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Measuring Energy Performance for Regional Sustainable Development in China: A New Framework based on a Dynamic Two-Stage SBM Approach

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Abstract: Sustainable development has always been an important issue for all policy makers, even more so now, as global warming has seriously threatened the whole world. To understand the efficacy of regional sustainable policies, we proposed a dynamic, two-stage, slacks-based measure (SBM) model with carry-over and intermediate variables, highlighting the importance of an electricity portfolio, to measure overall energy performance for the purpose of regional sustainable development. In this unified linear programming framework with intertemporal evaluation, we estimated the effects of a clean electricity supply by the abatement of CO_2 emissions and the gain of economic growth. The results can be used as a reference for decision makers to shape regional sustainable development policies. Using data of 30 provincial administration regions in China for the period of 2012–2017, we postulate that the lower energy performance of the Chinese regional economic system for sustainable development may be attributed to a lower electricity portfolio performance. We then postulate that investment in low-carbon energy infrastructure can combat CO_2 emissions, and is also a major driving force in the regional economic growth.

Keywords: energy performance; regional sustainable development; China; two-stage evaluation framework; dynamic two-stage SBM model

1. Introduction

Over the last decade, global warming has become aggravated, and extreme weather conditions have threatened the living environment of all species. The culprit is believed to be the greenhouse gas (GHG) emissions, mainly from the burning of fossil fuels [1–3]. However, because energy is always indispensable among the many resources required to support economic development, the overdependence on fossil fuels had gone unchallenged for a long time, especially in developing countries [4]. As China experienced unprecedented economic growth after the nation's markets were opened up to the world, it has also become the world's largest GHG emitter [2]. In order to fight climate change, the consensus is for the world to abate CO_2 emissions, so that the Earth's temperature rises by no more than 1.5 °C. Sustainable development has thus become a priority on every government's policy plate. Electrification and decarbonizing the production of electricity have become major directives in long-term sustainable development [5]. China is no exception.

The Chinese government has laid out a set of energy policies in its strategic planning on national development, i.e., the 11th–13th Five-Year Plans (from 2006 to 2020), and also participates in the Nationally Determined Contribution (NDC) that spells out the CO_2 abatement goal by 2030. Nonetheless, the real challenge is to improve the efficiency and productivity of energy, without sacrificing potential economic growth. China has long been involved in renewable energy investment and has made structural changes in its electricity mix by raising the renewable energy share—which had maintained decade-long rising trend over 2006–2015 [6]. However, to remain economically competitive while fulfilling international climate responsibility, it is important for the government to evaluate the consumption of primary energy and electricity mix, the current state of CO_2 emissions, and economic performance as a whole. Policy makers can thus optimize the allocation of limited resources in order to achieve sustainable development goals (SDGs). In general, one could imagine that making low-carbon electricity infrastructure investment would be a win-win strategy for both the economy and the environment. Therefore, when it comes to regional sustainable development, authorities should evaluate energy performance, not only from the traditional economic standpoint, but also from an environmental one.

Zhou et al. [7] had reviewed the literature on data envelopment analysis (DEA) application for regional energy and/or environmental performance evaluation. The number of studies applying a DEA model in China's provincial administration regions has since increased (e.g. [8–12]). However, some crucial but often neglected ingredients in modelling energy and/or environmental performance in Chinese provincial regions are intermediate and intertemporal structures, which incorporate (but are not limited to) energy consumption, gross regional product, and CO_2 emissions. There were a handful of studies working on that aspect: when evaluating the generation performance of China's provincial power systems, Xie et al. [13] treated power capacity as an intertemporal factor in their model specification; Guo et al. [14] incorporated energy stock in their study, and treated it as a carry-over input/output from one period to another. As the previous literature had pointed out, the electricity generated from power infrastructure is idle before it is used to support economic or household activities. In that sense, we argue that a two-stage model, with electricity playing the intermediate role, would reflect more correctly on the energy performance in the real world. Moreover, in line with the progress of renewable energy in China, we also consider different types of energy, i.e., thermal power and clean power, as the intermediate variables, and model their corresponding installed capacity as the intertemporal elements, in order to evaluate the regional energy performance in China more effectively.

DEA is commonly used to estimate the performance score among homogenous decision-making units (DMUs). In a traditional DEA model, as proposed by Tone and Tsusti [15], there is no intertemporal dependency of the inputs and outputs for each DMU. There are some other approaches, such as windows analysis and the Malmquist index with dynamic DEA structure, that have been used to handle the specific characteristics of time effect under a DEA-based framework. However, these previous models failed to consider the effect of carry-over activities between two consecutive periods. In a real business environment, however, for long-term strategic planning, it is important to consider intertemporal effects in order to comprehensively assess a DMU's efficiency.

Dynamic DEA models with inter-connected activities have been proposed to evaluate the relative performance behavior of DMUs in an intertemporal setting for long-term optimization. The subsequent development was proposed by Guo et al. [14] for further applications. Tone and Tsutsui [16] also expanded dynamic DEA in terms of slacks-based measure (SBM), and introduced the dynamic network SBM model to evaluate performance. Furthermore, traditional DEA treats the operational structure of each DMU as a black box, in which the information on internal inefficiency cannot be deciphered. It overlooks valuable managerial information on how to improve efficiency in the value-creation chain. Using a two-stage framework, we are able to open the DMU black box and decompose it into different stages, under a divisional structure with network connections. This method is commonly used to depict the operational structure in many industries [17–22]. In this paper, we adopt the basic assumptions of Tone and Tsutsui [16]. Details of the model are presented in the following section.

The purpose of this paper is to evaluate the energy performance of provincial administration regions in China and to see how cleaner (i.e., with lower CO_2 emissions) electricity had helped regional sustainable development. To do so, we employ a two-stage dynamic slacks-based measure model, in which we introduced a carry-over variable in the electricity portfolio stage. By considering the overall effort to supply clean electricity, to abate CO_2 emissions, and to stimulate economic growth in a unified framework, we hope to shed some light on regional sustainable development policy. In this paper, we use a sample of 30 provinces in China to estimate their energy performance over the period 2012–2017 in terms of performance in electricity portfolio and energy productivity. In particular, we evaluate the regional sustainable development based on the proposed energy performance model with an intertemporal effect, where we put the emphasis on installed capacity used as the carried-over activity linking two consecutive periods in the electricity portfolio stage. Our model not only makes measuring the overall and stage performance and observing dynamic changes possible, but could identify variables that contribute to improvement in each performance stage. In this regard, our model contains more information to be translated into policy planning strategies.

