficient regression models are regarded as very useful tools for analysing the relationship between a response and a group of covariates [31]. The varying coefficient model allows coefficients to depend on some informative variables and model flexibility. Therefore, varying coefficient models have been popular in longitudinal data and in panel data studies and have been applied in fields such as finance and economics. In addition, because they take on spatiotemporal characteristics, panel data can well describe and depict the systematic and dynamic characteristics of the decision objects.

A varying coefficient panel data model includes the time- and individual-varying coefficient panel data models. The time-varying coefficient panel data model allows us to detect the time-varying impacts of the conventional and new driving forces on the GTFP. Since various responses to GTFP may be expected at different times, it is more suitable for us to employ the time-varying coefficient panel data model to detect the time-varying characteristics of the conventional and new driving forces' contributions to the GTFP. The estimation methods of the time-varying coefficient panel data model include the intragroup dispersion method and the least squares dummy variable method. In this paper, we employ the least squares dummy variable method to estimate the coefficients. Therefore, we construct a time-varying coefficient panel data model for province i at time t as follows:

$$\mathrm{GTFP}_{it} = D\alpha_i + \beta_{1t} * gf_{it} + \beta_{2t} * \mathrm{inno}_{it} + \beta_{3t} * st_{it} + \mu_{it}, \tag{5}$$

where D is the dummy variable, i and t represent province i and time t, respectively, GTFP denotes green total factor productivity, gf stands for gross fixed capital formation, *inno* represents innovation capacity, and st refers to structural transformation; β denotes a vector of estimated parameters in the equation; and μ_{it} is the error term.

3. Variables Selection and Data Source

In this section, we introduce the variables selection and data source. In Section 3.1, we introduce the samples. In Section 3.2, we briefly describe the variables employed to measure GTFP. In Section 3.3, we select the driving forces.

3.1. Samples. This paper is conducted in China and focuses on the economic growth driving force conversion. Considering the integrity and availability of data, the sample excludes Tibet, Hong Kong, Macao, and Taiwan. We divide

the sample into three subsamples: east, middle, and west areas. The east area (sample 1) includes Beijing, Shanghai, Tianjin, Jiangsu, Guangdong, Liaoning, Hainan, Hebei, Fujian, Shandong, and Zhejiang. The middle area (sample 2) includes Anhui, Hubei, Hunan, Henan, Jiangxi, Heilongjiang, Jilin, and Shanxi. The west area (sample 3) includes Gansu, Guangxi, Sichuan, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Xinjiang, Yunnan, Chongqing, and Guizhou. Annual data are used for 30 Chinese provinces during the period from 1997 to 2015. The data are obtained from the Easy Professional Superior (EPS) macro database and the National Bureau of Statistics.

3.2. Variables to Measure GTFP. This study measures the GTFP of 30 Chinese provinces. The measurement of GTFP integrated three dimensions: the economy, resources, and environment. According to the existing literature, we know that labour, capital, and energy are the most frequently used resource input indicators [10], while real gross domestic product (GDP) is the most frequently used economy indicator and desirable output [32], and waste water, waste gas, and solid waste are the most frequently used environmental indicators and undesirable outputs in measuring GTFP [33]. In this paper, because of the availability of data, we employ three resource indicators (labour input, capital input, and energy input) as input variables, one economy indicator (real GDP) as desirable output, and two environmental indicators (waste water and waste gas) as undesirable outputs to measure the GTFP. These inputs and outputs indicators are specified as follows.

3.2.1. Labour Input. Labour input refers to the amount of labour. Due to labour mobility, the amount of labour input is different at different times in one year, so the number of year-end employed persons is taken as the indicator [20], where a unit is ten thousand persons. The data of the labour of China's 30 provinces from 1997 to 2015 were directly obtained from the EPS macro database.

3.2.2. Capital Input. Capital input is measured by capital stock. We employ the perpetual inventory method to estimate capital stock, for which the basic equation is $K_{it} = I_{it} + (1 - \delta)K_{i(t-1)}$, in which K_{it} is the actual capital stock in province i in period t, and I_{it} is the gross fixed capital formation in area i in period t. Compared with the fixed assets investment of the whole society, the gross fixed capital formation is slightly better than the former when measuring capital stock [10]. Therefore, we use the gross fixed capital formation to calculate capital stock. Additionally, δ represents the depreciation rate. Different depreciation rates are adopted to calculate capital stock among different provinces. Because of the partial lack of data from the Chinese provinces, we follow the study of Zhang [34] to estimate the Chinese provinces' capital stock and adopt 9.6% as the depreciation rate. The base period is 1997. Capital stock is calculated in 100 million at the constant price in 1997. The corresponding data for 1997–2015 come from the National Bureau of Statistics.

