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Economic Growth Effect and Optimal Carbon Emissions under China's Carbon Emissions Reduction Policy: A Time Substitution DEA Approach

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Abstract: In this paper, provincial panel data for China during 1995–2015 and the time substitution data envelopment analysis (DEA) model were used to measure the influences of China's carbon emissions reduction policy on economic growth under various reduction targets and to determine optimal economic growth and optimal carbon emissions of each province. In addition, this paper empirically examines the factors that influence the optimal economic growth and carbon emissions. The results indicate that not all provinces will suffer from a loss in gross domestic product (GDP) when confronted by the constraints of carbon emissions reductions. Certain provinces can achieve a win-win situation between economic growth and carbon emissions reductions if they are allowed to reallocate production decisions over time. Provinces with higher environmental efficiency, higher per capita GDP, smaller populations, and lower energy intensity might suffer from a larger loss in GDP. Therefore, they should set lower carbon emissions reduction targets.

Keywords: carbon emissions reduction policy; optimal economic growth; optimal carbon emissions; time substitution DEA model

1. Introduction

China's economic transition has suffered from constraints generated by both resources and the environment. With the acceleration of industrialization and urbanization and the upgrading of the consumption structure, the demand of China's energy has experienced a rapid increase. However, the limitation of China's domestic resource capacity has led to an increasing number of energy and environmental problems on China's economic growth. In pursuit of sustainable development, the promotion of energy conservation and emissions reductions is a long-term, arduous task for China's national development strategy. China is actively investigating a development path and a mode of building a conservation-oriented society. At the Copenhagen Climate Summit, China and other contracting parties reached a binding agreement on greenhouse gas reductions in the post-Kyoto era to reduce the intensity of carbon dioxide emissions per unit of gross domestic product (GDP) in 2020 by 40–45% compared with that in 2005. The State Council's "12th Five-Year Plan" and "13th Five-Year Plan" for energy conservation and emissions reductions also clearly outlined specific objectives and tasks related to conserving energy and reducing emissions. However, considering that energy conservation and emissions reduction may slow economic growth, certain policymakers show a lack of motivating power in energy conservation and emissions reductions.

In this paper, we use the time substitution data envelopment analysis (DEA) model to analyze the economic growth effect and optimal carbon emissions under the various constraints of carbon emissions reduction targets. We want to discover what costs China must pay to achieve energy conservation and emissions reduction targets and uncover China's emissions reduction policy on economic growth. What should China do to choose appropriate targets and design an optimal path for energy conservation and emissions reduction? The structure of the remainder of the paper is organized as follows: The next section provides a review of the relevant literature. Section 3 introduces the time substitution approach under the directional distance function framework. Section 4 describes the database used in this study. Section 5 discusses the estimated optimal GDP, the optimal carbon emissions, and influencing factors in detail. Section 6 draws some conclusions and provides policy implications.

2. Literature Review

The relationship between energy conservation, emissions reductions, and economic growth has long been a research focus in environmental economics and growth economics. An extensive body of literature focuses on the relationship among economic growth, energy conservation, and emissions reductions. Most of these studies have reached a consensus that economic growth improves both energy consumption and carbon emissions [1–3]. Nevertheless, when studies focus on how carbon emissions exert influence on economic growth, the empirical results remain mixed and debatable. In addition, very few analyses have been devoted to the case of China within China's regional panel framework. China has become the second largest economy in the world and its total carbon emission ranks first in the world. Thus, it is very meaningful to figure out the impact of China's carbon emissions on economic growth. The Porter hypothesis argues that environmental protection can improve the quality and technological capabilities of the environment [4,5]. The strong form of the double dividend hypothesis also asserts that a green tax (such as carbon tax) does not only reduce pollution emissions and improve the environmental quality, but also increases non-environmental welfare and economic performance (economic efficiency or economic growth) [6,7].

The results from several studies support the argument that reducing carbon emissions and conserving energy will inevitably lead to a loss of economic growth [8]. The economic estimates of Stern [9] indicate that global GDP will shrink between 5% and 20% because of the impacts of climate change unless emissions are reduced. These estimates have inspired a call for immediate action to reduce greenhouse emissions by 30–70% in the next 20 years. A study by Chen [10] reaches a similar conclusion: if carbon emissions remain unchanged compared with those levels in 1990, Taiwan's GDP will be reduced by 34%. Studies by Heil and Selden [11] and Jaffe et al. [12] have found a monotonically increasing relationship between CO_2 and GDP. Other studies have shown that energy conservation and emissions reduction will not necessarily result in a decrease in the level of economic growth and may potentially result in a win-win mode [13]. Ang [13] employs a co-integration test and determined pollution and energy use are positively related to output in the long-run. Lise and Van Montfort [14] reject the Environmental Kuznets Curve (EKC) hypothesis for the period from 1970 to 2002 using the Engle-Granger co-integration approach. Auffhammer and Carson [15] also reject the static EKC specification and indicate that a downturn is highly unlikely unless there are substantial changes in China's energy policies. Wei et al. [16] also find that the inverted U-shaped relationship between per capita CO_2 emissions and economic development level is not strongly supported. Based on the methodology, most of the studies use three methods to test the relationship between energy use, carbon emissions and economic growth. The first method is Granger causality testing and co-integration analysis [17,18], used to test for unit roots, co-integration, and Granger causality. Al-Iriani [19] uses panel co-integration and causality techniques to determine a unidirectional causality running from GDP to energy consumption and no support for the hypothesis that energy consumption is the source of GDP growth in the GCC countries. Lee and Chang [20] use panel unit root, heterogeneous panel co-integration, and panel-based error correction models to determine that although economic growth and energy consumption lack short-run causality, there is long-run unidirectional causality running from energy consumption to economic growth. Furthermore, there are a substantial number of studies using Granger causality testing and co-integration analysis for different regions and countries, such as [21], a study for Malaysia [22]; the ASEAN countries [23]; and Italy and the Middle East countries [24]. The literature on the economic growth-energy consumption has been summarized in [22,24].

The second method includes economy-oriented top-down models, such as computable general equilibrium (CGE) models in order to measure the marginal abatement cost, which is typically measured by the economic growth loss rate caused by emissions reductions. Böhringer et al. [25] construct a marginal abatement cost model using policy analysis based on computable equilibrium. Chen [26] derives China's marginal abatement cost for carbon emissions for 2010, 2020, and 2030, and the results of the scenario simulation show that compared with the baseline year, China's marginal abatement cost is expected to be a reduction rate ranging from 5 to 45%. Wang et al. [27] employ a CGE model and reach the conclusion that China's implementation of a carbon emissions reduction policy will have negative impacts on GDP and employment, but will be conducive to energy efficiency improvements. Zhang et al. [28] use a CGE model with global coverage that disaggregates China's 30 provinces and includes energy system details, and they apply it to assess the impact of the current binding provincial CO_2 emissions intensity targets nationwide.

The third method uses shadow price approaches based on the Directional Distance Function (DDF) to measure the marginal abatement cost. Färe et al. [29] employ DDF in quadratic form and measured the shadow price of SO_2 for coal-fired power plants in the U.S. in 1993 and 1997. Xie et al. [30] employ a parametric quadratic DDF to investigate the inefficiency level, shadow price, and substitution elasticity of Chinese industrial SO_2 emissions from 1998 to 2011, and the results show that the shadow price continuously and substantially increases throughout the period, which implies that controlling additional SO_2 emissions becomes costlier. Related studies include Coggins and Swinton [31], Marklund and Samakovlis [32], Matsushita and Yamane [33], Rezek and Campbell [34], Swinton [35]. For a comprehensive review on the use of efficiency models to estimate the shadow prices of undesirable outputs, see [36]. In this paper, we use the time substitution DEA model instead of the shadow price method to analyze economic growth in China. Our aim was to discover the costs associated with achieving energy conservation and emissions reduction targets and reveal the potential impacts of China's energy conservation and emissions reduction policy on economic growth over the course of the economic transition. Very few studies focus on this topic in China. Additionally, there are many studies using empirical models, the shadow price model, or the CGE model to study the Chinese emission-economic growth nexus (see Table 1) but, to our knowledge, this is the first paper using the time substitution DEA method to analyze China's regional problem.

