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Productivity Growth-Accounting for Undesirable Outputs and Its Influencing Factors: The Case of China

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Abstract: Presently, China's social development is facing the dilemma of supporting economic growth and reducing emissions. Therefore, it is crucial to analyse productivity growth and examine its relationship with influencing factors in China. This study evaluated the total factor productivity (TFP) growth of 30 provinces in China by adopting the Malmquist-Luenberger (ML) productivity index and incorporating undesirable outputs from 2011–2014. Then, a Tobit regression model was employed to explore the factors that influence China's TFP growth. The results show that the average annual growth of the Malmquist-Luenberger productivity index was lower than that of the traditional Malmquist (M) productivity index growth during the research period. The findings reveal several key conclusions: First, the true TFP growth in China will be overestimated if undesirable outputs are ignored. Second, technical changes are the main contributor to TFP growth. Third, there are huge regional disparities of productivity growth in China. Fourth, coal intensity, environmental regulations, and industrial structure have significantly negative effects on productivity growth, while real per capita gross domestic product (GDP) and foreign direct investment (FDI) have strongly positive effects on productivity growth.

Keywords: total factor productivity (TFP); Malmquist-Luenberger productivity index; undesirable outputs; Tobit Model

1. Introduction

China has experienced rapid economic growth following its reform and opening-up policy in 1978. China became the world's second largest economic entity behind the USA, and its gross domestic product (GDP) accounted for 8.6% of global economic output in 2010 [1]. However, China's economic growth came at the expense of massive energy consumption. In 2010, China became the largest energy consumer, accounting for 20.3% of global consumption [2]. Currently, China's energy usage faces several challenges, such as low resource utilization efficiency and high pollution emissions, which might restrict China's sustainable economic and social development. To respond to this problem, protect the environment and achieve sustainable development, the State Council issued the *Twelfth Five-Year Energy Saving and Emissions Reduction Comprehensive Plan* [3] and set the goal of reducing energy consumption by 16% per 10,000 CNY GDP by 2015 from 2010 levels and 32% from 2005 levels in 2011 [4]. At the 2015 climate conference in Paris, China's government promised to reduce greenhouse gas emissions by 60%–65% per unit of GDP by 2030 compared the levels of 2005.

In traditional economic growth theory, productivity has acted as a significant engine of economic growth and improved the people's living standards [5]. However, during production processes, desirable or good outputs are frequently obtained alongside harmful by-products (what we call undesirable or bad outputs), such as water and air pollution that may lead to environmental damage [6]. The traditional measures of productivity growth ignore undesirable outputs, which can lead to a biased evaluation [7]. Therefore, the proper assessment of economic development performance must consider the influence of environmental factors on the basis of traditional productivity research [8]. To reveal the influence of undesirable outputs on total factor production (TFP), Chung et al. developed the Malmquist-Luenberger (ML) productivity index to evaluate productivity growth by considering the inputs, as well as the desirable and undesirable outputs [7]. In accordance with the Malmquist productivity (M) index, the ML index can capture technical and efficiency changes that are constrained by undesirable outputs [9]. When evaluating TFP growth, some scholars have concluded that the productivity growth will be overestimated if undesirable outputs are ignored. Zhang et al. applied the ML index to evaluate the growth of China's TFP, and the results showed that the true TFP growth in China will be overestimated if undesirable outputs are ignored [6]. Arabi et al. used the ML index to measure power industry productivity growth. The results showed that the ML index had a lower value than the M index [10]. Other scholars have concluded that the productivity growth will be underestimated if pollution is not considered. Hailu and Veeman studied productivity improvements in the Canadian pulp and paper industry from 1959–1994 and found that conventional productivity measures ignoring undesirable outputs underestimate true productivity growth [11]. Fare et al. calculated manufacturing productivity growth. The results of the ML index had a higher value than those of the traditional M index [9]. Yu et al. employed the ML index to evaluate the pulp and paper productivity growth. The results showed that the productivity of the pulp and paper industry was underestimated when the undesirable outputs were ignored [12].

Many scholars have considered pollutants when exploring China's productivity growth from two levels. From the industry perspective, the ML index has been used to evaluate the iron and steel industry productivity growth [13], the nonferrous metals industry productivity growth [14], the power industry productivity growth [10], and the pulp and paper industry productivity growth [12]. From the regional perspective, Zhang et al. employed the ML index to evaluate China's growth in total factor productivity (TFP) from 1989 to 2009 [6]. The results showed that the true TFP growth in China is overestimated if undesirable outputs are ignored. Zhang studied the total factor productivity (TFP) growth of the Wan Jiang and northern Anhui regions using ML index. The results showed that the ML index had a lower value than the M index [8].