3.2.3. Energy Input. The total energy consumption, GDP divided by GDP per unit of energy consumption, is employed to measure energy input. Total energy consumption refers to the total consumption of various kinds of energy by the country's production sectors in a given period of time and shows the scale, composition, and pace of the increase in energy input [4, 35]. The unit of energy input is 10000 tce, and the data come from the EPS macro database.

3.2.4. Desirable Output. Similar to much of the existing literature, we use the real GDP to represent the desirable output. To ensure the comparability of the data, it is converted based on the year 1997. The data originate from the National Bureau of Statistics.

3.2.5. Undesirable Output. The existing literature concerning undesirable outputs mainly includes three forms: waste water, waste gas, and solid waste. However, due to the unavailability of data regarding provincial solid waste, it was excluded from this study. Therefore, we employ the total industrial waste water discharge and the total industrial waste gas discharge as undesirable outputs to calculate GTFP. A unit of waste water is 10,000 tons, and a unit of waste gas is 100 million cube meters. The data for the period from 1997 to 2015 were obtained from the EPS macro database.

3.3. Driving Forces. In this paper, we select GTFP as the explained variable. Human capital and gross fixed capital formation are regarded as the conventional driving forces, while innovation capacity and structural transformation are regarded as the new driving forces.

First, human capital, which is calculated by the number of year-end employed people multiplied by their average years of schooling, is considered as an important driving force of economic growth [36]. Human capital is usually the sum of the knowledge, technical skills, capabilities, and qualities that can create economic and social value. The average years of schooling have been commonly used as the specification of the quantity of human capital stock empirically [37]. The proportion of employees at the primary, junior, middle, and higher education levels to the total employees calculates the average years of education of the labours in a certain area. The effect of human capital on GTFP involves multiple channels. On one hand, an increase in human capital directly affects GTFP by enhancing labour productivity in production. On the other hand, human capital is an important input into R&D and therefore indirectly increases labour productivity by accelerating technological change [38]. Human capital is conducive to producing and adopting new technologies, improving resource utilization efficiency and GTFP, thus promoting economic growth. The human capital data can be obtained from the EPS macro database.

Second, gross fixed capital formation is regarded as a crucial driving force of GTFP. Economic growth can be promoted by gross fixed capital formation through creating

massive benefits, increasing investments by creating enlarged markets and economies of scale, and transferring information, technology, and knowledge spillovers. To ensure the comparability of the data, it is converted based on the year 1997. The data originate directly from the National Bureau of Statistics.

Third, innovation capacity is an important driving force for productivity growth [1]. Technological innovation plays an important role in optimizing energy structure and in promoting economic growth. As pointed out by Pan et al. [39], the information on patent grants is covered in patent applications. Simultaneously, pendency from patent applications to grant is necessary, as patent grants cannot truly reflect the current level of regional innovation capacity. Therefore, in this paper, the natural logarithm of patent applications is used to calculate innovation capacity, and the original data was obtained from the EPS macro database.

Fourth, structural transformation is measured by the coefficient of industrial structure, which can reflect the industrial distribution. According to the principle of industrial evolution, we adopt the sum of the proportion of the added value of the three industries accounting for the added value of the primary industry to calculate the coefficient of industrial structure. Structural transformation results in changes in energy consumption and pollution emission, consequently, having great effects on GTFP. It is asserted that differences in industry structure may inevitably affect GTFP. The structural transformation data was collected from the EPS macro database.

The measurements and sources of the conventional and new driving forces are shown in Table 1.

4. Case Study

In this section, we mainly perform a case study. Firstly, we present the GTFP characteristics of 30 Chinese provinces in Section 4.1. In Section 4.2, we analyse the results of economic growth driving forces conversion. In Section 4.3, we further analyse the results of the time-varying characteristics of the conventional and new driving forces' contributions to the GTFP.