Table 1. Summary of existing literature on emissions-economic growth nexus in China.

Author(s)	Country	Study Period	Empirical Strategy
Wang et al. [27]	China aggregated level	2010	CGE model
Chen [26]	China aggregated level	2010, 2020, 2030	CGE model
Wang [37]	28 provinces	1995–2007	Empirical models
Meng [38]	30 provinces	1997–2009	Empirical models
Lee and Zhang [39]	Chinese manufacturing industries	2009	Shadow price model
Du et al. [40]	29 province	1995–2009	Empirical models
Wei et al. [16]	29 provinces	1995–2007	DEA model
Bian et al. [41]	29 provinces	2010	Shadow price model
Zhou et al. [42]	29 provinces	1996–2005	Empirical model
Zhang et al. [28]	30 provinces,	2011–2015	CGE model
Du et al. [43]	30 provinces	2001–2010	Shadow price model
Jie et al. [44]	30 provinces	2006–2010	A two-stage network DEA model
Zhang et al. [45]	Chinese manufacturing industries	1990-2012	Shadow price model
Du et al. [46]	coal-fuelled power plants	2008	Shadow price model
Tang et al. [47]	30 provincial regions	2003–2012.	Shadow price model
Zhang and Zhang [48]	Shanghai Emission Trading Scheme	2013-2015	Empirical models

The DEA method has been used by numerous researchers, including Chung et al. [49]. Lee et al. [50], and Boyd et al. [51], to estimate the directional output distance function and efficiency and productivity changes associated with energy and environmental issues. The major advantage of the DEA approach is that it does not need to impose a specific functional form on the underlying technology [52]. However, because the DDF estimated via DEA is not differentiable, it is not well suited for estimations via the shadow price method. Therefore, to use the DEA to analyze marginal abatement costs and carbon reduction effects, we must develop a new method, which is named the time substitution DEA. The time substitution DEA model was originally proposed by Färe et al. [53] and Färe et al. [54], and it is an extension of the DEA model in terms of inter-temporal dynamics. Although this model is rarely applied to economics research, it has great practical value in decision-making for the optimal allocation of government resources. The time substitution DEA model assumes that if resources are limited and can be inter-temporally allocated, then problems such as when to begin the application of resources or inputs and the number of periods over which these resources should be allocated can be resolved by the time substitution DEA model.

Compared with previous shadow price models, the time substitution DEA model has two advantages. First, shadow price models can only be used to measure current temporal marginal abatement costs, and they neglect the inter-temporal dynamic connection between carbon emissions and economic growth. Therefore, measurements of potential losses of economic growth may be biased because the reduction of carbon emissions generally corresponds to a period and not a time point. Second, targets for the reduction of carbon emissions are often top-down compulsory constrained targets. Although studies have investigated the impacts of carbon emissions on economic growth, the shadow price method and co-integration method have not gone far enough, and a comparison of the loss rates of economic growth under different constraints of carbon emissions reduction targets have not been performed. This gap is not conducive for determining reasonable reduction targets for carbon emissions.

Compared with available studies, this paper makes three contributions. First, this paper fully considers the dynamic features of a carbon emissions reduction policy and employs additional constraints in the time substitution DEA model to obtain a unique linear programming solution of the optimal carbon emissions during each period in each province. Second, this paper incorporates carbon emissions reduction targets into the analytical framework, fully considers the variability of carbon emissions reduction targets, and analyzes the impacts of carbon emissions reduction on economic growth and optimal carbon emissions under various constraints of carbon emissions reduction targets; thus, it presents the process of obtaining an optimal carbon emissions reduction target based on the realities of each province. Third, under the framework of the time substitution DEA model, this paper measures not only the potential optimal GDP under the various constraints of carbon emissions reduction targets, but also the optimal carbon emissions reduction to realize the potential optimal GDP in each year for each province.

3. Method

The time substitution DEA model can be used in place of a DEA model regardless of whether undesirable outputs are incorporated. However, when undesirable outputs are included, the DDF method to solve the time substitution DEA model is preferable.

3.1. Undesirable Output DEA Model

Carbon dioxide is a type of greenhouse gas and can be considered an undesirable (bad) output. Färe and Pasurka [55] called the technological structure between the "bad" product and the "good" product the input "environmental technology." Compared with traditional technologies, environmental technology should be given a corresponding technological structure; that is, reducing pollutant emissions may also result in a decrease in the "good" product output. This characteristic between pollutants and good products is referred to as jointly weak disposability, in other words, "good" and "bad" products have the characteristic of a sliding scale, and "bad" products are inevitable byproducts.

$$P(x) = \{(y,b): \ x \ can \ prodcue \ (y,b)\} \quad (1)$$

All productive combinations of good outputs y and bad outputs b invested by x inputs can be measured by the set $P(x)$. Assuming that there are M desirable outputs represented by $y \in R_+^M$, J undesirable outputs represented by $b \in R_+^J$, and N inputs represented by $x \in R_+^N$, then $k = 1, \ldots, K$ represents the decision-making units, and $t = 1, \ldots, T$ represents the periods.

For the decision-making unit in period t, the production possibility can be expressed as follows:

$$\begin{aligned} P^t(x_o^t) = \Big\{ (y,b): y_m^t \leq \sum_{k=1}^{K} z_k^t y_{km}^t,\ m = 1,\ldots,M \\ x_{on}^t \geq \sum_{k=1}^{K} z_k^t x_{kn}^t,\ n = 1,\ldots,N \\ b_j^t = \sum_{k=1}^{K} z_k^t b_{kj}^t,\ j = 1,\ldots,J \\ z_k^t \geq 0, k = 1,\ldots,K, t = 1,\ldots T \Big\} \end{aligned} \quad (2)$$

3.2. Directional Distance Function

To measure the efficiency of environmental technology, a DDF must be introduced. The DDF reflects public attitudes toward environmental pollution, i.e., requiring both rapid economic development and reduced environmental pollution. Based on the production possibility set, we create the following DDF:

$$D_o(x,y,b,g) = \sup\{\beta: \ (y,b) + \beta g \in P(x)\} \quad (3)$$

where $g = (g_y, g_b)$ represents a direction vector. The undesirable output must possess jointly weak disposability. Based on different forms of direction vectors, the intensity of environmental regulation can be further divided as described below:

(1) Neutral environmental regulation, i.e., the direction vector is $g = (g_y, 0)$, which means that the desirable outputs should be improved as much as possible in the event that undesirable outputs remain unchanged.

(2) Strong environmental regulation, i.e., the direction vector is $g = (g_y, -g_b)$, which represents the conventional radial DDF and indicates that undesirable outputs (inputs) should be reduced, and desirable outputs (inputs) should be increased at the same rate.

Many studies, such as Chung et al. [49], and Färe et al. [56], use this conventional DDF in economics and environmental studies. Chen [57] and Chen and Delmas [58] indicate that the DDF model environmental efficiency may improve by increasing its undesirable output, which is not a real case, and the radial DDF tends to overestimate the efficiency score in the presence of a slack variable. However, Zhang and Choi [52] indicate that the conventional radial DDF has been widely used to measure environmental technical efficiency because it is closely related to the shepherd distance function; therefore, it can easily provide a Farrell-type efficiency measure.

(3) No environmental regulation, which indicates that the undesirable outputs are not considered and can be simplified as the general DEA-CCR model.