However, in the literature, there is less emphasis on sulphur dioxide (SO_2), nitrogen oxides (NO_x), and soot as environmental factors when accounting for total factor productivity growth. At present, China is facing serious air pollutant and greenhouse gas emissions problems, and smog has especially plagued several regions in China. The emissions of SO_2, NO_x, and soot have become the root cause of climate change in China. Therefore, this paper evaluates total factor productivity, accounting for undesirable outputs (SO_2, NO_x, and soot): Do they cause a change in productivity growth? Which factors influence China's regional total factor productivity?

In this context, this study expands the field of study based on the following aspects: First, we employ the ML index, incorporating undesirable outputs (SO_2, NO_x, and soot) to evaluate China's region TFP growth and to investigate true regional productivity changes affected by environmental factors. Second, we conduct a Tobit regression of the factors that influence total factor productivity. The purpose of this exercise is to provide a reference for governmental policy-making with respect to the establishment of a project for optimal regional productivity growth.

2. Methodology

2.1. Malmquist-Luenberger Index (ML Index)

This study defines the ML index by means of directional distance functions. The ML index is originally based on the traditional Malmquist indexes. The main difference is that the ML index is constructed from directional distance functions rather than Shepherd distance functions. The ML index requires a definition of the directional distance function with two different periods.

$$D_0^{\rightarrow t+1}\,(x^t, y^t, b^t; g) = \sup\,\{\beta : (y^t, b^t) + \beta\, g \in P^{t+1}\,(x^t)\} \tag{1}$$

Here, x is the total input; y is the good output; b is the bad output; g denotes the vector of the directions in which outputs are scaled; θ is the expansion proportion of good outputs and the contraction proportion of bad outputs; P (x) represents the production possibility; and t denotes the period.

This version of the directional distance function measures observations at time t based on the technology at time t + 1. Following Chung et al. [7], the ML index between time t and t + 1 can be defined with the following equation:

$$\begin{aligned} ML_t^{t+1} = {} & [(1 + D_0^{\rightarrow t+1}\,(x^t, y^t, b^t; y^t, -b^t))/(1 + D_0^{\rightarrow t+1}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})) \\ & * (1 + D_0^{\rightarrow t}\,(x^t, y^t, b^t; y^t, -b^t))/\,(1 + D_0^{\rightarrow t}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))]^{1/2} \end{aligned} \tag{2}$$

The index can be decomposed into two components: efficiency change (MLEFFCH) and technical change (MLTECH) as follows:

$$ML_t^{t+1} = MLEFFCH_t^{t+1} * MLTECH_t^{t+1} \tag{3}$$

$$MLEFFCH_t^{t+1} = (1 + D_0^{\rightarrow t+1}\,(x^t, y^t, b^t; y^t, -b^t))/(1 + D_0^{\rightarrow t+1}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}) \tag{4}$$

$$\begin{aligned} MLTECH_t^{t+1} = {} & [(1 + D_0^{\rightarrow t+1}\,(x^t, y^t, b^t; y^t, -b^t\,))/(1 + D_0^{\rightarrow t}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})) \\ & * (1 + D_0^{\rightarrow t+1}(x^t, y^t, b^t; y^t, -b^t\,))/(1 + D_0^{\rightarrow t}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}))]^{1/2} \end{aligned} \tag{5}$$

The first component, MLEFFCH, measures the output efficiency change between the two periods. The second component, MLTECH, measures the technical change. If there are no changes in inputs and outputs over the two time periods, then. $ML_t^{t+1} = 1$ If there is an increase in productivity, then $ML_t^{t+1} > 1$. Finally, a decrease leads to $ML_t^{t+1} < 1$. Changes in efficiency are captured by $MLEFFCH_t^{t+1}$, which gives a ratio of a region's distance to its respective technology frontiers in time periods t and t + 1. If $MLEFFCH_t^{t+1} > 1$, then there has been a movement towards the frontier in period t + 1. If $MLEFFCH_t^{t+1} < 1$, the region is further away from the frontier in t + 1. If technical change enables more production of good outputs and less production of bad, then $MLTECH_t^{t+1} > 1$, whereas if $MLTECH_t^{t+1} < 1$, there has been a shift of the frontier towards fewer good outputs and more bad outputs [7].