The contributions of this paper are as follows. First, using installed clean power capacity as the carry-over variable and clean electricity as the intermediate variable, we have improved the discriminatory power of the DEA-based model, highlighting the importance of an electricity portfolio in energy performance for sustainable development. Second, we showed that capital investment in electricity infrastructure, especially in clean power capacity, is closely related to the effectiveness of massive electrification and the decarbonizing of electricity production, as the benefits of these investments will be carried forward into the future.

The reminder of this paper is organized as follows. In Section 2, we develop the evaluation model and introduce our research methodology. Data collection and the model validity test are presented in Section 3. An overview of the empirical results based on the model are discussed in Section 4. A summary of the main findings and remarks are presented in the final section.

2. Model Framework and Methodology

2.1. Conceptual Framework

Guo et al. [14], used the dynamic DEA model to evaluate China's energy performance. They also considered energy stock, i.e., the difference between energy supply and its usage at national level, to be a carry-over variable from one period to another. Undertaking massive electrification and decarbonizing the production of electricity are important actions to promote an economic system for sustainable development [5]. Obviously, investment in electricity infrastructure plays a crucial role on planning for low-carbon future by increasing reliance on clean electricity and adopting clean fuels on thermal electricity. Extending Guo et al. [14], we constructed a two-stage network structure, composing of an electricity portfolio stage and an energy productivity stage, to evaluate the overall energy performance and sustainable development of provincial administration regions in China. Installed thermal and clean power capacity were treated as two carry-over variables in the electricity portfolio stage, and electricity generation, and were employed as two intermediate variables to link the electricity portfolio stage and the energy productivity stage. In addition, we also added the importance of outside electricity from other regions through national grid as an exogenous input in the energy productivity stage. The modified dynamic two-stage network DEA model with SBM approach developed in this paper is illustrated in Figure 1.

In the electricity portfolio stage, we assumed DMUs (e.g., provincial administration regions) invested in modern electricity infrastructure to decarbonize the production of electricity for a visible future. Installed thermal and clean power capacity built in the past were carry-over inputs for electricity generation in the present period, which would satisfy regional electricity demand. In the energy productivity stage, the aims were regional economic growth and its environmental protection. Thermal and clean electricity from the electricity portfolio stage would be considered as intermediate inputs. The exogenous input, primary energy consumption, was used to produce gross region product and to mitigate as much undesirable CO_2 emissions as possible. Meanwhile, the regional economic system may also need to import extra electricity from other regions. These imports were treated as another exogenous input to support the regional economic system.

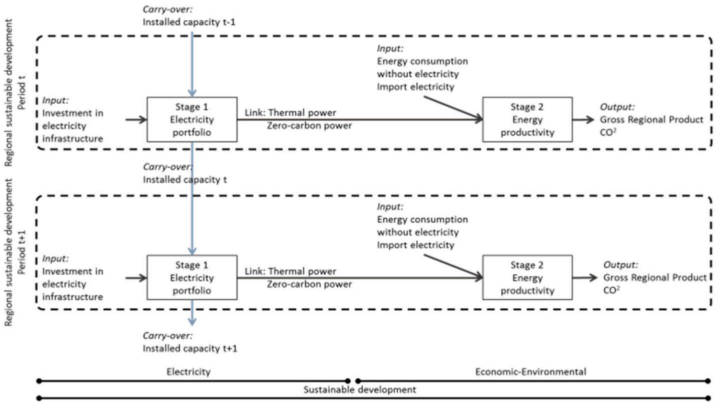

Figure 1. Two-stage dynamic network structure for regional sustainable development.

2.2. *Variable Selection*

As shown in Figure 1, the variables we selected to build the evaluation framework for regional sustainable development were based on both the previous literatures [14,22–26] and the role of low-carbon electricity in energy consumption. Note that the pursuit of low-carbon economy transition should also involve energy consumption, and, in this regard, we took a value-added approach to our model. In the electricity portfolio stage (stage 1), we considered three variables, namely, investment in electricity infrastructure (Investment) (input), thermal power installed capacity (ThermalPIC) (carry-over), and clean power installed capacity (CleanPIC) (carry-over). Here, "Investment" referred to the expenditure used for electricity infrastructure in any given provincial region. Thermal power installed capacity was the electricity infrastructure using fossil fuels to generate electricity. Clean power installed capacity referred to infrastructure using hydro, nuclear, and renewable energies for electricity generation. Two intermediate variables, thermal electricity (ThermalE) (intermediate) and clean electricity (CleanE) (intermediate), were used to link the electricity portfolio stage (stage 1) and the energy productivity stage (stage 2). Compared with previous studies, we used thermal power installed capacity (ThermalPIC) and clean power installed capacity (CleanPIC) as indicators for performance analysis in the electricity portfolio stage. Accordingly, in the energy productivity stage (stage 2), there were four inputs and two outputs. The four inputs consisted of two dedicated inputs and two intermediate inputs, ThermalE and CleanE, from the preceding stage. One of the two dedicated inputs was the primary energy consumption (PEC) (input), referring to the consumption of coal, gas, fuel oil, etc., excluding electricity used for regional economic system; and the other was the import of outside region electricity (IOE) (input), the extra electricity from other region(s) through national grid. The electricity imported from outside regions was measured by the difference between the production and consumption of electicity at the given provincial administration region. The two final outptuts of the energy productivity stage were gross regional product (GRP) and CO_2 emissions (CO_2). Gross regional product was used to measure regional economic performance as the corresponding desirable final output in the energy productivity stage, while CO_2 emissions was the undesirable output.