Under the condition of strong environmental regulation, a DDF can employ the DEA method to solve the following linear programming problem:

$$
\begin{aligned}
D_o(x_o, y_o, b_o) &= \max_{\beta, z} \beta \\
s.t. \quad (1+\beta) y_{om}^t &\le \sum_{k=1}^{K} z_k^t y_{km}^t, m = 1, \ldots, M;\ x_{on}^t \ge \sum_{k=1}^{K} z_k^t x_{kn}^t,\ n = 1, \ldots, N, \\
(1-\beta) b_{oj}^t &\le \sum_{k=1}^{K} z_k^t b_{kj}^t,\ j = 1, \ldots, J;\ z_k^t \ge 0;\ k = 1, \ldots, K;\ t = 1, \ldots, T
\end{aligned}
\tag{4}
$$

We can solve the linear programming problem on the condition of neutral environmental regulation or no environmental regulation in a similar manner.

According to Färe et al. [56], Shephard's output distance function is a special case of the DDF; therefore, environmental efficiency can be written as follows:

$$ETE_o = 1/[1 + D_o(x_o, y_o, b_o)] \tag{5}$$

3.3. Time Substitution DEA Model

Based on the DEA model, we assume that the government expects to control the undesirable outputs for the decision-making units o. In other words, the amount of undesirable outputs for the decision-making units o is allowed to produce in t periods is less than $\overline{b_j}$, which can be expressed as follows:

$$\sum_{t=1}^{T} b_{oj}^t \le \overline{b_j}, \quad j = 1, \ldots, J \tag{6}$$

where $\overline{b_j}$ represents the allowed maximal emissions for j undesirable outputs under the constraint of environmental regulations. In accordance with the foregoing general concepts of the time substitution DEA model, decision-makers should determine when to start (τ_0) and stop ($\tau_0 + T_0$) producing the undesirable outputs, thereby maximizing the desirable outputs (economic growth).

The time substitution DEA model can determine the optimal efficiency value in accordance with the optimal input and output. Next, a method of allocating the limited inputs based on the optimal efficiency value is determined. If there is only one desirable output and one undesirable output, according to the undesirable output DEA model, the time substitution DEA model can be expressed as follows:

$$
\begin{aligned}
&\max_{z^\tau, \tau_0, T^0, b^\tau, y^\tau} \sum_{\tau=\tau^0}^{\tau^0+T^0} y^\tau \\
&s.t. \quad y^\tau \le \sum_{k=1}^{K} z_k^\tau y_k^\tau,\ x_n^\tau \ge \sum_{k=1}^{K} z_k^\tau x_{kn}^\tau,\ n = 1, \ldots, N \\
&\qquad b_j^\tau = \sum_{k=1}^{K} z_k^\tau b_{kj}^\tau,\ j = 1, \ldots, J,\ \sum_{\tau}^{\tau+T^0} b_j^\tau \le \overline{b}_j \\
&\qquad z_k^t \ge 0, k = 1, \ldots, K,\ (\tau, \tau + T^0) \subseteq (t = 1, \ldots T)
\end{aligned}
\tag{7}
$$

As shown in Figure 1, we begin to input the resources from period τ^0, and the entire process of allocation lasts T^0 periods. Accordingly, such resources will be allocated in the time interval [τ^0, $\tau^0 + T^0$]. Figure 1 clearly shows two methods of moving the input to support [τ^0, $\tau^0 + T^0$]. First, we can slide it horizontally, and if $\tau_1 \ne \tau_0$ is selected, then the number of periods of production T^0 is unchanged $\tau_1 \ne \tau_0$; if $\tau_1 < \tau_0$ is selected, then production begins earlier; and if $\tau_1 > \tau_0$ is selected, then production is delayed. Thus, the optimization problem in equation (7) can be solved in two steps. The first step is to fix the initial time τ^0 and determine the optimal number of periods T^0 to maximize the desirable output. The second step is to change the initial time τ^0 and determine the optimal desirable outputs one-to-one, which each correspond to τ^0. By comparing these pairs of τ^0 and T^0 with the information drawn from the first step, we can obtain the optimal τ^*, T*, b*, and y* disposability and solve the optimal problem.

Figure 1. Timeline of input use.

We can solve the time substitution problem for each province for all possible starting periods τ^0 and intervals T^0. Because τ^0 can take 17 values coinciding with 1995-2014, and T^0 can take values from 1 to 17 coinciding with production ending in 1996-2015.

4. Data

To estimate the time substitution DEA model, we need the input and output panel data for 29 provinces between 1995 and 2015. The panel database for the time substitution DEA model includes the variables of one desirable output (regional gross output value), one undesirable output (CO_2 emissions), and three inputs (capital stock, labor force, and energy consumption).

Chongqing was promoted as China's fourth municipality in China; this caused us to combine Chongqing's data from Sichuan Province. Energy input data for Tibet was not available for this research. This paper selects GDP data from 29 provinces, municipalities directly under the central authority and autonomous regions in China from 1995–2015, to represent the desirable outputs of these districts. The associated carbon dioxide emissions are used to represent the undesirable outputs.

In recent years, many studies have concluded that incorporating energy as a part of an intermediate input in the production process is appropriate. For instance, we have the well-known KLEM model, in which the decomposition of inputs into capital, labor, energy, and intermediate materials for the analysis of productivity growth was first proposed and applied to the post-war U.S. economy by Jorgenson et al. [59], and subsequently used by many other researchers. Following that study, energy consumption was introduced as an intermediate input and plays a role together with labor and capital in the production function.

(1) Desirable output (GDP). The output data employed in this paper are obtained from the GDP data of every province in China, and all GDP data are processed into more comparable data calculated based on the fixed price in 1995 with the price adjustment index. (2) Physical capital investment. In general, the perpetual inventory method is adopted to transfer the physical capital into material capital stock. In China, there are two frequently used physical capital stock data: one is the data used by Zhang et al. [60], and the other is the data used by Shan [61]. The data used by Shan Haojie was adopted here, and this paper expands the data to the year 2015 according to the calculation method in Shan's article. (3) Labor input. Labor is measured by the effective labor time of nationwide employees. However, because of the lack of statistical data for China's average working time, this paper uses the total number of employees in each of China's provinces. The data from 1995 to 2008 are obtained from the China Compendium of Statistics 1949–2008, whereas data after 2008 are obtained from the China Statistical Yearbook. (4) Energy input. The energy consumption data are obtained from the China Energy Statistical Yearbook. To compensate for the lack of Ningxia energy consumption data in 2001, the linear interpolation method is used. (5) Undesirable output (carbon emissions). Currently, the frequently adopted method for the measurement of carbon emissions is the inventory-based method presented in the Intergovernmental Panel on Climate Change (IPCC) Guideline for National Greenhouse Gas Inventories. Following the IPCC [62], we estimated the CO_2 emissions from the burning of fossil fuels with the following formula:

$$CO_2 = \sum_{i=1}^{17} E_i \times CF_i \times CC_i \times COF_i \times (44/12) \tag{8}$$

where i represents an index of different types of fossil fuels; the term 44/12 represents the ratio of the mass of one carbon atom when combined with two oxygen atoms to the mass of an oxygen atom; and the variables E_i, CF_i, CC_i, and COF_i represent the total energy consumption, the low calorific value of fossil fuels, the unit fuel carbon content and the carbon oxidation factor of fuel *i*, respectively. The data for provincial fuel consumption are obtained from the regional energy balance tables in the China Energy Statistical Yearbooks. We define $CF_i \times CC_i \times COF_i \times (44/12)$ as the carbon emissions factors.