2.2. Tobit Regression Model

In the second stage, this study uses multivariate analysis to explore the relationships between the influencing factors and total factor productivity growth. This paper uses the ML index to calculate the efficiency scores, whose values are bound between 0 and 1. When the dependent variable is a non-negative and fragmented value, the ordinary least square (OLS) regression of the calculated efficiency scores may lead to inconsistent and biased conclusions. Thus, to achieve consistent parameter estimation, the Tobit model is employed, based on the principle of maximum likelihood estimation [15]. The standard model is described as follows:

$$a_i^* = t_i\beta + \varepsilon_i\ \varepsilon_i\text{: } N(0, \delta^2) \tag{6}$$

$$a_i = a_i^*,\ \text{if } a_i^* \geq 0;\ \text{otherwise, } a_i = 0,\ \text{if } a_i^* \leq 0 \tag{7}$$

where i represents the i-th decision-making unit (DMU), a_i is a latent (i.e., unobservable) variable, t_i is an independent variable, β is the correlation coefficient, ε is the stochastic error based on $N(0, \delta^2)$, and δ is a scaling parameter introduced to obtain the likelihood function and estimated along with the parameter β. In model (7), when $a_i^* \geq 0$, a_i represents the actual values. When $a_i^* \leq 0$, $a_i = 0$.

3. Data and Variables

3.1. Data

This paper used provincial panel data to analyse the regional total factor productivity growth in China. Panel data from China's 30 provinces (except Tibet) from 2011 to 2014 were employed. The data were collected from the China Statistical Yearbooks (2012–2015) [16], the China Energy Statistical Yearbooks (2012–2015) [17], the China Statistical Yearbooks on Science and Technology (2012–2015) [18].

3.2. Variables

The appropriate selection of input and output variables is vitally important for the data envelopment analysis (DEA) method. Based on the data availability and the principles of DEA theory, this study selected three input variables and four output variables. It suggests that the number of decision-making units is at least five times that of the input and output variables.

3.2.1. Three Input Variables

(1) **Labour input:** Generally, the labour force is the number of workers involved in the actual production process. However, in developed countries, the labour force can be measured based on the working hours associated with standard labour intensity [19]. Due to the lack of relevant data in China, most studies use the number of employees at the provincial level as the labour force input. Based on Song et al. [20] and Long et al. [21], this study used the number of provincial employees at the end of each year as input indicator. The data were sourced from the China Statistical Yearbooks (2012–2015) [16].

(2) **Capital input:** Many researchers deem that capital stock represents the overall capital resources of the enterprise and can represent a variety of investment capitals. However, this approach is not able to respond to changes in capital investment per year [19]. Based on Long et al. [21] and Zhou et al. [22], this study used the variable of "investment in fixed assets" to represent the capital input. The data were collected from the China Statistical Yearbooks (2012–2015) [16].

(3) **Energy input:** The energy efficiency concept treats energy as an economic investment that supports economic development. Therefore, energy should be used as an input variable. Based on Zhang et al. [6], this study used the total energy consumption of each province as an input variable. The data are sourced from the China Energy Statistical Yearbooks (2012–2015) [17].

3.2.2. Four Output Variables

(1) **Economic output:** GDP is a key indicator of economic output. In accordance with Long et al. [21] and Deng et al. [23], GDP at the provincial level was selected as the desired output variable. GDP variables were deflated, using 2011 as the base year. The data were sourced from the China Statistical Yearbooks (2012–2015) [16].

(2) **Environmental variables:** This study selected the emissions of SO_2, NO_x, and soot from each province as the undesirable output variables. The data were collected from the China Statistical Yearbooks (2012–2015) [16]. The distribution of inputs and outputs variables is summarized in Table 1. In the second stage of the regression analysis, this study selected the following factors that usually show strong relations with total factor productivity growth.

Coal intensity: Coal is the material base for the development of the national economy and society in China. The effective utilization of coal resources is closely related to economic and social sustainable development in China. However, massive coal use has produced large quantities of SO_2, NO_x, and soot, which can cause serious environmental problems, such as frequent haze and foggy weather in Central and Eastern China, global warming and damage to natural ecosystems in China. These problems not only pose a threat to human health but also hamper sustainable economic and social development in China [24], and the increase of per capita coal consumption may lower the productivity growth. Therefore, we defined coal intensity as the ratio of local coal consumption to local GDP, which was an important influencing factor to evaluate the total factor productivity.