4.1. Stylized Facts of GTFP. Based on the above data, the MaxDEA software is used to measure the GTFP of 30 Chinese provinces from 1998 to 2015, and the average GTFP of China and its east, middle, and west areas is presented in Figure 1.

There is rising and spatial heterogeneity concerning China's GTFP. On one hand, from a national perspective, China's GTFP increased from 0.983 to 1.159 during the period from 1998 to 2015, showing an overall upward trend. This means that during the sample period, China's GTFP development rose continuously. This is mainly due to the increasing awareness of the damage of environmental pollution and the importance of sustainable economic development in China. Consequently, China tried to accelerate the transformation of the mode of economic growth by enacting a series of policies on energy conservation and emission reduction, which can promote economic growth, reduce environmental pollution, and improve the GTFP.

On the other hand, from the perspective of regional distribution, there is a spatial heterogeneity of GTFP. First, in the east regions, GTFP shows a rising trend. This is in accordance with the fact that the provinces in the east area are almost developed provinces, such as Beijing, Shanghai, Tianjin, Jiangsu, and Guangdong, which possess strong economic power, rich educational resources, convenient transportation, and advanced environmental technology. As a result, their GTFP is maintained at a high level, a win-win situation for sustainable economic growth and environmental protection. However, the GTFP in the middle and west areas implies a trend of falling and then rising. The GTFP is lower than 1 during the period from 1998 to 2015, which is at a low level. This is mainly owing to the relatively weak economic foundation of the middle and west provinces and inadequacy in the introduction of technical talents, as well as shortages of technological innovation capabilities and pollution control equipment, which has led to environmental technology lagging behind the eastern coastal areas. At the same time, the central and western provinces also need to undertake the transfer of heavy pollution, high investment, and labour-intensive industries from the eastern provinces, thereby further aggravating environmental pollution and causing the low GTFP.

Therefore, the GTFP among the 30 Chinese provinces has spatial heterogeneity. This is in line with the current imbalance in China's regional economic development. High-tech industries are developed in developed areas, while high-pollution and high-energy industries are transferred to the less developed regions, resulting in more environmental pollution and decreases in the GTFP of these less developed provinces.

4.2. Conversion of Economic Growth Driving Forces. Before investigating the economic growth driving force conversion, we conduct a panel unit root test. For the preliminary investigation, we perform a panel unit root test by applying the Levin–Lin–Chu (LLC) test proposed by Levin et al. [40] and the Fisher-augmented Dickey–Fuller (ADF) test proposed by Maddala and Wu [41]. The results of the panel unit root test are exhibited in Table 2. The decision criterion is that the variable is stationary if the unit root tests confirm nonrejection of the null hypothesis at a 10% level of significance. The results of the LLC and Fisher-ADF tests indicate that all variables reject the null hypothesis (nonstationary) at a 10% significance level. That is to say, all variables used in this study are stationary.

Subsequently, we use Hausman tests to choose the specific panel regression model. The results of the Hausman tests reject the null hypothesis in the full sample and sample 1, while they did not reject the null hypothesis in samples 2 and 3. In other words, we should employ a fixed effects (FE) model for the full sample and sample 1 and a random effects (RE) model for samples 2 and 3 to implement the regression analysis. The standardized coefficients of the panel regression model are documented in Table 3, where columns 2, 3, 4, and 5 report the impact of the driving forces on the GTFP in the full sample and in samples 1, 2, and 3, respectively.

Table 1: Conventional and new driving forces.

Driving force	Variable	Measurement	Source
Conventional	Human capital	Based on the years of education of the labours and measured by millions of persons	EPS macro database
	Gross fixed capital formation	Gross fixed capital formation	National Bureau of Statistics
New	Innovation capacity	Log (patent applications)	EPS macro database
	Structural transformation	Coefficient of industrial structure	EPS macro database

Notes: this table exhibits the measurement and source of conventional and new driving forces of economic growth.