Many studies have used carbon emissions factors from the IPCC [62], although the unit fuel carbon content and low calorific value of different types of fossil fuels and the carbon oxidation factor from IPCC [62], which is assumed to be 1, does not meet the reality of China. For greater accuracy in the measurement outcomes, we choose to follow the Guidance for Compiling Provincial Greenhouse Gas Emissions Lists published by the China National Development and Reform Commission (NDRC) in May 2011 and relevant data from the Energy Balance Table by Region. In the guidebook, the NRDC provides the actual value of fossil energy varieties in China. In this paper, the unit fuel carbon content and carbon oxidation factor of different fossil energy are collected from the guidebook and low calorific value of different fossil energy are collected from the China Energy Statistical Yearbook.

Most studies focus only on the three main types of fossil fuel (coal, crude oil, and natural gas) when measuring carbon emissions via the inventory-based method; thus, emissions are estimated by the sum of the product of those three primary energies and the corresponding carbon emissions factors in a region. Although these primary energies are the main sources of carbon emissions, this practice neglects the carbon emissions of other energy materials. To measure carbon emissions, we incorporate the consumption of 17 energies: raw coal, cleaned coal, other washed coals, briquette coal, coke, coke oven gas, other gases, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery dry gas, natural gas, other petroleum product, and other coke chemicals. In addition, the consumption of heat supply, thermal power generation, and other secondary energies may also generate carbon emissions; thus, we add the consumption of end-use energies, heat supply, and thermal power generation, and the sum is used to represent the total energy of the 17 main types of fossil fuel consumption E_i. The fossil energy carbon emissions factors are shown in Table 2 below.

Table 2. Carbon emissions factors of various energy sources.

Energy	Carbon Emissions Factors	Energy	Carbon Emissions Factors
Raw Coal	1.90	Petroleum	2.98
Cleaned Coal	2.29	Kerosene	3.04
Other Washed Coal	0.91	Diesel	3.10
Briquette Coal	1.95	Fuel Oil	3.17
Coke	2.86	Liquefied Petroleum Gas	3.11
Coke Oven Gas	0.76	Refinery Dry Gas	3.01
Other Gas	0.89	Natural Gas	2.16
Crude Oil	3.02	Other Petroleum Products	2.53
Other Coking Products	3.83		

5. Empirical Results and Analysis

5.1. Designs for Carbon Emission Reduction Targets

China's government has established different carbon emissions targets for energy conservation and emissions reduction in different periods, and several targets for energy conservation and emissions reduction are presented below. First, the development planning of the "National 11th Five-Year Plan" noted that the energy consumption of per unit GDP would be reduced by 20% and the discharge of major pollutants would be reduced by 10% compared with 2005 levels by 2010. Second, the "Outlines of the National 12th Five-Year Plan for Energy Conservation and Emissions Reduction"published by the State Council mentioned that by 2015, the national chemical oxygen demands and sulfur dioxide emissions would be controlled to 23.476 million tons and 20.864 million tons, which represent decreases of 8% from the 25.517 million tons and 22.678 million tons observed in 2010, respectively. By 2015, the national ammonia nitrogen and nitrogen oxide emissions would be controlled within 2.38 million tons and 20.462 million tons, respectively, which represent decreases of 10% from the 2.644 million tons and 22.736 million tons observed in 2010. Third, the "Work Plan for Greenhouse Gas Emissions Control during the National 12th Five-Year Period" published by the State Council determined the target reduction of national carbon dioxide emissions per unit of GDP by 17% by 2015 from 2010 levels. Fourth, pursuant to the commitment made by China at the Copenhagen Climate Summit, China will reduce the intensity of carbon dioxide emissions per unit of GDP in 2020 by 40–45% compared with that of 2005.

Taking these targets for energy conservation, emissions reductions and demands into account, we set the following constraint reduction targets for carbon emissions.

For the first target for carbon emissions reduction, the total carbon emissions remain unchanged, and only the inter-temporal allocation of carbon emissions is altered. For the second target for carbon emissions reduction, to easily test the conclusion drawn by Stern [9] and conform to the targets in the "Work Plan for Greenhouse Gas Emissions Control during the National 12th Five-Year Period", we set a reduction of 5% in carbon emissions. The third target for carbon emissions reduction: According to the commitment made by China at the Copenhagen Climate Summit and the goal of a GDP growth rate of up to 7.5% during the national 12th Five-Year Plan Period, we set a reduction of 15% for carbon emissions. For the fourth target for the reduction of carbon emissions, to ascertain the losses in economic growth from the reduction of carbon emissions, we set a reduction of 40% in carbon emissions.

5.2. Measurement of Environmental Efficiency

Environmental efficiency is a key factor in determining the technological production frontier and potential GDP of each province. According to the analysis set forth above, each province's environmental efficiency under different environmental regulations is measured by Equation (5). Table 3 presents the results of the average annual environmental efficiency measurement of each province over 21 years.

Table 3. Annual environmental efficiency in provinces (1995–2015).

Province	ETE1	ETE2	ETE3	Province	ETE1	ETE2	ETE3
Beijing	0.92	0.95	0.84	Henan	0.67	0.73	0.56
Tianjin	1.00	1.00	1.00	Hubei	0.67	0.75	0.61
Hebei	0.66	0.67	0.58	Hunan	0.73	0.81	0.69
Shanxi	0.82	0.59	0.49	Guangdong	1.00	1.00	0.99
Inner Mongolia	0.95	0.61	0.54	Guangxi	0.79	0.85	0.77
Liaoning	1.00	1.00	1.00	Hainan	0.97	0.98	0.93
Jilin	0.88	0.70	0.66	Sichuan	0.80	0.87	0.73
Heilongjiang	0.86	0.85	0.82	Guizhou	0.52	0.60	0.37
Shanghai	1.00	1.00	1.00	Yunnan	1.00	1.00	1.00
Jiangsu	0.98	0.96	0.93	Shaanxi	0.58	0.70	0.51
Zhejiang	0.95	0.94	0.93	Gansu	0.32	0.61	0.31
Anhui	1.00	0.98	0.92	Qinghai	0.44	0.67	0.40
Fujian	1.00	1.00	1.00	Ningxia	0.86	0.57	0.43
Jiangxi	0.77	0.77	0.70	Xinjiang	0.60	0.66	0.54
Shandong	0.78	0.78	0.70	Nation	0.81	0.81	0.72

Notes: ETE1 is the measurement result under a neutral environmental regulation, ETE2 is the measurement result under a strong environmental regulation, and ETE3 is the measurement result under no environmental regulation.

Table 3 shows that the measurement results of these three technical efficiencies under different environmental regulations exhibit few differences. The provinces consistently located at the production frontier of environmental efficiency are Tianjin, Liaoning, Shanghai, Fujian, Guangdong, and Yunnan. The provinces with relatively low environmental efficiency are Shanxi, Inner Mongolia, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The environmental efficiency of the remaining provinces fall between these two groups. The provinces with relatively low environmental efficiency are mainly the central and western provinces, whose low technical environmental efficiency are caused by their smooth economic growth and low rate of energy utilization efficiency. This opinion is also supported by Hu and Wang [63]. Apart from Yunnan, the provinces situated at the production frontier of environment efficiency are generally economically prosperous provinces located in Eastern China whose high-technical environmental efficiency could be caused by their rapid economic growth, relatively reasonable industrial structure, and high rate of energy utilization efficiency.

5.3. Measurement of Optimal GDP

According to Equation (7), we can obtain the optimal y^* for each year. Thus, we can calculate the optimal GDP that each province can reach under different reduction targets for carbon emissions by employing the equation $OptimalGDP = \sum_{t=1}^{21} y^*$. The measurement results are presented in Table 4.

By comparing the levels of optimal economic growth under various constraints of carbon emissions in Table 4, the following conclusions can be reached:

First, if carbon emissions reductions do not occur, and only the resource allocation over the past 21 years is changed, then the following is observed: output0 $\geq$ sum GDP. In other words, for every province, the optimal GDP would be larger than the actual GDP. The optimal GDP in Guizhou and Shanxi would be twice the actual GDP, which indicates that, in many provinces, considerable room is available for reducing carbon emissions. If carbon emissions are reasonably allocated, then economic growth can be promoted through the effective allocation of resources.