Environmental regulation: Environmental regulation can enhance the public awareness of environmental protection. It also encourages enterprises to accelerate technological innovation and upgrade their industrial structures [25]. Hamamoto and Yang et al. found that environmental regulation promotes productivity growth [26,27]. However, environmental regulation increases an enterprise's transition costs through compulsive investments in pollution controls. It may form a key obstacle for technological innovation and induce enterprises to reduce research and development (R&D) investments [28]. Generally, if a firm causes severe environmental problems, government-based environmental regulators would rather charge environmental pollution fees than invest money in preventing potential environmental pollution problems [22]. Greenstone et al. concluded that strict environmental regulations caused declining TFP among manufacturing plants in the USA [29]. Researchers have different opinions about the relationship between environmental regulation and productivity growth. In this paper, environmental regulation was selected as an important indicator to measure the TFP growth. There are different means to represent environmental regulation. Based on Song et al. [20] and Song and Guan [28], this study defined environmental regulation as the ratio of the investment in treating pollution regulations to the GDP.

(3) **Foreign direct investment (FDI):** The pollution haven hypothesis states that pollution-intensive industries tend to be built in countries or regions with relatively low environmental standards. However, researchers have not yet reached a consensus regarding the pollution haven hypothesis. Some scholars believe that FDI can bring capital, advanced technology, and management experience to the host country, and that FDI has a significant positive effect on promoting productivity growth [28,30]. However, some authors concluded that economic development driven by FDI is at the cost of energy depletion and environmental deterioration [31,32]. Wang and Shen found that FDI had a significant negative correlation with total factor productivity [4]. Other observations support the pollution haven hypothesis [33,34]. Therefore, to explore the relationship between FDI and China's total factor productivity growth, this paper selected FDI as an important influencing indicator to evaluate the total factor productivity growth. Based on Zhou et al. [22], FDI is defined as the ratio of total FDI to GDP.

(4) **Industrial structure:** Industrial structure refers to the ratio of the output values of industrial enterprises to GDP. Industry plays an important role in the Chinese national economy. Although China's rapid industrialization has consumed a large amount of fossil energy, industrialization is the foundation of national modernization, which is the main force of productivity growth in China [35]. Thus, this study selected the industrial structure index to measure TFP growth. Based on Song et al. [20], we defined industrial structure as the ratio of the industrial production value to the local GDP.

Economic development is an important cause of carbon dioxide emissions and promotes total factor productivity growth accounting for undesirable outputs [8]. Therefore, this study selects the per capita GDP, defined as the ratio of GDP to total population.

The regression equation is as follows:

$$\mathrm{ML}_{it} = \lambda_0 + \lambda_1 \mathrm{coal}_{it} + \lambda_2 \mathrm{regulation}_{it} + \lambda_3 \mathrm{industry}_{it} + \lambda_4 \mathrm{fdi}_{it} + \lambda_5 \mathrm{per}_{it} + \varepsilon_{it} \tag{8}$$

where t represents the year, i refers to the province, *ML* is the total factor productivity index, λ_i (i = 0, 1, ... , 6) are the unknown parameters, *coal* stands for coal intensity, *regulation* is environmental regulation, *industry* is the industrial structure, *fdi* is the foreign direct investment, *per* is the real per capita GDP, and ε_{it} is the stochastic disturbance term.

Table 1. Descriptive statistics.

	N	Mean	Maximum	Minimum	Standard Deviation
Inputs					
Labour (10,000 persons)	120	2964.62	6880.9	309.18	1871.20
Capital (100 million CNY)	120	14,347.32	38,732.9	1435.58	8021.41
Energy consumption (10,000 tons)	120	18,753.2	35,362.6	1888	15,632.7
Outputs					
GDP (100 million CNY)	120	19,753.23	71,877.7	1670.44	14,632.1
SO_2 (1000 tons)	120	752.65	2030.9	32.41	433.78
NO_x (1000 tons)	120	801.1	2000	95.39	490.9
Soot (1000 tons)	120	466.11	1455.60	15.82	304

GDP: gross domestic product; SO_2: sulphur dioxide; NO_x: nitrogen oxides.