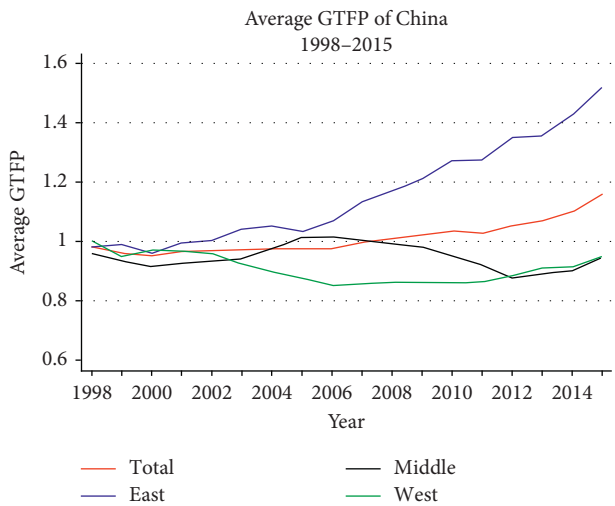

Figure 1: China's average GTFP. The red line represents China's average GTFP, while the blue, black, and green lines indicate the mean average GTFP of China's east, middle, and west areas, respectively. The sample period is from 1998 to 2015.

Table 2: Results of the panel unit root test.

Variables	LLC	Fisher-ADF test
GTFP	−15.615 (0.000)	160.161 (0.000)
hc	−2.409 (0.008)	145.170 (0.000)
gf	−3.398 (0.000)	167.332 (0.000)
inno	−5.810 (0.000)	161.382 (0.000)
st	−4.769 (0.000)	175.940 (0.000)

Notes: P values are shown in parentheses. The sample period is from 1998 to 2015.

China's economy has undergone driving force conversion. It is apparent from the standardized results given in Table 3 that, whether in the full sample or in subsamples 1 and 2, new driving forces (innovation capacity and structural transformation) promote economic growth more than conventional driving forces (human capital and gross fixed capital formation), which means that China's economic growth driving forces have been transformed from traditional ones to new ones. This is in accord with the current economic growth driving force conversion in China's economic development.

The impacts of different driving forces on the GTFP are spatially heterogeneous. In the full sample, the conventional driving force affecting the GTFP is gross fixed capital formation, while the new driving forces are innovation capacity and structural transformation. The results imply that human

Table 3: Results of the panel regression model.

	Full Sample	Sample 1	Sample 2	Sample 3
hc	0.110	0.028	−0.110	0.696***
	(0.0599)	(0.109)	(0.118)	(0.0363)
gf	−0.719***	−0.485***	0.051	−1.344***
	(0.0299)	(0.0608)	(0.0576)	(0.0196)
inno	0.283**	−0.316*	0.062	0.758***
	(0.0290)	(0.0634)	(0.0502)	(0.0160)
st	1.293***	2.825***	−0.127	0.211**
	(0.0674)	(0.122)	(0.127)	(0.0493)
N	540	198	144	198
R^2	0.258	0.564		

Notes: this table presents the standardized coefficients of the panel regression model. Symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Standard errors are shown in parentheses.

capital has an insignificant impact on the GTFP, whereas gross fixed capital formation has a significant negative impact on the GTFP. In other words, in the full sample, the conventional driving force affecting the GTFP is only gross fixed capital formation. This negative impact may be closely related to the following phenomenon: with the development of the economy, the investment efficiency in China is decreasing. Furthermore, in the full sample, the new driving forces, innovation capacity and structural transformation, have significant and positive effects on the GTFP. The reasons may be that improving innovation capacity and transforming industrial structure can improve resource allocation efficiency and GTFP.

In the east area, gross fixed capital formation and innovation capacity have a significant negative impact on the GTFP, while structural transformation exerts a positive and significant effect on the GTFP. These results may be because the east provinces have always had abundant capital, advanced environmental technology, and strong innovation capacity. Consequently, the transformation of industrial structure will boost productivity. However, the improved productivity may not be environment friendly, which will cause more environmental pollution, thus reducing the GTFP. The transformation of industrial structure is beneficial to improving resource allocation efficiency and GTFP.

In the middle area, neither the conventional nor the new driving forces exert a significant impact on the GTFP, while both the conventional and the new driving forces exert a significant impact on the GTFP in the west area. The middle areas develop their economies through introducing capital and technology while simultaneously introducing a large amount of environmental pollution. Therefore, neither the conventional

Table 4: Results of the varying coefficient panel data model.