Second, the data in Table 4 show that output40 $\leq$ output15 $\leq$ ouput5 $\leq$ output0. Carbon emissions act as an output of economic activities; therefore, the reduction targets of carbon emissions inevitably constrain the level of economic activities, thereby resulting in a decrease in total economic output. As a result, a larger reduction of carbon emissions will cause a larger loss of economic growth. If the reduction of carbon emissions were increased from 5% to 15%, then the average loss rate of GDP would be 2.83%. If the reduction of carbon emissions were increased from 15% to 40%, then the average loss rate of GDP would be 18.66%. When only the optimal GDP under various constraints of reduction targets for carbon emissions is considered, and the actual GDP is neglected, if the resources can obtain an effective allocation and the time is substitutable, then a win-win effect between the reduction of carbon emissions and economic growth might not occur, and the Porter hypothesis or the double dividend hypothesis may not be applicable. However, if an efficiency loss occurs because the resources is not effectively allocated, a win-win effect between the reduction of carbon emissions and economic growth should still occur, and the two hypotheses would be suitable in China.

Third, by comparing the optimal and actual GDP, we find that, in most provinces, a dilemma does not occur between the reduction of carbon emissions and economic growth, and the results of these provinces support the Porter hypothesis or the double dividend hypothesis. In other words, a win-win effect occurs between the reduction of carbon emissions and economic growth; thus, a reduction of carbon emissions will contribute to an increase in the GDP. The provinces supporting the two hypotheses are Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Jiangxi, Shandong, Henan, Hubei, Hunan, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The provinces that do not support the two hypotheses are Tianjin, Liaoning, Shanghai, Fujian, Guangdong, and Yunnan. These provinces have obtained an average decrease of 1.45% in potential GDP compared with the actual GDP under a reduction target for carbon emissions of only 5%. The validity of the two hypotheses in certain provinces is related to the target size of the carbon emissions reductions, which applies to the following provinces: Beijing, Jiangsu, Anhui, Guangxi, Hainan, and Sichuan. Except for Hainan, the two hypotheses in all of these provinces is valid under reduction targets for carbon emissions of 5% and 15%. However, when the reduction target for carbon emissions is increased to 40%, the two hypotheses are invalid.

Table 4. Total amount of optimal GDP measurement under different carbon emissions reduction targets (1995~2015) (Unit: billion yuan).

Province	SumGDP	Output0	Output5	Output15	Output40	Province	Sum GDP	Output0	Output5	Output15	Output40
Beijing	104,995.3	113,082.9	110,771.5	105,787.2	88,971.25	Henan	220,019.4	376,806	376,806	376,675.2	314,877.6
Tianjin	91,608.26	91,608.26	91,358.6	896,93.48	78,870.88	Hubei	160,318.2	251,826.8	251,683	244,115.3	197,206.8
Hebei	207,374.1	360,833.8	360,833.8	360,413.4	333,373.7	Hunan	156,393.3	215,877.6	212,250.4	202,167.3	161,350.3
Shanxi	74,741.92	159,620.8	159,620.8	159,620.8	158,137.6	Guangdong	457,341.7	458,476.8	455,707.1	433,267.2	338,740.9
Inner Mongolia	89,309.64	161,985.5	161,985.5	161,985.5	161,985.5	Guangxi	104,002.6	137,351.1	135,854.4	128,051.8	100,827.5
Liaoning	194,466.5	194,466.6	193,618.2	189,055.2	164,489.4	Hainan	22,786.49	24,878.32	24,103.68	22,309.05	16,976.21
Jilin	85,807.44	126,961.7	126,961.7	126,961.7	121,869.2	Sichuan	264,682.3	305,169.1	299,483.5	285,827.5	230,632.3
Heilongjiang	130,995.4	160,290.9	160,252.3	159,608.2	144,099.2	Guizhou	43,793.07	114,666.1	114,666.1	114,138.8	101,422.8
Shanghai	183,349.5	183,349.5	180,762.1	172,897.8	142,625.7	Yunnan	75,435.63	75,435.63	73,356.44	69,084.55	56,522.93
Jiangsu	428,517.8	442,910	442,910	441,046.2	374,349.7	Shaanxi	80,401.38	146,654	146,654	146,429.9	125,683.7
Zhejiang	275,062.6	293,854	293,435	283,407	227,765	Gansu	37,204.18	116,171.3	116,171.3	115,092.7	92,793.77
Anhui	133,859.5	139,420.5	139,420.5	137,752.3	121,971.1	Qinghai	12,278.5	29,651.72	29,207.03	27,861.59	22,372.68
Fujian	171,992.2	171,992.2	167,216.9	156,363.9	121,649.7	Ningxia	12,928.73	32,641.42	32,641.42	32,641.42	32,641.42
Jiangxi	87,117.18	119,674	119,674	119,610.5	106,829	Xinjiang	49,248.28	98,128.82	98,125.62	97,057.69	87,987.06
Shandong	403,930.9	560,955.5	560,955.5	554,048.1	472,746.4	National Sum	4,359,962	5,664,741	5,636,487	5,512,971	4,699,769

Notes: sumGDP is the actual sum GDP of each province from 1995 to 2015. Outuput0 represents the optimal GDP in that only the resource allocation is changed under no constraint of reduction targets for carbon emissions. Output5 refers to the optimal GDP under the constraint of a reduction target for carbon emissions of 5%. Output15 refers to the optimal GDP under the constraint of a reduction target for carbon emissions of 15%. Output40 refers to the optimal GDP under the constraint of a reduction target for carbon emissions of 40%.

Certain provinces support two hypotheses, while others do not because certain provinces have low environmental efficiency and their energy consumption cannot be effectively utilized, and under the framework of the time substitution DEA model, the GDP's increasing amplitude caused by the promotion of environmental efficiency exceeds the GDP's decreasing amplitude caused by resource constraints. Therefore, a win-win effect might occur between the reduction of carbon emissions and economic growth in the Porter hypothesis or the double dividend hypothesis. However, once the resources are effectively utilized, neither an increase in GDP caused by the promotion of environmental efficiency nor a win-win effect between the reduction of carbon emissions and economic growth in the Porter hypothesis or the double dividend hypothesis will occur.

5.4. Measurement of Optimal Carbon Emissions

The optimal carbon emissions b^* of each province can be measured according to Equation (7). The results are shown in Figure 2.

By comparing the optimal carbon emissions under various limits of carbon emissions reductions and actual carbon emissions for each province, we can draw the following conclusions:

First, to achieve the optimal output, each province must have implemented the carbon emissions reduction policy from 1995 to 2015. This criterion indicates that the implementation of energy conservation and emissions reduction cannot be delayed, and greater economic growth can be completed only by implementing the constraints of carbon emissions reduction over a relatively long period. If the period is too short, then fewer paths will be available to reduce carbon emissions, and the potential optimal output will not be reached.

Second, a comparison of the optimal carbon emissions and actual carbon emissions shows that the actual carbon emissions of several provinces, such as Beijing, are larger than the optimal carbon emissions under a carbon emissions reduction limit of 5% before 2000, however, the findings for the two emissions are reversed after 2000. This finding indicates that optimal carbon emissions are not always uniformly reduced. In addition, based on the time substitution and principle for the inter-temporal allocation of resources, we must fully consider the realities of each province in each year and, thus, guarantee the minimum loss of economic growth.