4. Results and Discussion

4.1. Total Factor Productivity (TFP) Growth

4.1.1. Dynamic ML Index and Malmquist Index (M Index) and Their Decomposition

Based on the provincial panel data, this study calculates the TFP growth of China's 30 provinces considering undesirable outputs using the ML index and demonstrating its decomposition with MaxDEA software (*MaxDEA pro*, 6.16; Beijing Realworld Software Company, Ltd.: Beijing, China, 2016). As a comparison, the traditional M index that ignores bad outputs and its decompositions are also presented. The annual average ML and M indexes are geometric means. As shown in Table 2, from 2011–2014, the average dynamic change of M index achieved an increase of 7.8%. This value was the combination of an efficiency decline of 0.8% and a technical advance of 8.7%. Thus, technical change can be viewed as the major promoter of TFP, while efficiency change has an inhibiting effect on TFP. The finding implies that China's low efficiency level is inadequate to fully realise the potential of resource endowments and technology to promote TFP growth. There remains much room for China to improve TFP by upgrading its energy utilization efficiency. If environmental constraints were incorporated into TFP, the average dynamic ML index would increase by 4.6%. The decompositions of the ML index indicated that average efficiency change decreased by 1.1%, while technical change increased by 5.8% during this period. A comparison between the ML index and M index shows that the TFP, technical change, and efficiency change considering undesirable outputs were reduced by 3.2%, 0.3%, and 2.9%, respectively, compared with their use ignoring environmental outputs. Therefore, environmental factors affect evaluation of China's TFP growth, while the annual growth rates of TFP, technical change, and efficiency change would be overestimated if the environmental factors were ignored.

From the perspective of dynamic changes, from 2011–2012, 2012–2013, and 2013–2014, the growth rates of the M index and its technical change were 4.2%, 7.1%, and 12.1%, and 5.9%, 8%, and 12.2%, and efficiency decreased by 1.6%, 0.8%, and 0.1%, respectively. The growth rates of the ML index and its technical change were 4%, 4.3%, and 5.6%, and 4.2%, 5.5%, and 7.6%, with the efficiency decreasing by 0.2%, 1.1%, and 1.9%, respectively. Therefore, the TFP and its decompositions suggested that both the TFP and technical change presented a tendency to increase, while efficiency change showed a diminishing trend from 2011–2014, regardless of whether the environmental factors were considered. The difference suggests that environmental factors exert negative influences on the growth of efficiency change. In both cases, technical change showed positive growth rates, whereas efficiency change showed a declining trend. The findings suggest that technical change promoted TFP growth and that efficiency change was an impediment for TFP growth in most years. The above result reveals that

China's TFP was generally inefficient from 2011–2014, and efficiency should be improved to increase TFP growth.

Table 2. The dynamic ML index and M index and their decomposition between 2011 and 2014.

Year	Considering Undesirable Outputs			Not Considering Undesirable Outputs		
	ML Index	MLTECH	MLEFFCH	M Index	MTECH	MEFFCH
2011–2012	1.040	0.998	1.042	1.042	0.984	1.059
2012–2013	1.043	0.989	1.055	1.071	0.992	1.080
2013–2014	1.056	0.981	1.076	1.121	0.999	1.122
Mean	1.046	0.989	1.058	1.078	0.992	1.087

ML Index: Malmquist-Luenberger Index; MLEFFCH: Malmquist-Luenberger Efficiency Change; MLTECH: Malmquist-Luenberger Technical Change; M Index: Malmquist Index; MEFFCH: Malmquist Efficiency Change; and MTECH: Malmquist Technical Change.

4.1.2. Static ML Index and M Index and Their Decomposition of China's 30 Provinces

Table 3 presents the average static total factor productivity change of 30 provinces in China from 2011–2014. To compare the regional differences in total factor productivity growth, this paper divided the 30 provinces into eastern, western, central, and northeast areas. The results are shown in Table 4.