Year	gf	inno	is
1998	0.181	−0.292**	−0.382
1999	0.130	−0.265	−0.293***
2000	0.045**	−0.199*	−0.231***
2001	−0.031***	−0.130**	−0.224***
2002	−0.049**	−0.121**	−0.177***
2003	−0.096***	−0.084**	−0.143***
2004	−0.135***	−0.050**	−0.125***
2005	−0.141***	−0.044**	−0.108***
2006	−0.188***	0.002***	−0.107***
2007	−0.205***	0.007***	−0.045***
2008	−0.227***	0.014***	0.019***
2009	−0.232***	0.010**	0.076***
2010	−0.238***	0.006**	0.131***
2011	−0.249***	0.015**	0.144***
2012	−0.251***	−0.003**	0.244***
2013	−0.239***	0**	0.203***
2014	−0.258***	0.005**	0.268***
2015	−0.273***	0.020**	0.285***

Notes: symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

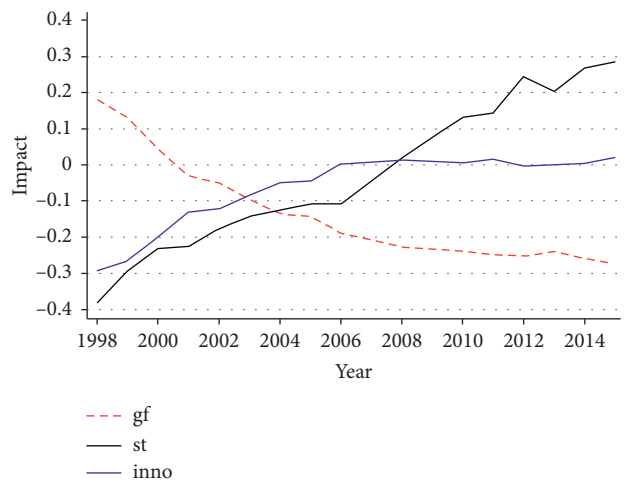

Figure 2: Results of the varying coefficient panel data model. Notes: the sample period is from 1998 to 2015. The red dash line denotes the impact of the conventional driving force (gross fixed capital formation) on the GTFP. The solid blue and black line represents the impact of innovation capacity and structural transformation on the GTFP, respectively.

nor the new driving forces exert a significant impact on the GTFP. The west areas, which remain at a low level, boost their economies and GTFP by improving the human capital level and innovation capacity, introducing advanced technology, and accelerating industrial structure transformation. Overall, there are spatial heterogeneous impacts among the different areas. These heterogeneous impacts may be closely connected with the following phenomenon: different provinces have achieved different economic development levels and various economic development modes.

4.3. Time-Varying Impacts of the Conventional and New Driving Forces on GTFP. Table 4 presents the results of the time-varying coefficient panel data model for our 30 Chinese provinces in the period from 1998 to 2015. Columns 2, 3, and 4 in Table 4 report the time-varying impacts of gross fixed capital formation, innovation capacity, and structural transformation on the GTFP, respectively. Figure 2 intuitively presents the time-varying characteristics of the conventional and new driving forces' contributions to the GTFP.

The time-varying characteristics of the conventional and new driving forces that contribute to the GTFP are heterogeneous. As seen in Table 4 and Figure 2, the contributions to the GTFP among the different driving forces are inconclusive, which indicates that the time-varying impacts of the conventional and new driving forces that contribute to the GTFP are various. On one hand, the contribution of the conventional driving forces (gross fixed capital formation) is not promising. This result is consistent with the study of Li and Lin [5], which examined the impacts of an investment-driven economic growth model on green productivity in 30 Chinese provinces and found that the investment-driven growth model, which usually leads to the overexploitation of resources and increases environmental pollution, produces a negative effect on green productivity. This is mainly because China's investment efficiency has declined since the twenty-first century.

On the other hand, the contributions of the new driving forces on the GTFP perform well. The contributions of innovation capacity and structural transformation are increasing, perhaps because they could optimize and upgrade industrial and energy structure and improve resource allocation efficiency, thus decreasing environmental pollution, improving the GTFP, and promoting economic growth.