Third, based on the summarized results for the optimal carbon emissions under different carbon emissions reduction limits, the entirety of each province's optimal carbon emissions are not equal to the constrained carbon emissions $\overline{b_j}$, and certain provinces' optimal carbon emissions are even smaller than the targets set for carbon emissions. Based on this conclusion, we assume that the optimal carbon emissions in each situation are all smaller than the constrained carbon emissions $\overline{b_j}$, and we define the potential carbon emissions reductions of this province will be the largest. If the optimal carbon emissions are in the range of 5% to 15% of the constrained carbon emissions $\overline{b_j}$, we then define the potential of this province's carbon emissions reduction as relatively large. If the optimal carbon emissions are all less than 5% of the constrained carbon emissions, we define the potential carbon emissions reduction of this province as average potential. Finally, if the optimal carbon emissions in each situation are all equal to the constrained carbon emissions $\overline{b_j}$, we define the potential carbon emissions reduction of this province as a relatively low potential. Therefore, the following conclusions are drawn:

The province with the largest potential for carbon emissions reduction is Inner Mongolia.

The provinces with a relatively large potential for carbon emissions reduction are Shanxi, Jilin, and Ningxia.

The provinces with an average potential for carbon emissions reduction are Hebei, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Guizhou, and Shaanxi.

The provinces with a relatively low potential for carbon emissions reduction are Beijing, Tianjin, Liaoning, Heilongjiang, Shanghai, Zhejiang, Fujian, Hubei, Hunan, Guangdong, Guangxi, Hainan, Sichuan, Yunnan, Gansu, Qinghai, and Xinjiang.

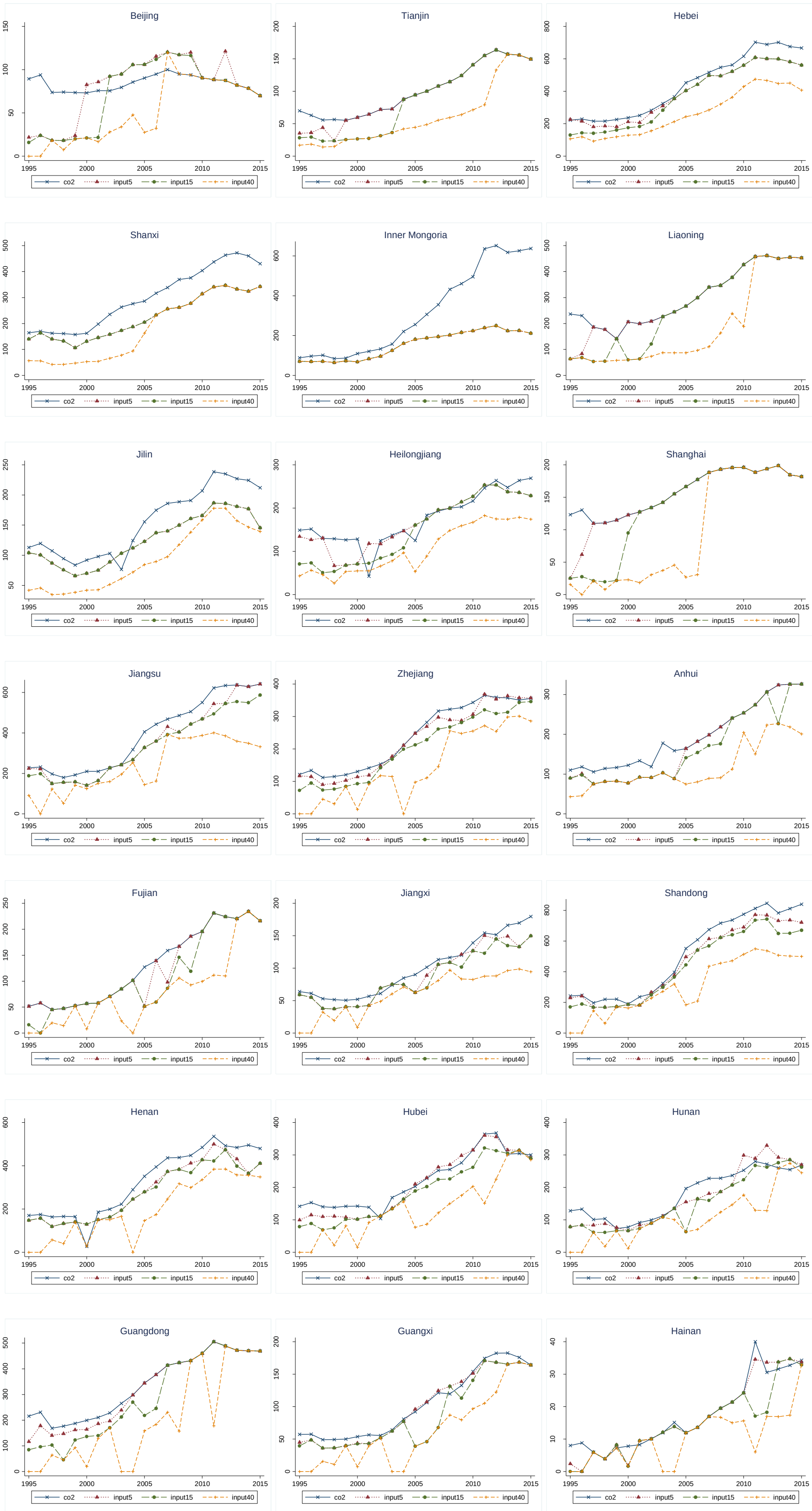

Figure 2. *Cont.*

Vertical axis unit: 1000,000 tons; Horizontal axis unit: year. CO_2 is the actual carbon emissions. Input0 represents the optimally allocated carbon emissions under the condition that total carbon emissions remain unchanged. Input5 is the optimal carbon emissions under the constraint of a reduction target for carbon emissions of 5%. Input15 is the optimal carbon emissions under the constraint of a reduction target for carbon emissions of 15%. Input40 is the optimal carbon emissions under the constraint of a reduction target for carbon emissions of 40%.

Figure 2. Actual Carbon emissions and optimal carbon emissions under various targets for the reduction of carbon emissions in each province.

The provinces with a larger potential for carbon emissions reduction are almost all western provinces, and the provinces with a relatively low potential for carbon emissions reduction are mostly eastern provinces. Wei, Ni, and Du [16] also find that the eastern region has the least inefficient emissions and the highest marginal abatement costs, and the western region has the largest potential reduction capability and the lowest marginal costs associated with reducing CO_2 emissions. Wang et al. [64] use the ZSG-DEA model and find that achieving both the emissions intensity reduction and the energy intensity reduction targets will require the provinces of Ningxia, Inner Mongolia, Shanxi, and Qinghai to shoulder heavier burdens of more than 60%; the provinces of Anhui, Jiangxi, Jiangsu, Sichuan, Shaanxi, and Hainan to shoulder comparatively light burdens below 30%; and the remaining Chinese regions to shoulder medium reduction burdens between 30% and 60%.

5.5. Analysis of Influencing Factors for the Potential GDP Loss Rate and Optimal Rate of Carbon Emissions

After obtaining the optimal GDP and optimal carbon emissions via measurements, identifying the influencing factors will provide definite objects for the establishment of carbon emissions reduction targets. For this purpose, we employed a regression analysis to identify the influencing factors of the potential GDP loss rate and optimal rate of carbon emissions.