The results in Table 3 reveal significant provincial disparities of TFP growth. When environmental factors were excluded from consideration, Shandong province experienced the highest average annual growth of 19.8% in TFP, and Hainan province had the lowest TFP growth of 0.1%; all provinces presented positive trends of TFP growth. After considering environmental factors, Jiangsu province had the highest TFP growth of 7.3%. Ningxia and Xinjiang provinces showed reductions of 3.7% and 0.3% in TFP, respectively. Significant declines in TFP growth are found in most provinces, while only Liaoning, Jilin, Shanghai, Jiangxi, Hainan, Shaanxi, Gansu, and Qinghai presented upward trends. In terms of technical change, Shandong province had the highest average annual growth of 19.8%, and the lowest growth of 0.1% occurred in Hainan province. After taking environmental factors into consideration, Jiangsu and Jiangxi province achieved 7.3% in annual growth of technical change, and only Ningxia demonstrated a decreasing trend of 2.4%. It seems that the growth of technical change in Central and Eastern China was much higher than that in western areas. Without considering environmental factors, the total factor productivity growth of Jilin, Shanghai, Zhejiang, Hainan, Hunan, Chongqing, Sichuan, and Guizhou increased by 2.4%, 1.4%, 9.5%, 1.2%, 9%, 1.4%, 1.8%, and 6.7%, respectively. After considering environmental factors, the TFP growth of Gansu province increased by 0.6%, while that of other provinces tended to show decreasing trends.

The research findings reveal great regional differences in static TFP growth among the four areas. Without considering the environmental factors, the average TFP changes in the four areas were 7.6% for Eastern China, 5.8% for Central China, 5.8% for Northeast China, and 5.5% for Western China. When environmental factors were considered, the average TFP changes were 3.9% for Eastern China, 3.6% for Central China, 3.5% for Northeast China, and 2.1% for Western China. After comparing the two situations, it is evident that the TFP growth of the four regions is mainly driven by technical change. The role of efficiency change is relatively weak, and the growth rate of technical change in the four regions is much higher than the growth of efficiency change. Eastern China has a relatively high TFP growth because of several advantages, e.g., superior geographical position, higher level of economic development, advanced technical equipment and human capital development. More importantly, relevant policies and measures for energy savings and emission reductions have been implemented in the eastern part of the country. These advantages contributed to the higher growth rate of the eastern region. In addition, the TFP change of Central and Northeast China has significantly increased. The improvements are mainly due to the supportive policies for these areas, such as, "The Rise of Central China" and "The Revitalization of the Northeast Old Industrial Base" policies [21].

Without considering environmental factors, the TFP growth of Western China was slightly lower than the national average. When considering the environmental factors, the TFP growth of Western China was far below the national average. It is obvious that the influence of the environment on the service industry's productivity is much greater in Western China than in Eastern China for self-evident reasons. In general, Western China has a low level of economic development. The human capital, science and technology research, development capabilities, and level of technology have significantly lagged behind the national average. Supported by western developmental policy, a large number of high-pollution, high-energy-consuming projects have been transferred to Western China, which causes huge damage to the local environment. Related regulations for energy conservation and emissions reduction are difficult to implement in the western provinces. Since the ecological environment in Western China is vulnerable, the impacts of pollution emissions on the region's productivity are considerable. Thus, these realities result in the relatively low TFP growth in Western China.

Table 3. The static ML index and M index and their decomposition between 2011 and 2014.

Region	Considering Undesirable Outputs			Not Considering Undesirable Outputs		
	ML Index	MLTECH	MLEFFCH	M Index	MTECH	MEFFCH
Beijing	1.051	1.000	1.051	1.067	1.000	1.067
Tianjin	1.026	1.000	1.026	1.032	1.000	1.032
Hebei	1.011	0.993	1.018	1.031	0.998	1.033
Shanxi	1.018	0.998	1.020	1.032	1.000	1.032
Neimenggu	1.021	0.978	1.044	1.022	0.972	1.051
Liaoning	1.031	0.992	1.039	1.024	0.979	1.046
Jilin	1.041	0.997	1.044	1.035	1.024	1.011
Heilongjiang	1.033	0.997	1.036	1.116	0.993	1.124
Shanghai	1.041	1.000	1.041	1.011	1.014	0.997
Jiangsu	1.073	1.000	1.073	1.081	1.000	1.081
Zhejiang	1.045	1.000	1.045	1.123	1.095	1.026
Anhui	1.018	0.989	1.029	1.045	0.971	1.076
Fujian	1.021	0.994	1.027	1.184	0.989	1.197
Jiangxi	1.043	0.972	1.073	1.013	0.941	1.077
Shandong	1.067	1.000	1.067	1.198	1.000	1.198
Henan	1.022	0.991	1.031	1.111	1.012	1.098
Hubei	1.050	0.997	1.053	1.109	1.000	1.109
Hunan	1.063	0.998	1.065	1.104	1.090	1.013
Guangdong	1.021	1.000	1.021	1.032	1.000	1.032
Guangxi	1.031	0.989	1.042	1.084	0.943	1.150
Hainan	1.032	1.000	1.032	1.001	1.000	1.001
Chongqing	1.013	0.999	1.014	1.109	1.014	1.094
Sichuan	1.051	0.994	1.057	1.066	1.018	1.047
Guizhou	1.011	0.997	1.014	1.111	1.067	1.041
Yunnan	1.040	0.995	1.045	1.076	0.979	1.099
Shaanxi	1.053	0.998	1.055	1.031	0.967	1.066
Gansu	1.042	1.006	1.036	1.012	0.976	1.037
Qinghai	1.042	1.000	1.042	1.011	1.000	1.011
Ningxia	0.963	0.987	0.976	1.018	0.969	1.051
Xinjiang	0.997	0.997	1.000	1.008	0.969	1.040
Eastern	1.039	0.999	1.040	1.076	1.010	1.066
Central	1.036	0.990	1.046	1.058	0.994	1.065
Western	1.021	0.996	1.025	1.055	0.993	1.063
Northeast	1.035	0.995	1.040	1.058	0.999	1.027
Mean	1.032	0.995	1.037	1.063	0.999	1.065