2.3. *The Dynamic Two-Stage Energy Perforamnce Model for Regional Sustainable Development*

In this paper, we proposed a dynamic two-stage energy perforamce model, based on the DNSBM approach, to rate the energy perforamnce of provincial regions in China in terms of their sustainable development, as shown in Figure 1. We took the DNSBM approach in order to integrate the productions of DMUs with multiple inputs, intermediate outputs/inputs, carry-over variables, and outputs into a unified mathamtic programming framework [16,27]. The advantage was that we were able to observe overall energy perfroamnce in separate stages: electricity portfolio stage and energy productivity stage.

The energy performance score of an efficient DMU in any period would be equal to 1 in both stages. This also suggested that there was no room for improvement, and vice versa.

The non-oriented dynamic two-stage SBM model under the assumption of variable returns to scale (VRS) is illustrated in Figure 1. Notations of variables in this paper are definied as follows. Consider that there were n $(j = 1, 2, 3, \ldots, n)$ provincial adminstration regions in China, as separate DMUs, and that each DMU was involved in two stages, the electricity portfolio stage (k) and the energy productivity stage (h), during T terms $(t = 1, 2, 3, \ldots, T)$. There were L_{hk} serial connection link between the electricity portfolio stage and the energy productivity stage in period t, as donated by $(k, h)_1^{\mathrm{t}}$ $(l = 1, \ldots, L_{hk})$, and L_k carry-over activities between two consecutive periods in the electricity portfolio stage (k), denoted as $c_{jkl}^{(t,t+1)}$ $(j = 1, \ldots, n; \quad l = 1, \ldots, L_k; \quad t = 1, \ldots, T)$. In the electricity portfolio stage, a regional economic system consumed m_k^t inputs at time t, which was denoted x_{ijk}^t $(i = 1, \ldots, m_k^t; \quad j = 1, \ldots, n; \quad t = 1, \ldots, T)$, and $c_{jkl}^{(t,t+1)}$ carry-over variables from the previous time $t-1$, while the number of intermediate outputs generated from the electricity portfolio stage, as donated $z_{i(h,k)l}^t$ $(j = 1, \ldots, n; \quad l = 1, \ldots, L_{hk}; \quad t = 1, \ldots, T)$. In addition, at the energy productivity stage, the imtermediate outputs, $z_{i(h,k)l}^t$, to be the intermediate inputs as well as u_h^t inputs, as denoted x_{ijh}^t $(i = 1, \ldots, u_h^t; \quad j = 1, \ldots, n; \quad t = 1, \ldots, T)$, were consumed to create r_h^t desirable output, as denoted y_{rjh}^t $(r = 1, \ldots, r_h^t; \quad j = 1, \ldots, n; \quad t = 1, \ldots, T)$ and b_h^t undesirable output, as denoted y_{bjh}^t $(b = 1, \ldots, b_h^t; \quad j = 1, \ldots, n; \quad t = 1, \ldots, T)$ at time t, respectively. The input and output constraints of oberved $DMU_o (o = 1, \ldots, n)$ are listed in Euation (1) below.

$$
\begin{aligned}
x_{iok}^t &= \sum_{j=1}^n x_{ijk}^t \lambda_{jk}^t + s_{iok}^{t-} \\
x_{ioh}^t &= \sum_{j=1}^n x_{ijh}^t \lambda_{jh}^t + s_{ioh}^{t-} \\
y_{boh}^t &= \sum_{j=1}^n y_{bjh}^t \lambda_h^t + s_{boh}^{t-} \\
y_{roh}^t &= \sum_{j=1}^n y_{rjh}^t \lambda_{jh}^t - s_{roh}^{t+} \\
\sum_{j=1}^n \lambda_{jk}^t &= 1; \quad \sum_{j=1}^n \lambda_{jh}^t = 1
\end{aligned}
\tag{1}
$$

where x_{iok}^t (Investment) and x_{ioh}^t (PEC and IOE) were inputs used into the electricity portfolio stage (k) and the energy productivity stage (h) of observed $DMU_0 (0 = 1, \ldots, n)$, respectively. y_{boh}^t (CO_2 emission) was the undesirable output generated by the energy productivity stage (h), which was also fed as the input of that in the mathmatic programming. y_{roh}^t (GRP) was the desirable output produced by the energy productivity stage (h), s_{iok}^{t-}, s_{ioh}^{t-}, and s_{boh}^{t-} were slacks calculated as the difference between the input of DMU_o and its optimal level, and s_{roh}^{t+} was the slacks demonstrated as the improvement of the given output of DMU_o into its optimal level, respectively. λ_{ijk}^t and λ_{ijh}^t were the intensity vectors of DMU_j corresponding to the electricity portfolio stage and the energy productivity stage at the specific time t.

There were four kinds of links: free, fix, bad, and good, with respect to the intermediate linking constraints [28]. ThermalE and CleanE were outputs from the preceding stage (i.e., the electricity portfolio), and were carried over to the subsequent stage (i.e., energy productivity) as inputs. ThermalE and CleanE played crucial roles in regional sustainability evaluations, as Fay et al. [5] argued that massive electrification and decarbonizing the production of electricity were two major actions promoting sustainable development. ThermalE was given a free link, which may increase or decrease in the optimal problem of Equation (4); CleanE had a good link, as it was the desirable output from the electricity portfolio stage due to zero CO_2 emissions. Any shortages of ThermalE and CleanE of observed DMU were counted as inefficient performance, as demonstrared in Eqution (2).

$$\begin{aligned}
\sum_{j=1}^{n} z^t_{(k,h)_l free}\lambda^t_{jh} &= \sum_{j=1}^{n} z^t_{(k,h)_l free}\lambda^t_{jk} \\
\sum_{j=1}^{n} z^t_{(k,h)_l out}\lambda^t_{jh} &= \sum_{j=1}^{n} z^t_{(k,h)_l out}\lambda^t_{jk} \\
z^t_{o(k,h)_l free} &= \sum_{j=1}^{n} z^t_{(k,h)_l free}\lambda^t_{jk} + s^{t-}_{o(k,h)_l free} \\
z^t_{o(k,h)_l out} &= \sum_{j=1}^{n} z^t_{(k,h)_l out}\lambda^t_{jk} - s^{t+}_{o(k,h)_l out}
\end{aligned} \tag{2}$$

where $s^{t-}_{o(k,h)_l out}$ and $s^{t+}_{o(k,h)_l out}$ were slacks to the two intermediate outputs we introduced.