A number of studies have analyzed the influencing factors of carbon emissions. For example, Wei, Ni, and Du [16] use the initial income levels, the share of the heavy industry sector in the economy, the share of the tertiary industry in GDP, the share of coal in the total energy, and the share of international trade in GDP to analyze the CO_2 abatement potential. Additionally, Wei, Ni, and Du [16] use the per capita GDP, energy consumption structure, industry structure, urbanization level, technology progress, and trade openness to analyze the forecasting CO_2 emissions. Many studies focused on the influencing factors of carbon emissions and optimal GDP have drawn on the STIRPAT equation proposed by York et al. [65]. The equation indicates that carbon emissions are primarily influenced by environmental pressure, population size, the degree of affluence, and the technology level. Depending on the equation, this paper replaces the technology level with environmental efficiency, the degree of affluence with per capita GDP, population size with the population in each province, and environmental pressure with energy intensity. Thus, the following regression model is proposed:

$$\begin{aligned} LGDP_{it} &= \beta_0 + \beta_1 \ln ETE_{it} + \beta_2 \ln PGDP_{it} + \beta_3 \ln P_{it} + \beta_4 \ln EG_{it} + \mu_{it} \\ GInput_{it} &= \beta_0 + \beta_1 \ln ETE_{it} + \beta_2 \ln PGDP_{it} + \beta_3 \ln P_{it} + \beta_4 \ln EG_{it} + \mu_{it} \end{aligned} \quad (9)$$

where $LGDP$ represents the potential economic growth rate of loss, wherein $LGDP_{it} = SumGDP_{it}/Output_{it}$; $SumGDP$ represents the sum of the actual GDP; $Output$ represents the optimal output, and the ratio between them represents the potential GDP loss rate, wherein a larger ratio may represent a larger relative optimal output of the actual GDP and larger actual GDP loss rate; $GInput_{it}$ represents the growth rate of optimal carbon emissions, wherein $GInput_{it} = Input_{it}/CO_{2it}$ and $Input$ represent the optimal carbon emissions under the condition of optimal output. CO_2 represents the actual carbon emissions, and larger values of $GInput$ indicate that more CO_2 should be exhausted based on the original actual carbon emissions if the optimal output is reached; $PGDP$ represents per capita GDP; P represents the total population scale; EG represents energy intensity, which is found by dividing the total amount of energy consumption by the total GDP; ETE represents the technology efficiency value; i represents the province; t represents the year; we also control time effects; β represents the coefficient term; and μ represents the residual term. This paper employs the fixed effect model of panel data to test the influences of the above factors on the optimal output and optimal carbon emissions. Firstly, we use variance inflation factors (VIFs) to test for multicollinearity and find that the VIF value between all independent variables is less than 2; therefore, multicollinearity is not observed. We then use the Hausman test to determine whether to use a fixed effects model or random effects model. Based on the Hausman test result, we select the fixed effects model to conduct the analysis. To rule out the heteroscedasticity, we also use White-Huber robust standard errors fixed-effects estimator. The regression results are shown in Table 5:

Table 5 shows the influences of different factors on the optimal GDP loss and the optimal rate of carbon emissions.

(1) Environmental efficiency. Most previous studies have neglected the influence of environmental efficiency on carbon emissions; however, this type of variable has been added into the analysis in this paper. As shown in Table 5, environmental efficiency has a significantly positive influence on the potential optimal GDP, the potential loss rate and the optimal rate of carbon emissions. This conclusion explains why the win-win effect of the Porter hypothesis or the double dividend hypothesis could occur in certain provinces but not in others. Higher environmental efficiency can contribute to higher resource utilization efficiency. In this case, if certain constraints of carbon emissions reductions are provided, then additional GDP losses will not occur. In addition, higher environmental efficiency associated with reaching the optimal output under the foregoing condition corresponds to a greater amount of carbon emissions because of the higher energy resource utilization and higher the optimal carbon emissions. If more energy resources are input during the years with lower environmental efficiency, then the carbon emissions will not be fully utilized, and low utilization efficiency will inevitably result in a failure to reach the optimal GDP output.

(2) Per capita GDP. Although per capita GDP significantly increases the potential optimal GDP loss rate, it significantly decreases the optimal carbon emissions. This conclusion indicates that provinces with a higher per capita GDP will incur greater GDP losses once the constraints of carbon emissions reductions are implemented. Therefore, to achieve the potential optimal GDP, provinces with a higher per capita GDP should reduce carbon emissions smaller than those provinces that have higher living

standards and demands for energy; therefore, the constraints for carbon emissions reductions will cause a larger output decrease compared with provinces with a lower per capita GDP (to some extent). Similarly, provinces with a higher per capita GDP will generally have larger energy demands; therefore, the amount of the carbon emissions that can be reduced will not be large.

(3) Population. The population scale significantly reduces the potential optimal GDP loss rate and significantly enlarges the optimal carbon emissions. This conclusion indicates that provinces with larger population scales will obtain smaller GDP losses when certain constraints of carbon emissions reductions are provided and, accordingly, more carbon emissions on an original basis are required. Moreover, in a given region, a greater population may correspond to the increased production of carbon emissions to meet the demand of economic activities. In general, provinces with a larger population are also large energy consumers. Furthermore, provinces with a low level of economic development often have relatively low resource utility efficiency. In this case, greater carbon emissions reductions can be achieved, and a lower GDP loss rate may occur under the constraints of carbon emissions reductions. In addition, because provinces with larger population scales and higher energy consumption have relatively large carbon emissions, their ability to reduce carbon emissions and achieve optimal carbon emissions will be considerable.

(4) Energy intensity. Energy intensity significantly reduces the potential optimal GDP loss rate but has a non-significant influence on optimal carbon emissions, which is likely because the provinces with higher energy intensity have relatively high energy consumption per unit GDP, thereby resulting in relatively low energy utilization efficiency. In addition, the provinces in China with higher energy intensity generally have relatively high energy consumption, which results in large carbon emissions, low technical environmental efficiency, and a considerable ability to reduce carbon emissions.

These findings summarizing the foregoing analysis provide decision-makers with suggestions for setting reduction targets for carbon emissions. Decision-makers should set higher reduction targets for carbon emissions in provinces with lower environmental efficiency, smaller per capita GDP, larger population scales, and higher energy intensity. These findings indicate that the realities of each province should be considered when setting reduction targets for carbon emissions. Considering that provinces have different environmental efficiency levels, per capita GDPs, and population scales, a uniform reduction target for carbon emissions would require certain provinces to incur relatively large losses in economic growth when implementing carbon emissions reduction policies.

Finally, to ensure that our results are robust to model selection, we conduct several robustness checks. We find that the model showed heteroscedasticity, serial correlation, and cross-sectional dependence. In the case of heteroscedasticity, serial correlation, and cross-sectional dependence, the fixed-effects model estimator is biased. In order to obtain unbiased estimators, we use panel-corrected standard error (PCSE) estimators (a panel-corrected when the errors are assumed to be contemporaneously correlated and panel heteroscedastic) as suggested by Beck and Katz [66]. For a better comparison, Driscoll and Kraay [67] standard errors for coefficients estimated by fixed-effects (within) regression is utilized. The Driscoll and Kraay [67] standard errors are robust to disturbances being heteroscedastic, autocorrelated, and cross-sectionally dependent. The results are shown in Tables 6 and 7.

As we can see in Tables 6 and 7, comparing to Table 5, although the significance level of some coefficients, such as PGDP in Table 6 with the Driscoll-Kraay estimator is decreasing, but the main results still remain consistent, so we could say with strong evidence the results show that the choice of the estimation methods does not affect the robustness of our results. Our results can rule out the heteroscedasticity, serial correlation, and cross-sectional independence.

Table 5. Regression results for factors influencing the potential GDP loss rate and optimal rate of carbon emissions.