ML Index: Malmquist-Luenberger Index; MLEFFCH: Malmquist-Luenberger Efficiency Change; MLTECH: Malmquist-Luenberger Technical Change; M Index: Malmquist Index; MEFFCH: Malmquist Efficiency Change; and MTECH: Malmquist Technical Change.

Table 4. Geographic divisions of China's 30 provinces.

Region	Provinces
Eastern	Beijing, Tianjin, Shanghai, Hebei, Fujian, Guangdong, Zhejiang, Shandong, Jiangsu, Hainan
Central	Shanxi, Shaanxi, Jiangxi, Henan, Hubei, Inner Mongolia, Anhui, Hunan
Western	Guizhou, Sichuan, Guangxi, Yunnan, Xinjiang, Chongqing, Gansu, Qinghai, Ningxia
Northeast	Liaoning, Heilongjiang, Jinlin

In conclusion, the productivity shown by the ML index was higher than that of the M index, and there are huge differences among the regions and provinces. Therefore, environmental factors significantly affect evaluation of the TFP growth of China's 30 provinces. The traditional method that neglects environmental factors leads to overestimation of the growth of TFP. This means that China's air pollution regulations regime may be ineffective. The conclusion is consistent with the views of Kumar et al. [5] and Zhang et al. [6]. The reasons for this situation may be high-pollution industries have shown little initiative in establishing cleaner production processes. Presently, China's energy utilization is still relatively extensive and inefficient. It has caused serious pollution and damage to the air and environment and is not conducive to China's long-term economic development. Although China has adopted a wide array of policy measures to promote energy saving, it is difficult to ensure their perfect implementation given the great regional disparities. In addition, the use of efficiency change to improve China's TFP growth is vitally important. China's current situation does not apply to the Porter hypothesis, as the theory believes that appropriate environmental factors can stimulate technological innovation, thereby reducing costs, improving product quality, enhancing competitiveness, and increasing productivity [36].

4.2. Influence Factor Analysis of Coal Utilization Efficiency

In the second stage, this study used influence factor data associated with total factor productivity growth from Equation (8) and Stata software (*Stata*, 13.0; Stata Corp. LP: College Station, TX, USA, 2013) to perform a stochastic Tobit panel regression analysis. For a detailed introduction to the stochastic Tobit regression model, please refer to Pérez-Reyes and Tovar [37]. A variance inflation factor (VIF) analysis was used to examine the multicollinearity among the explanatory variables. The results show that the VIF values of all influencing factors are less than 10, suggesting that there is no multicollinearity among the variables. Therefore, a Tobit regression analysis was conducted, and the regression results are shown in Table 5.

Table 5. Tobit regression results.

Variable	Coefficient	*Z*-Statistic
Constant	2.142 ***	6.21
Coal	−1.794 **	−5.13
Regulation	−1.531 ***	−3.86
Industry	−0.982 ***	−2.41
Foreign Direct Investment (FDI)	0.795 ***	1.22
Per capital GDP	0.551 *	2.18

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Coal intensity has a significant negative correlation with total factor productivity growth. This means that with a higher coal intensity, TFP growth will be lower. This may be because increasing per capita GDP coal consumption promotes the growth of productivity costs. The added burden of economic growth is not conducive to TFP growth. Thus, reducing per capita GDP coal consumption is the key issue the government is facing. The government should promote an enterprise industrial structure adjustment, improve coal utilization efficiency, and increase the renewable energy extension and utilization, gradually improving total factor productivity growth through corresponding policies and measures.