Regarding to the carry-over constraints, there were also four options: free, fix, bad, and good. ThermalPIC and CleanPIC were assigned free and good carry-over activities in the electricity portfolio stage between two consecutive periods, as shown in Equation (3).

$$\begin{aligned}
\sum_{j=1}^{n} c^{(t,t+1)}_{jk,good}\lambda^t_{jk} &= \sum_{j=1}^{n} c^{(t,t+1)}_{jk,good}\lambda^{t+1}_{jk} \\
\sum_{j=1}^{n} c^{(t,t+1)}_{jk,free}\lambda^t_{jk} &= \sum_{j=1}^{n} c^{(t,t+1)}_{jk,free}\lambda^{t+1}_{jk} \\
c^{(t,t+1)}_{oh,good} &= \sum_{j=1}^{n} c^{(t,t+1)}_{jh,good}\lambda^t_{jh} - s^{(t,t+1)}_{oh,good} \\
c^{(t,t+1)}_{oh,good} &= \sum_{j=1}^{n} c^{(t,t+1)}_{jh,free}\lambda^t_{jh} + s^{(t,t+1)}_{oh,free}
\end{aligned} \tag{3}$$

where $s^{(t,t+1)}_{oh,good}$ and $s^{(t,t+1)}_{oh,free}$ were slacks to the two carry-over variables (See Tone and Tsustui [15] for more details on the definition of links).

The overall energy performance of observed $DMU_o(o = 1, \ldots, n)$, θ^*_o, was evaluated by Equation (4):

$$\theta^*_0 = \min \frac{\sum_{t=1}^{T} W^t\left[w^k\left[1 - \frac{s^{t-}_{iok}}{x^t_{iok}}\right] + w^h\left[1 - \frac{1}{u^t_h + b^t_h}\left(\sum_{i=1}^{u^t_h} \frac{s^{t-}_{ioh}}{x^t_{ioh}} + \frac{s^{t-}_{boh}}{y^t_{boh}}\right)\right]\right]}{\sum_{t=1}^{T} W^t\left[w^k\left[1 + \frac{1}{linkout^t_k + ngood^t_k}\left(\sum_{(k,h)_l=1}^{linkout^t_k} \frac{s^t_{o(kh)_l out}}{z^t_{o(kh)_l out}} + \sum_{k_l=1}^{ngood^t_k} \frac{s^{(t,t+1)}_{ok_l good}}{c^{(t,t+1)}_{ok_l good}}\right)\right] + w^h\left[1 + \frac{1}{r^t_h}\left(\sum_{t=1}^{r^t_{th}} \frac{s^{t+}_{roh}}{y^t_{roh}}\right)\right]\right]} \tag{4}$$

subjected to Equations (1)–(3) for the selected variables.

The numerator included elements related to relative slacks of inputs in the electricity portfolio stage and the energy productivity stage, respectively, whereas the denominator contained relative slacks of good intermediate link and good carry-over from the electricity portfolio stage, and that of desirable output from the energy productivity stage. They were weighted by the stage weights w^k and w^h, as well as the period weight W^t, and the ovrall energy performance θ^*_o of observed DMU_o could be estimated in Equation (4). $\theta^*_o = 1$ if and only if all slacks of that were zero, and the DMU would be treated as an efficient one.

The weights to stage and time were exogenous and satisfied the constraint of Equation (5). w^k and w^h were the weights assigned to stages k and h, respectively, and the sum of the weights was in unity. W^t was the weight assigned to time t, and the sum of that was also in unity.

$$\begin{aligned}
w^k + w^h &= 1 \\
\sum_{t=1}^{T} W^t &= 1
\end{aligned} \tag{5}$$

In addition, the performance of observed DMU_o in each period was τ_o^{t*}, period-R&D stage was ρ_{ok}^{t*}, and period-commercialization stage was ρ_{oh}^{t*}. They were calculated by Equations (6)–(8), respectively.

$$\tau_0^* = \frac{w^k\left[1-\frac{s_{iok}^{t-}}{x_{iok}^t}\right]+w^h\left[1-\frac{1}{u_h^t+b_h^t}\left(\sum_{i=1}^{u_h^t}\frac{s_{ioh}^{t-}}{x_{ioh}^t}+\frac{s_h^{t-}}{y_{boh}^t}\right)\right]}{w^k\left[1+\frac{1}{linkout_k^t+ngood_k^t}\left(\sum_{(k,h)_l=1}^{linkout_k^t}\frac{s_{o(kh)_l out}^t}{z_{o(kh)_l out}^t}+\sum_{k_l=1}^{ngood_k^t}\frac{s_{ok_l good}^{(t,t+1)}}{c_{ok_l good}^{(t,t+1)}}\right)\right]+w^h\left[1+\frac{1}{r_h^t}\left(\sum_{t=1}^{r_{th}^t}\frac{s_{roh}^{t+}}{y_{roh}^t}\right)\right]} \tag{6}$$

$$\rho_{0k}^* = \frac{w^k\left[1-\frac{s_{iok}^{t-}}{x_{iok}^t}\right]}{w^k\left[1+\frac{1}{linkout_k^t+ngood_k^t}\left(\sum_{(k,h)_l=1}^{linkout_k^t}\frac{s_{o(kh)_l out}^t}{z_{o(kh)_l out}^t}+\sum_{k_l=1}^{ngood_k^t}\frac{s_{ok_l good}^{(t,t+1)}}{c_{ok_l good}^{(t,t+1)}}\right)\right]} \tag{7}$$

$$\rho_{0h}^* = \frac{w^h\left[1-\frac{1}{u_h^t+b_h^t}\left(\sum_{i=1}^{u_h^t}\frac{s_{ioh}^{t-}}{x_{ioh}^t}+\frac{s_h^{t-}}{y_{boh}^t}\right)\right]}{w^h\left[1+\frac{1}{r_h^t}\left(\sum_{t=1}^{r_{th}^t}\frac{s_{roh}^{t+}}{y_{roh}^t}\right)\right]} \tag{8}$$