Explained Variable / Explaining Variable	LGDP0	LGDP5	LGDP15	LGDP40	GIput0	GIput5	GIput15	GIput40
ETE	0.295 *** (3.96)	0.303 *** (3.88)	0.326 *** (3.64)	0.469 *** (3.16)	2.817 ** (2.66)	2.556 ** (2.31)	2.046 * (1.83)	1.131 ** (2.75)
PGDP	0.0669 * (1.72)	0.0641 ** (2.18)	0.0523 * (1.87)	−0.0229 (−0.24)	−0.357 ** (−2.40)	−0.295 * (−1.70)	−0.237 (−0.75)	−0.459 * (−1.76)
P	−0.0409 (−0.53)	−0.0365 (−0.46)	−0.0200 (−0.24)	0.0828 (0.68)	0.208 (0.70)	0.510 * (1.73)	0.923 ** (2.37)	0.567 * (1.95)
EG	−0.0626 ** (2.11)	−0.0624 ** (−2.06)	−0.0602 * (−1.85)	−0.0419 (−0.77)	0.175 (1.02)	0.0786 (0.37)	−0.184 * (−1.78)	−0.357 ** (−2.59)
Constant	1.203 * (2.00)	1.168 * (1.90)	1.029 (1.56)	0.163 (0.17)	−0.447 (−0.20)	−2.936 (−1.16)	−6.246 ** (−2.13)	−4.112 * (−1.85)
Time dummies	Control	Control	Control	Control	Control	Control	Control	Control
R^2	0.477	0.478	0.492	0.646	0.331	0.269	0.289	0.480
Hausman Value	165.23	425.43	225.56	53.28	130.76	107.54	112.63	109.35
F value	21.15	21.26	22.45	42.32	11.46	8.511	9.398	21.40
No. obs.	609	609	609	609	609	609	609	609

Notes: *** denotes significance at the 1% level. ** denotes significance at the 5% level. * denotes significance at the 10% level.

Table 6. Robustness checks result for Factors influencing the potential GDP loss rate.

Explained Variable / Explaining Variable	LGDP0	LGDP5	LGDP15	LGDP40	LGDP0	LGDP5	LGDP15	LGDP40
Method	Panel-corrected standard error(PCSE)				Driscoll−Kraay estimator			
ETE	0.0678 *** (4.93)	0.0686 *** (4.98)	0.0603 *** (4.55)	0.0655 *** (3.77)	0.288 *** (4.34)	0.290 *** (4.35)	0.290 *** (4.29)	0.242 *** (2.86)
PGDP	0.102 *** (7.24)	0.0986 *** (7.49)	0.0850 *** (5.82)	0.0924 *** (2.65)	0.00673 (1.64)	0.00656 (1.56)	0.00661 (1.46)	0.0234 * (1.94)
P	−0.000875 (−0.04)	−0.00144 (−0.07)	0.0200 (0.84)	0.132 *** (3.00)	−0.113 *** (−7.63)	−0.108 *** (−6.73)	−0.0826 *** (−3.81)	0.0840 * (1.86)
EG	−0.0458 *** (−6.83)	−0.0503 *** (−7.66)	−0.0419 *** (−5.61)	−0.0284 *** (−2.94)	−0.0542 *** (−9.40)	−0.0568 *** (−8.67)	−0.0665 *** (−6.61)	−0.134 *** (−3.34)
Constant	1.017 *** (51.33)	0.897 *** (5.18)	0.889 *** (4.43)	−0.0831 (−0.24)	1.725 *** (15.21)	1.679 *** (13.81)	1.483 *** (8.91)	0.171 (0.48)
Time dummies	Control	Control	Control	Control	Control	Control	Control	Control
R^2	0.996	0.997	0.996	0.982	0.453	0.453	0.450	0.466
F/Wald value	5132307.6	1876486.0	565231.3	71603.3	403.7	360.6	374.3	52.30
No. obs.	609	609	609	609	609	609	609	609

Notes: *** denotes significance at the 1% level. * denotes significance at the 10% level.

Table 7. Robustness checks result for factors influencing the optimal rate of carbon emissions.

Explained Variable / Explaining Variable	GIput0	GIput5	GIput15	GIput40	GIput0	GIput5	GIput15	GIput40
Method	Panel-corrected standard error(PCSE)				Driscoll-Kraay estimator			
ETE	3.617*** (11.15)	3.465*** (10.18)	3.132*** (9.51)	1.097*** (4.89)	2.631*** (3.27)	2.443*** (2.90)	2.197** (2.65)	0.925*** (3.42)
PGDP	−0.544*** (−3.83)	−0.384** (−2.28)	−0.703*** (−3.09)	−0.279 (−1.57)	−0.0834*** (−3.01)	−0.0952*** (−3.19)	−0.104** (−2.62)	−0.0731 (−1.37)
P	−0.0291 (−0.11)	0.488* (1.89)	0.605* (1.90)	0.717*** (3.76)	0.479** (2.59)	0.729*** (2.98)	1.121*** (3.87)	0.973*** (9.51)
EG	0.414*** (4.85)	0.283*** (2.86)	0.163 (1.42)	−0.230** (−2.01)	0.0926 (1.22)	−0.00552 (−0.07)	−0.163* (−1.75)	−0.547*** (−7.62)
Constant	1.179 (0.63)	−2.681 (−1.43)	−3.645 (−1.58)	−4.790*** (−3.47)	−2.406* (−1.73)	−4.462** (−2.33)	−7.706*** (−3.40)	−6.851*** (−8.96)
Time dummies	Control	Control	Control	Control	Control	Control	Control	Control
R^2	0.783	0.758	0.651	0.511	0.310	0.251	0.274	0.370
F value	12984.6	22194.3	2851.2	6266.8	13.20	17.14	45.12	70.59
No. obs.	609	609	609	609	609	609	609	609

Notes: *** denotes significance at the 1% level. ** denotes significance at the 5% level. * denotes significance at the 10% level.

6. Conclusions and Policy Implications

This paper employed the newly-developed time substitution DEA model to measure the economic growth effect and optimal carbon emissions under the constraints of reduction targets for carbon emissions in China in recent decades and used the model to analyze the factors that influence optimal carbon emissions. According to the empirical results, the following conclusions can be drawn: First, a relationship is observed between carbon emissions and economic growth; thus, larger constraints on reduction targets for carbon emissions may result in a lower level of potential optimal economic growth. Second, China currently has a considerable potential for carbon emissions reduction and can experience a win-win situation between the reduction of carbon emissions and economic growth by changing its inter-temporal resource allocation. However, if China's technical environmental efficiency reaches the optimum, a dilemma between the reduction of carbon emissions and economic growth will occur. Third, a dilemma might occur between the reduction of carbon emissions and economic growth in provinces that have a relatively high technology efficiency. Fourth, to achieve the potential optimal GDP under any constraint for carbon emissions, carbon emissions reduction policies should be implemented immediately.

Our results have important implications for policymakers:

First, improving environmental efficiency is a key factor for achieving the potential optimal output, which indicates that high environmental efficiency and no waste of energy and resources in certain provinces would lead to a high level of economic growth losses. As a result, provinces with higher environmental efficiency should be given smaller reduction targets for carbon emissions, and provinces with lower environmental efficiency should be given larger reduction targets for carbon emissions. The realities of each province should be fully considered when formulating policies for carbon emissions reductions, and a uniform policy for carbon emissions reductions is inappropriate because such a policy could cause larger economic growth losses in provinces with lower technical environmental efficiency.

Second, because of the relatively low opportunity costs for the reduction of carbon emissions, governments can reasonably allocate energy resources and make reasonable plans for carbon emissions reductions, especially by setting reasonable reduction targets for carbon emissions at different time nodes. In this way, the win-win situation of reducing the pollutant emissions without slowing down economic growth can be achieved.

Third, this paper demonstrated the strong likelihood of realizing a win-win situation between a reduction in carbon emissions and economic growth. Therefore, government decision-makers should fully predict future carbon emissions and the level of economic growth, reasonably evaluate the costs of implementing a carbon emissions reduction policy, and set appropriate reduction targets for carbon emissions.

Fourth, carbon reduction is tightly related to the sustainable development of the economy and society. Moreover, the overwhelming pressure on the natural environment indicates the urgency to limit carbon emission. China's carbon policy is undoubtedly an important factor of its economic development, even that of the whole world. Our research found that it takes time to relieve the negative influence of carbon limitation on economic growth so that the earlier carbon reduction is put into effect, the more chances we get to find the optimal carbon reduction paths and further accomplish the smallest GDP loss.

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