5. Conclusions

The main objective of this study is to investigate the economic growth driving force conversion in China and the time-varying characteristics of driving forces. To achieve these objectives, we attempt to study economic growth from the perspective of GTFP, in which the previous research about economic growth mainly focuses on per capita income growth or national income [42, 43], using a GML index based on the SBM-DDF to measure the GTFP of 30 Chinese provinces during the period 1998–2015. Then, we construct a panel regression model to discover the economic growth driving force conversion, in which existing studies only explored the influencing factors of economic growth [36, 44]. Finally, we adopt a time-varying coefficient panel data model to further investigate the time-varying

characteristics of the conventional and new driving forces that contribute to the GTFP.

Based on the empirical results, several important conclusions are drawn as follows. First, China's GTFP is rising and spatially heterogeneous. On one hand, from a national perspective, the GTFP of China shows an overall upward trend. On the other hand, from the perspective of regional distribution, the GTFP in the east regions show a rising trend. However, the GTFP in the middle and west areas imply a trend of falling and then rising. These heterogeneous impacts are in line with the current imbalance in China's regional economic development.

Additionally, China's economy has undergone driving force conversion. Specifically, China's economic growth driving forces have been transformed from traditional ones (human capital and gross fixed capital formation) to new ones (innovation capacity and structural transformation). This is in accordance with the current economic growth driving force conversion in China's economic growth. Besides that, the impacts of the different driving forces on the GTFP are spatially heterogeneous. First, in the full sample, the conventional driving force affecting the GTFP is gross fixed capital formation, while the new driving forces are innovation capacity and structural transformation. Second, in the east area, gross fixed capital formation and innovation capacity have a significant negative impact on the GTFP, while industrial transformation exerts a positive and significant effect on the GTFP. Third, in the middle area, neither the conventional nor the new driving forces exert a significant impact on the GTFP, while in the west area, both the conventional and the new driving forces exert a significant impact on the GTFP. These heterogeneous impacts may be closely connected with the following phenomenon: different provinces have achieved different economic development levels and various economic development modes.

Furthermore, the time-varying characteristics of conventional and new driving forces imply that China is in a period of transformation from traditional driving forces to new driving forces. The contributions to the GTFP among the different driving forces are inconclusive, which indicates that the time-varying impacts of the conventional and new driving forces that contribute to the GTFP are various. On one hand, the contribution of the conventional driving forces is not promising. This is mainly because China's investment efficiency has declined since the twenty-first century. On the other hand, the impacts of the new driving forces on the GTFP perform well. The contributions of innovation capacity and structural transformation are increasing, perhaps because they could optimize and upgrade industrial and energy structure and improve resource allocation efficiency, thus decreasing environmental pollution, improving the GTFP, and promoting economic growth.

Accordingly, the following policy implications can be pursued to improve the GTFP of these 30 Chinese provinces. First, to foster economic growth, the Chinese government ought to enact various policies conducive to enhancing innovation capacity and accelerating structural transformation. Second, these results show us that the GTFP of the less developed provinces in China is not optimistic, and more action should be taken in practice by both industry and government to handle the undesirable outputs of industrial enterprise, thus improving economic growth and reducing the environmental pollution.

This paper has several limitations and can be expanded by further research in the following regards. First, although the GTFP can be measured by the GML index based on the SBM-DDF, the inputs and outputs cannot be completely represented, owing to the lack of data. Better data availability permitting, future work could improve upon the input and output indicators presented here and expand the coverage to other, equally important, innovation input, the use of natural resources such as land, sea, forests, or mineral resources, and environmental pollution, such as the emission of carbon dioxide, sulfide, and solid waste. Another limitation is that the empirical research in this paper is based on the analysis of macro data to analyse the driving forces of economic growth. Further research could expand on the micro perspectives.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Nature Science Foundation of China (Grant no. 61672223).

References

[1] L. Kogan, D. Papanikolaou, A. Seru, and N. Stoffman, "Technological innovation, resource allocation, and growth," *The Quarterly Journal of Economics*, vol. 132, no. 2, pp. 665–712, 2017.

[2] J. Zeira, "Innovations, patent races and endogenous growth," *Journal of Economic Growth*, vol. 16, no. 2, pp. 135–156, 2011.

[3] O. Galor and D. N. Weil, "Population, technology, and growth: from malthusian stagnation to the demographic transition and beyond," *American Economic Review*, vol. 90, no. 4, pp. 806–828, 2000.

[4] A. Emrouznejad and G.-L. Yang, "A framework for measuring global malmquist-luenberger productivity index with CO_2 emissions on Chinese manufacturing industries," *Energy*, vol. 115, pp. 840–856, 2016.