3. Data Collection, Descriptive Statistics, and Model Validity

3.1. Data Collection and Descriptive Statistics

We used data from thirty provincial administration regions in China, covering the six years from 2012 to 2017. The data of all selected variables were obtained from *China Energy Statistics Yearbook* and *China Electric Power Yearbook* (2013–2018), except for CO_2 emissions. The data on regional CO_2 emissions was calculated by the amount of regional consumption of coal, oil, natural, and electricity, times their corresponding coefficients of calorific value, carbon emission factor, and carbon oxidation factor, according to the Intergovernmental Panel on Climate Change (IPCC) Guideline for National Greenhouse Gas Inventories [29], as shown in Equation (9):

$$\sum_{i=1}^{E} CO_{2ijt} = E_{ijt} \times NCV_i \times CEF_i \times COF_i \times (44/12) \tag{9}$$

where CO_{2ijt} denoted the CO_2 emissions from energy type $i(i = 1, \ldots, E)$, such as coal, crude oil, natural gas, and electricity in region j at year t; E_{ijt} denoted the total consumption of each type of energy in region j at year t; NCV_i was the net calorific value of each type of energy; CEF_i denotes the carbon emission factor of each type of energy; and COF_i denotes the carbon oxidation factor of each type of energy. The constant value of 44 and 12 are the molecular weights of CO_2 and carbon, respectively. The descriptive statistics of variables are summarized in Table 2. It should be noted that all monetary variables used in this paper were in 2012 RMB, which have been deflated with the consumer price index (CPI index 2012 = 100). Table 1 summarizes the descriptive statistics of all selected variables to the proposed model.

Table 1. Descriptive statistics.

Variables	Mean	Std. Dev.	Max	Min
Inputs-Electricity portfolio				
Inv (100 million RMB)	567.83	376.92	2214.23	73.10
Intermediate outputs				
ThermalE (100 million kWh)	1420.17	1131.58	4671.00	120.00
CleanE (100 million kWh)	479.61	606.89	3215.00	4.90
Carry-over				
ThermalPIC (MW)	3217.33	2312.75	10,335.00	230.00
CleanPIC (MW)	1629.91	1572.94	8059.00	23.70
Inputs- Energy productivity				
PEC (MTOE)	143.97	99.04	482.90	15.85
IOE (100 million kWh)	1394.81	607.65	3144.00	1.00
Final outputs-Energy productivity				
CO_2 (Million ton)	526.79	346.09	1757.02	75.62
RGP (100 million RMB)	22,282.84	16,804.72	81,571.96	1893.54

Note: Inv refers to the expenditure on the energy industry for electricity infrastructure; ThermalE is the electricity generated from the thermal power installed capacities; CleanE is the electricity produced by the clean power installed capacities; ThermalPIC denotes the thermal power installed capacities operation at a specific period; CleanPIC denotes the clean power installed capacities operation at specific period; PEC denotes the total consumption of primary energies without electricity; IOE is the import of outside region electricity, as measured the difference between the production and consumption of electricity at given provincial administration region; CO_2 is assumed to be the product of energy consumption, which calculated by the emission factors related to energy consumption; GRP denotes the real value of gross regional product.

3.2. Model Vadility

According to Tone et al. [27], there were four criteria to test DEA-based model validity: homogeneity, minimum number of DMUs, isotonicity, and relevance variables selection. We adopted these four criteria to verify the feasibility of the proposed dynamic two-stage SBM model. First in our model, we selected 30 provincial administration regions in China to be DMUs. Because these regions are all second-tier administrative bodies under the central government, and all have equally political statutes, it was safe to assume our model satisfied the homogeneity criterion. However, we considered that there are geographical differences in China, which brought us to comparisons among different areas, in Section 4.4.

Second, as Li et al. [30] had explained, for a DEA-based evaluation model to have acceptable discriminatory ability, the number of DMUs should be at least three times as many as the number of total input and output variables. Similarly, Golany and Roll [25] proposed that the minimum required ratio related to the number of DMUs and model variables was two. As we used data from 30 DMUs across 6 research years (from 2012 to 2017), we had a total of 180 province-year DMUs, which was more than three times that of the nine variables we employed, providing acceptable validity for analysis propose (Tibet was not included in this paper due to the lack of data).

Third, we conducted the Spearman's correlation analysis for the selected variables in the electricity portfolio and the energy productivity stages, and presented the results in Tables 2 and 3. The coefficients were mostly significantly positive, indicating that the variables were suitable for the proposed dynamic two-stage network SBM model. It is worth noting that the coefficient between two inputs in the energy productivity stage, zero-carbon power and the import of electricity, was −0.260, indicating the higher the electricity generation of zero-carbon capacity, as a supplement to thermal power capacity, the further it could reduce the need for imported electricity from outside regions. In summary, the variables have also satisfied the assumption of isotonicity proposed by Golany and Roll [31].

Lastly, we used regression to show that our variables selection was relevant. We were able to show that that the outputs in the electricity portfolio and energy productivity stages, could significantly explained by the input variables in each stage. The results are shown in Table 4. This also confirmed our model satisfied the validity criterion.

Table 2. Correlation coefficients for the selected variables in the electricity portfolio stage.

	Inv	CleanPIC	ThermalPIC	CleanE	ThermalE
Inv	1.000				
CleanPIC	0.606 ***	1.000			
ThermalPIC	0.641 ***	0.235 ***	1.000		
CleanE	0.497 ***	0.947 ***	0.153 **	1.000	
ThermalE	0.576 ***	0.124 *	0.968 ***	0.042	1.000

Note: Inv refers to the expenditure on the energy industry for electricity infrastructure; CleanPIC denotes the clean power installed capacities operation at specific period; ThermalPIC denotes the thermal power installed capacities operation at a specific period; CleanE is the electricity produced by the clean power installed capacities; ThermalE is the electricity generated from the thermal power installed capacities. *, **, *** represent significant at 0.10, 0.05, and 0.01 levels, respectively.