Environmental regulation has a significant negative correlation with TFP growth. This is consistent with the conclusions of Wang and Shen [4]. The reasons for this relationship may lie in the fact that China's environmental pollution control model is based on end treatment. With a lower energy utilization efficiency, the degree of damage to the environment will be greater. Then, the government has to invest more money in controlling the environmental pollution caused by energy usage and impose more pollution emission fees in areas of high pollution discharge instead of investing in the prevention of potential environmental pollution problems. This is also why China's investment in pollution control continually increases, and environmental problems have yet been effectively controlled. This is closely related to China's institutional mechanisms. Over the past few decades, the concept of "Pollution First, Treatment Later" has prevailed. Economic growth has been treated as the most important criterion to evaluate the government's achievements. Some local governments only focus on economic growth and ignore the environmental pollution problems. This leads to severe environmental damage.

The industrial structure has a significant negative correlation with TFP growth. Thus, with a higher proportion of the industrial output value, TFP will be lower. China's industrial growth largely relies on the consumption of fossil fuels, which seriously damage the environment. Presently, China is in the late stage of industrialization. Challenges, such as the overcapacity of production, industrial upgrading, and the new industrial revolution, are the main obstacles for future development. The Chinese government has taken proactive measures and made some achievements. In 2015, the proportion of industrial output of GDP was reduced to 40%, and the share of service industry output exceeded 50% [38]. Improvements on industrial structure are conducive to promoting TFP growth.

FDI has a significant positive correlation with TFP growth. FDI plays an important role in promoting energy conservation, emissions reduction, and industrial restructuring. In recent years, foreign investment in China has continually increased and been used to fund low pollution and high-tech industries. As a result, these investments have promoted industrial restructuring, advanced China's economic growth, reduced dependence on fossil energy, and promoted TFP growth.

In addition, per capita GDP and TFP growth are significantly positively correlated, which is consistent with the conclusions of Kumar [5]. Economic development has improved living standards, production technology, and the demands for environmental quality have continually increased. Thus, this is conducive to improving the total factor productivity growth.

5. Conclusions and Policy Implications

This paper adopted the ML index, incorporating undesirable outputs (SO_2, NO_x, and soot) to evaluate the TFP growth of 30 provinces in China from 2011–2014, and subsequently exploring the factors that influence TFP growth using the Tobit regression model. The results indicate that from 2011–2014, the average annual ML index growth was lower than the traditional M index growth. This means that the true TFP growth in China will be overestimated if undesirable outputs are ignored, indicating that air pollution regulations regime may be ineffective in most regions of China. Technical change was the main contributor to this growth, and TFP growth varied among the 30 provinces. This study further investigated the regional TFP growth in China. The regional disparities were obvious, with Eastern China displaying significantly higher TFP growth than other regions. Regarding the factors that influence TFP growth, coal intensity, environmental regulation, and industrial structure had significantly negative effects on TFP growth. Real per capita GDP and FDI had significantly positive effects on TFP growth. To prompt TFP growth, policy implications are summarized as follows:

(1) At present, China's environmental regulation regime may be ineffective. In order to improve the productivity growth, on the one hand, the government should encourage more enterprises to optimize clean production technologies and production processes by offering knowledge-sharing, access to information, financing, and increased market demand [2]. On the other hand, the government must make more practical and effective air pollution laws and regulations to deal with the relationship between productivity growth and environmental management.
(2) To achieve the aims of sustainable energy utilization efficiency, energy utilization should be transformed from extensive to conservative. Moreover, energy utilization technologies and capital investments should be enhanced, the development of a low-carbon economy strengthened, and the urbanization and industrialization development model improved to lower the emissions of SO_2, NO_x, and soot, and gradually increase productivity growth in China.
(3) Due to serious regional differences in China's TFP growth, the government should tailor policies according to the actual energy utilization circumstances of each region. Technical cooperation and exchanges among different areas should be encouraged to promote technology diffusion. This can effectively reduce the regional gap in TFP growth.

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