[5] K. Li and B. Lin, "Economic growth model, structural transformation, and green productivity in China," *Applied Energy*, vol. 187, pp. 489–500, 2017.

[6] M. J. Herrerias, R. Joyeux, and E. Girardin, "Short-and long-run causality between energy consumption and economic growth: evidence across regions in China," *Applied Energy*, vol. 112, pp. 1483–1492, 2013.

[7] Y. J. Feng, S. Y. Zhong, Q. Y. Li, X. M. Zhao, and X. Dong, "Ecological well-being performance growth in China (1994–2014): from perspectives of industrial structure green

adjustment and green total factor productivity," *Journal of Cleaner Production*, vol. 236, 2019.

[8] S. Chen and J. Golley, ""Green" productivity growth in China's industrial economy," *Energy Economics*, vol. 44, pp. 89–98, 2014.

[9] B. Lin and Z. Chen, "Does factor market distortion inhibit the green total factor productivity in China?" *Journal of Cleaner Production*, vol. 197, pp. 25–33, 2018.

[10] Z. Liu and L. Xin, "Has China's belt and road initiative promoted its green total factor productivity?—evidence from primary provinces along the route," *Energy Policy*, vol. 129, pp. 360–369, 2019.

[11] R. M. Solow, "Technical change and the aggregate production function," *The Review of Economics and Statistics*, vol. 39, no. 3, pp. 312–320, 1957.

[12] B.-H. Gong and R. C. Sickles, "Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data," *Journal of Econometrics*, vol. 51, no. 1-2, pp. 259–284, 1992.

[13] D. W. Caves, L. R. Christensen, and W. E. Diewert, "The economic theory of index numbers and the measurement of input, output, and productivity," *Econometrica*, vol. 50, no. 6, 1982.

[14] S. Managi and P. R. Jena, "Environmental productivity and kuznets curve in India," *Ecological Economics*, vol. 65, no. 2, pp. 432–440, 2008.

[15] Y. H. Chung, R. Färe, and S. Grosskopf, "Productivity and undesirable outputs: a directional distance function approach," *Journal of Environmental Management*, vol. 51, no. 3, pp. 229–240, 1997.

[16] J. T. Pastor and C. A. K. Lovell, "A global malmquist productivity index," *Economics Letters*, vol. 88, no. 2, pp. 266–271, 2005.

[17] D.-H. Oh, "A global malmquist-luenberger productivity index," *Journal of Productivity Analysis*, vol. 34, no. 3, pp. 183–197, 2010.

[18] H. Fukuyama and W. L. Weber, "A directional slacks-based measure of technical inefficiency," *Socio-Economic Planning Sciences*, vol. 43, no. 4, pp. 274–287, 2009.

[19] X. C. Xu, X. Q. Huang, J. Huang, X. Gao, and L. H. Chen, "Spatial-temporal characteristics of agriculture green total factor productivity in China, 1998–2016: based on more sophisticated calculations of carbon emissions," *International Journal of Environmental Research and Public Health*, vol. 16, no. 20, 2019.

[20] M. Song, J. Du, and K. H. Tan, "Impact of fiscal decentralization on green total factor productivity," *International Journal of Production Economics*, vol. 205, pp. 359–367, 2018.

[21] C. F. Chen, Q. X. Lan, M. Gao, and Y. W. Sun, "Green total factor productivity growth and its determinants in China's industrial economy," *Sustainability*, vol. 10, no. 4, 2018.

[22] S. Shao, R. Luan, Z. Yang, and C. Li, "Does directed technological change get greener: empirical evidence from Shanghai's industrial green development transformation," *Ecological Indicators*, vol. 69, pp. 758–770, 2016.

[23] Z. Huang, G. Liao, and Z. Li, "Loaning scale and government subsidy for promoting green innovation," *Technological Forecasting and Social Change*, vol. 144, pp. 148–156, 2019.

[24] N. Tripathy, "Does measure of financial development matter for economic growth in India?" *Quantitative Finance and Economics*, vol. 3, no. 3, pp. 508–525, 2019.

[25] P. Adjei Kwakwa, H. Alhassan, H. Alhassan, and S. Aboagye, "Environmental kuznets curve hypothesis in a financial development and natural resource extraction context: evidence from Tunisia," *Quantitative Finance and Economics*, vol. 2, no. 4, pp. 981–1000, 2018.