Table 3. Correlation coefficients for the selected variables in the energy productivity stage.

	CleanE	ThermalE	PEC	IOE	CO_2	GRP
CleanE	1.000					
ThermalE	0.042	1.000				
PEC	0.108	0.895 ***	1.000			
IOE	−0.260 ***	0.144 *	0.071	1.000		
CO_2	0.191 **	0.888 ***	0.981 ***	0.127 *	1.000	
GRP	0.148 **	0.543 ***	0.576 ***	0.518 ***	0.867 ***	1.000

Note: CleanE is the electricity produced by the clean power installed capacities; ThermalE is the electricity generated from the thermal power installed capacities; PEC denotes the total consumption of primary energies without electricity; IOE is the import of outside region electricity, as measured the difference between the production and consumption of electricity at given provincial administration region. CO_2 is assumed to be the product of energy consumption, which calculated by the emission factors related to energy consumption; GRP denotes the real value of gross regional product. *, **, *** represent significant at 0.10, 0.05 and 0.01 levels, respectively.

Table 4. Regression results on the relevance of variables.

	Electricity Portfolio Stage		Energy Productivity Stage
Inputs/Outputs	log(ThermalE)	log(CleanE)	log(GRP)
Constant	0.633	1.263 ***	6.754 ***
	(0.916)	(2.735)	(10.505)
log(Inv)	0.096 ***	0.038	
	(3.329)	(0.830)	
log(ThermalPIC)	0.738 ***		
	(8.551)		
log(CleanPIC)		0.583 ***	
		(9.961)	
log(ThermalE)			0.150 **
			(2.541)
log(CleanE)			0.050 *
			(1.950)
log(PEC)			0.650 ***
			(5.048)
log(IOE)			0.001
			(0.067)
log(CO_2)			1.212 ***
			(5.949)
Adj. R^2	0.987	0.989	0.995
F-statistic	390.211 ***	451.616 ***	976.811 ***

Note: *** denoted the 1% significance level, ** represented the 5% significance level, and * indicated the 10% significance level. Inv refers to the expenditure on the energy industry for electricity infrastructure; ThermalPIC denotes the thermal power installed capacities operation at specific period; CleanPIC denotes the clean power installed capacities operation at specific period; ThermalE is the electricity generated from the thermal power installed capacities; CleanE is the electricity produced by the clean power installed capacities; PEC denotes the total consumption of primary energies without electricity; IOE is the import of outside region electricity, as measured the difference between the production and consumption of electricity at given provincial administration region; CO_2 is assumed to be the product of energy consumption, which calculated by the emission factors related to energy consumption; GRP denotes the real value of gross regional product. *, **, *** represent significant at 0.10, 0.05, and 0.01 levels, respectively.

4. Empirical Results

4.1. Parameters Setting on the Proposed Dynamic Two-Stage SBM Model

In our dynamic two-stage SBM evaluation model, it should be noted that the choice of preferred weights for time periods and stages were important parameters in Equation (1). The last period T could be treated as having the largest contribution to the dynamic evaluation framework [16,32]. Therefore, we considered the possibility that the weight of time periods in the proposed model should increase yearly. We then used the sum-of-the-year's digits method to set the preferred weight of each period. As we had 6 years' research period (2012–2017), with 2012 being 1, 2013 being 2, and so on, we got a total sum of 21 as the denominator. So, the preferred weight in 2012 was 1 divided by 21, which equaled to 0.048. Following this calculation, the preferred weights assigned to the year during 2013 to 2017 were as followed: 2013 = 0.095, 2014 = 0.143, 2015 = 0.19, 2016 = 0.238, and 2017 = 0.286. It would also be reasonable to assume the overall performance of two-stage SBM framework with serial connection as the weighted sum of the performance behavior of the individual stages [7]. Thus, in this paper, we assumed that both the electricity portfolio stage and the energy productivity stage had the same contribution to the overall energy performance for regional sustainable development, and assigned each stage with the same weight of 0.5. Similarly, the preferred weights of periods and stages mentioned above were also employed under the dynamic SBM model, two-stage SBM model, and SBM model to obtain the overall energy performance for Chinese provincial administration regions.

The overall energy performance of provincial regions in China could be estimated by the Equations (1) and (2). To understand the applicability of our model, we also compared our evaluation results to those using other SBM models, including two-stage SBM models without carry-over activities, and regular single-stage SBM models; further details are discussed in the following section.

4.2. Comparsion among Dynamic Two-Stage SBM, Dynamic SBM, Two-Stage SBM and SBM Performormance Scores

To see the effectiveness of our model in evaluating performance, we have chosen three other SBM-related models to be compared with. The evaluation results of all four models were presented in Table 5. From Table 5, we observed that, if we ignored the two-stage structure (as the proposed model in this paper, namely Model 1) and used only a single-stage structure with dynamic component (Model 2), the average overall energy performance of these 30 DMUs almost doubled (0.3487 vs. 0.6118). This suggested that neglecting the internal structure within community, as the importance of electricity portfolio stage to regional sustainable development, might lead to overestimating the overall energy performance in China.

In Model 3, we removed the carry-over linkage, i.e., thermal and clean power installed capacity. the average overall energy performance of this static two-stage SBM model was also higher than that of Model 1. Ignoring the power installed capacity built from the past that could be carried over to the next periods, which could create a discrepancy in estimation of investment in electricity infrastructure, and this might consequently lead to overestimate the overall energy performance as well.

Model 4 was where a simple SBM model, with neither a two-stage structure nor a carry-over linage between two consecutives. The average overall energy performance of Model 1 was still lower than that of Model 4. Obviously, the black-box model might overestimate the overall energy performance and lack meaningful information to identify inefficient DMU.

Note that the number of efficient DMUs in the proposed dynamic two-stage model was two, which was significantly less than other three models, ranging from 6 to 10. We used the non-parametric Krukal-Waillis rank sum test to see whether the average overall energy performance obtained from four models (e.g., the proposed model was an experimental group and other three models were a control group) originated from the same distribution, i.e., if there were significant difference of performance scores among four models or on a pairwise comparison. Table 6 summarized the p-value of Krukal-Waillis rank sum test under the four model comparison or on a pairwise comparison. Most of the p-values were on the fare significant between 1% to 5% level under four model comparison scenario and three pairwise comparison scenarios. Based on the statistical test, we argued that the proposed dynamic two-stage SBM model had more discriminative power than the other three SBM-related models had to empirical applications.

Table 5. Overall performance score rank under the proposed dynamic two-stage SBM model.

		Dynamic Two-Stage SBM (Model 1)		Dynamic SBM (Model 2)		Two-Stage SBM (Model 3)		SBM (Model 4)	
No.	DMU	Performance Score	Rank	Performance Score	Rank	Performance Score	Rank	Performance Score	Rank
1	Beijing	0.0591	28	1.0000	1	1.0000	1	1.0000	1
2	Tianjin	0.0223	29	0.0886	30	1.0000	1	0.9999	7
3	Hebei	0.0988	21	0.1353	26	0.5816	29	0.3354	21
4	Shanxi	0.0823	24	0.0938	29	0.9928	12	0.1307	27
5	Inner Mongolia	0.3020	13	0.1896	22	1.0000	1	0.1228	28
6	Liaoning	0.2962	15	0.4579	18	0.5880	28	0.3805	18
7	Jilin	0.1943	17	1.0000	1	0.8540	16	0.4689	16
8	Heilongjiang	0.1820	18	0.2572	21	0.7703	22	0.3553	20
9	Shanghai	0.0817	25	1.0000	1	1.0000	1	1.0000	1
10	Jiangsu	0.2047	16	0.9996	11	1.0000	1	1.0000	1
11	Zhejiang	0.4200	11	0.5949	17	0.8140	19	0.6623	11
12	Anhui	0.0708	27	0.0991	28	0.9988	11	0.3000	23
13	Fujian	0.5013	7	0.6449	15	0.7534	24	0.4459	17
14	Jiangxi	0.3005	14	0.4193	19	0.7577	23	0.3761	19
15	Shandong	0.0824	23	0.9983	13	0.9509	13	1.0000	1
16	Henan	0.0894	22	0.1808	24	0.7769	21	0.6383	12
17	Hubei	0.8145	3	1.0000	1	0.9333	14	0.5567	14
18	Hunan	0.4668	8	0.9994	12	0.8312	18	0.8403	10
19	Guangdong	0.5503	5	1.0000	1	1.0000	1	1.0000	1
20	Guangxi	0.4606	9	0.6051	16	0.6671	27	0.3310	22
21	Hainan	1.0000	1	1.0000	1	1.0000	1	0.9998	8
22	Chongqing	0.4315	10	0.7029	14	0.7898	20	0.5514	15
23	Sichuan	1.0000	1	1.0000	1	1.0000	1	1.0000	1
24	Guizhou	0.5666	4	1.0000	1	0.9222	15	0.2142	25
25	Yunnan	0.9956	2	1.0000	1	1.0000	1	0.6274	13
26	Shaanxi	0.0812	26	0.1202	27	0.7157	25	0.2666	24
27	Gansu	0.3075	12	0.4086	20	0.6871	26	0.1561	26
28	Qinghai	0.5293	6	1.0000	1	1.0000	1	0.9995	9
29	Ningxia	0.1255	20	0.1721	25	0.8345	17	0.0723	30
30	Xinjiang	0.1424	19	0.1875	23	0.4020	30	0.0961	29
	Mean	0.3487		0.6118		0.8540		0.5643	
	Std.	0.2949		0.3808		0.1379		0.3333	
Number of efficient DMU		2		10		10		6	

Table 6. Krukal-Waillis rank sum test of the overall energy performance differences within/between the four models.

Performance Indicator	Group	Significant Sign	Significant Level
Overall energy performance	Independent sample	Y	1%
	Model1–Model2	Y	1%
	Model1–Model3	Y	1%
	Model1–Model4	Y	5%
	Model2–Model3	N	-
	Model2–Model4	N	-
	Model3–Model4	Y	5%

Note: The independent sample group denoted the Krukal-Waillis rank sum test was used to identify the performance difference within four independent samples as the overall results of the four models, as listed in Table 5; Y and N represented significant and insignificant sign, respectively; Model 1 was the proposed dynamic two-stage SBM model; Model 2 was the dynamic SBM model; Model 3 was the two-stage SBM model; Model 4 was the SBM model.

4.3. Energy Performance of Chinese Provincal Adminstration Regions

The results of the energy performance evaluation for provincial regions in China, including performance scores, overall energy performance ranking in both the electricity portfolio stage, and energy productivity stage were presented in Table 7. It can be seen, in Table 7, that only two DMUs (i.e., Hainan and Sichuan) were estimated as efficient with the overall energy performance score equal to 1 during 2012–2017; they were also efficient in both stages. Beijing and Tianjin had an overall energy performance score of 0.0591 and 0.0223, respectively, which were ranked the bottom two within the 30 DMUs we evaluated. As for stage evaluation results, we found that only Hainan and Sichuan were deemed efficient in the electricity portfolio stage, while there were another four DMUs (e.g., Beijing, Inner Mongolia, Jiangsu, and Guangdong), in addition to Hainan and Sichuan, were seen as efficient ones in the energy productivity stage. Beijing and Tianjin had the worst performance in the electricity portfolio stage, while Beijing was deemed efficient in the energy productivity stage. One possible explanation was that these two DMUs imported most of their electricity from other regions, rather than from their own installed power plants.

Table 7. Performance evaluation of the proposed dynamic two-stage SBM model.