[26] B. Kahouli, "The short and long run causality relationship among economic growth, energy consumption and financial development: evidence from south mediterranean countries (SMCs)," *Energy Economics*, vol. 68, pp. 19–30, 2017.

[27] F. Wen, F. Min, Y. J. Zhang, and C. Yang, "Crude oil price shocks, monetary policy, and China's economy," *International Journal of Finance & Economics*, vol. 24, no. 2, pp. 812–827, 2019.

[28] M. Qamruzzaman and J. Wei, "Do financial inclusion, stock market development attract foreign capital flows in developing economy: a panel data investigation," *Quantitative Finance and Economics*, vol. 3, no. 1, pp. 88–108, 2019.

[29] Z. Li, Z. Huang, and H. Dong, "The influential factors on outward foreign direct investment: evidence from the "the belt and road"," *Emerging Markets Finance and Trade*, vol. 55, no. 14, pp. 3211–3226, 2019.

[30] T. Hastie and R. Tibshirani, "Varying-coefficient models," *Journal of the Royal Statistical Society: Series B*, vol. 55, no. 4, pp. 757–779, 1993.

[31] B. U. Park, E. Mammen, Y. K. Lee, and E. R. Lee, "Varying coefficient regression models: a review and new developments," *International Statistical Review*, vol. 83, no. 1, pp. 36–64, 2015.

[32] S. Wu, B. Li, Q. Nie, and C. Chen, "Government expenditure, corruption and total factor productivity," *Journal of Cleaner Production*, vol. 168, pp. 279–289, 2017.

[33] J. F. Hu, Z. Wang, Y. H. Lian, and Q. H. Huang, "Environmental regulation, foreign direct investment and green technological progress-evidence from Chinese manufacturing industries," *International Journal of Environmental Research and Public Health*, vol. 15, no. 2, 2018.

[34] J. Zhang, "Estimation of China's provincial capital stock (1952–2004) with applications," *Journal of Chinese Economic and Business Studies*, vol. 6, no. 2, pp. 177–196, 2008.

[35] Z. Li, H. Dong, Z. Huang, and P. Failler, "Impact of foreign direct investment on environmental performance," *Sustainability*, vol. 11, no. 13, 2019.

[36] G. Jones and W. J. Schneider, "Intelligence, human capital, and economic growth: a bayesian averaging of classical estimates (bace) approach," *Journal of Economic Growth*, vol. 11, no. 1, pp. 71–93, 2006.

[37] D. Cohen and M. Soto, "Growth and human capital: good data, good results," *Journal of Economic Growth*, vol. 12, no. 1, pp. 51–76, 2007.

[38] F. Cinnirella and J. Streb, "The role of human capital and innovation in economic development: evidence from post-malthusian prussia," *Journal of Economic Growth*, vol. 22, no. 2, pp. 193–227, 2017.

[39] X. Pan, B. Ai, C. Li, X. Pan, and Y. Yan, "Dynamic relationship among environmental regulation, technological innovation and energy efficiency based on large scale provincial panel data in China," *Technological Forecasting and Social Change*, vol. 144, pp. 428–435, 2019.

[40] A. Levin, C.-F. Lin, and C.-S. James Chu, "Unit root tests in panel data: asymptotic and finite-sample properties," *Journal of Econometrics*, vol. 108, no. 1, pp. 1–24, 2002.

[41] G. S. Maddala and S. Wu, "A comparative study of unit root tests with panel data and a new simple test," *Oxford Bulletin of Economics and Statistics*, vol. 61, no. 1, pp. 631–652, 1999.

[42] P. Kalaitzidakis, T. P. Mamuneas, A. Savvides, and T. Stengos, "Measures of human capital and nonlinearities in economic

growth," *Journal of Economic Growth*, vol. 6, no. 3, pp. 229–254, 2001.

[43] G. C. Chow, "Capital formation and economic growth in China," *The Quarterly Journal of Economics*, vol. 108, no. 3, pp. 809–842, 1993.

[44] A. Sorensen, "R&D, learning, and phases of economic growth," *Journal of Economic Growth*, vol. 4, no. 4, pp. 429–445, 1999.