No.	DMU	Electricity Portfolio	Rank	Energy Productivity	Rank	Overall Energy Performance	Rank
1	Beijing	0.0273	29	1.0000	1	0.0591	29
2	Tianjin	0.0123	30	0.7516	12	0.0223	30
3	Hebei	0.0696	22	0.3160	26	0.0988	22
4	Shanxi	0.0638	23	0.2389	28	0.0823	25
5	Inner Mongolia	0.1385	16	1.0000	1	0.3020	14
6	Liaoning	0.3195	13	0.3298	25	0.2962	16
7	Jilin	0.1255	19	0.6516	18	0.1943	18
8	Heilongjiang	0.1300	18	0.4682	22	0.1820	19
9	Shanghai	0.0518	26	0.6941	15	0.0817	26
10	Jiangsu	0.0937	21	1.0000	1	0.2047	17
11	Zhejiang	0.2936	14	0.7772	11	0.4200	12
12	Anhui	0.0447	27	0.5848	19	0.0708	28
13	Fujian	0.3699	9	0.7829	9	0.5013	8
14	Jiangxi	0.1851	15	0.6584	17	0.3005	15
15	Shandong	0.0345	28	0.7231	14	0.0824	24
16	Henan	0.0526	25	0.5665	20	0.0894	23
17	Hubei	0.8549	5	0.7776	10	0.8145	4
18	Hunan	0.3529	10	0.7483	13	0.4668	9
19	Guangdong	0.3475	11	1.0000	1	0.5503	6
20	Guangxi	0.3971	6	0.5604	21	0.4606	10
21	Hainan	1.0000	1	1.0000	1	1.0000	1
22	Chongqing	0.3209	12	0.6835	16	0.4315	11
23	Sichuan	1.0000	1	1.0000	1	1.0000	1
24	Guizhou	0.9152	4	0.4282	24	0.5666	5
25	Yunnan	0.9968	3	0.9948	7	0.9956	3
26	Shaanxi	0.0540	24	0.4443	23	0.0812	27
27	Gansu	0.3807	8	0.2817	27	0.3075	13
28	Qinghai	0.3907	7	0.9363	8	0.5293	7
29	Ningxia	0.1254	20	0.1414	30	0.1255	21
30	Xinjiang	0.1303	17	0.1823	29	0.1424	20
	Mean	0.3093		0.6574		0.3487	

Notably, we found that the most regions in China had relatively better performance in the energy productivity stage than in the electricity portfolio stage, as shown in Table 7. This could be due to the fact that economic growth was an important criterion for promotion of the administrative officials, which then prompted governors to focus on productivity more. In summary, the Chinese government should make more effort to decarbonize the energy/electricity supply mix to improve deficiency of electricity portfolio stage, while maintaining economic growth momentum at the same time. Moreover, there existed great disparities of performance scores between the electricity portfolio stage and energy productivity stage among certain DMUs. Beijing was an example of them. To improve the performance in portfolio stage, we suggested that the government could increase the clean electricity capacity (through capital investment), as clean power produces "desirable" output, which would in turn translated into both better economic and sustainable performance.

4.4. Efficiency Analysis on Regional Discrepancy

Based on the geographical location and economic regional blocks from the seventh Five Year plan in 1987, the 30 regions in the research sample could be grouped into three areas: the east, the central, and the west, as listed in Table 8. We examined whether the performance score differences of three large economic regional blocks in China. Overall energy performance and stage-wise performance of each regional block are presented in Table 9. The East Area ranked first in the energy productivity stage, which could be due to significant effort it had put on to promote economic growth. The West Area ranked first in the electricity portfolio stage, which could be attributed to the effort on the improvement of electricity mix with lower CO_2 emissions. In summary, because the economic performance was still a crucial criterion for the political ascension, it was natural for the regional administration to focus on economic performance more. However, since the performance of energy productivity also played an important role in regional economic development, China's central government should pay more attention to the performance of the electricity portfolio stage regardless, as it would translate into better regional sustainable development.

Table 8. All selected provinces classified into three economic regional blocks in China.

Regional Block	Provinces
East	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
West	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Table 9. Performance scores of three economic regional blocks.

Regional Block	Electricity Portfolio			Energy Productivity			Overall Energy Performance		
	Mean	Efficiency	Inefficiency	Mean	Efficiency	Inefficiency	Mean	Efficiency	Inefficiency
Eastern	0.2382	1 (9%)	10 (91%)	0.7613	4 (36%)	7 (64%)	0.3015	1 (9%)	10 (91%)
Central	0.2262	0 (0%)	8 (100%)	0.5868	0 (0%)	8 (100%)	0.2751	0 (0%)	8 (100%)
Western	0.4409	1 (9%)	10 (91%)	0.6048	2 (18%)	9 (82%)	0.4493	1 (9%)	10 (91%)

5. Conclusions

In this paper, we proposed a dynamic two-stage SBM model for evaluating regional sustainable development, in terms of energy performance in China. Installed capacity and electricity generation, were the carry-over and intermediate variables, which we further decomposed into thermal and clean power. Incorporating these variables brings new insights to the energy performance evaluation by DEA-based modeling, as they reflect the dynamic and internal structure crucial to regional economic and sustainable development from an inter-connected perspective. We built the two-stage evaluation model consisting of electricity portfolio and energy productivity stage, in order to capture more valuable information in the model. The proposed model was designed to highlight the contribution of the electricity portfolio stage to overall energy performance, where installed clean power capacity and clean electricity were seen as desirable carry-over and intermediate outputs in the electricity portfolio stage, and then the latter will continuously to be beneficial input into the energy productivity stage. The main conclusions are as follows.

First, our results demonstrated that by incorporating installed capacity and electricity generation as carry-over and intermediate variables of the electricity portfolio stage in a dynamic two-stage SBM model, we can improve the discriminatory power of energy performance evaluation. Second, from our model, it can be inferred that, while investing in low-carbon electricity infrastructure could alleviate the pressure of CO_2 emissions, it would later be translated into better regional sustainable economic performance over long-term planning periods. Third, the group analysis in Section 4.4 suggests that the efforts to purse the growth of the economic system could play an important role for the eastern region in achieving impressive economic performance, and we therefore could conclude that regional imbalance did exist in China, leading to income imbalance among people in different regional economic blocks in terms of industrial development.

In summary, with this model, governors and policy makers could better understand the contribution of decarbonizing the electricity portfolio and comprehensively improving electricity investment with economic incentives. All provinces should be encouraged to make more efforts to improve performance in the electricity portfolio stage. As we know, decarbonizing electricity consumption is an effective strategy to mitigate the demand of primary energy with lower CO_2 emissions.

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