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Examining the Relationship between Energy Consumption and Unfavorable CO_2 Emissions on Sustainable Development by Going through Various Violated Factors and Stochastic Disturbance–Based on a Three-Stage SBM-DEA Model

Wengchin Fong [1], Yao Sun [1] and Yujie Chen [2,*]

[1] School of Business, Macau University of Science and Technology, Taipa, Macau 999078, China; anniefong.wsu@gmail.com (W.F.); crystal.yaosun@gmail.com (Y.S.)
[2] Faculty of Hospitality and Tourism Management, Macau University of Science and Technology, Taipa, Macau 999078, China
* Correspondence: 2009853lbm20001@student.must.edu.mo

Abstract: The article applies a three-stage Slacks-Based Measure-Data Envelopment Analysis (SBM-DEA) pattern to examine the relationship between energy consumption and unfavorable CO_2 emissions on green sustainable development, for the 11 cities of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) during 2010–2016, by going through various violated factors and stochastic disturbance. Labor, capital and energy resource are chosen as input variables, while GDP and CO_2 emission as output variables. During the three phases consisting of the SBM-DEA model (first stage and third stage) and SFA analysis (second stage), CO_2 emission is considered as an unfavorable outcome, while stochastic statistical disturbances and external environmental influences are identified. The results show that the average efficiency of the GBA cities is 0.708, with only Shenzhen, Macao SAR and Hong Kong SAR having an efficiency of 1 during the whole study period. Based on the findings, suggestions are made for the GBA cities' sustainable development aspects.

Keywords: Guangdong-Hong Kong-Macao Greater Bay Area (GBA); energy efficiency; slack-based model (SBM); undesirable output; three-stage DEA; influencing factors

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1. Introduction

The World Commission on Environment and Development defined sustainable development as "development that meets current demands without jeopardizing future generations' ability to meet their needs" in 1987 [1]. In June 1992, in Rio de Janeiro, Brazil, at the United Nations Conference on Environment and Development, Agenda 21 first proposed sustainable development as the common development strategy of mankind toward the 21st century, transforming sustainable development strategy from a concept to a global scale of action and making sure that the most central part is economic sustainable development. Liu (1997) defines economic sustainable development as, "What we call sustainable development economy can be expressed as sustainable economic development, which should be the economy with the lowest ecological cost and social cost of economic development" [2]. Such economic sustainable development is economic development under the interests of future generations and the protection of natural resources. In addition to economic sustainability being at the core of sustainable development, energy consumption and environmental protection are also major focus of sustainable development strategies. Both show a one-way Granger causality and an inverted U-shaped relationship with sustainable development, respectively. In the early days, labor and energy-intensive industries were used for high economic development. But now, with sustainable development as a core value, cities are improving their energy consumption efficiency and increasing investment in environmental protection. At the same time, it is expected that they would attain sustainable development in the future. Here, the Greater Bay Area (GBA) in China is used as an example of sustainable development.

Figure 1 shows the total energy consumption, total CO_2 emission and total GDP of the GBA cities from 2010–2016. Although the total GDP kept on increasing since 2010, the total energy consumed has not changed tremendously. The amount of total CO_2 emission also demonstrated a decline to some extent.

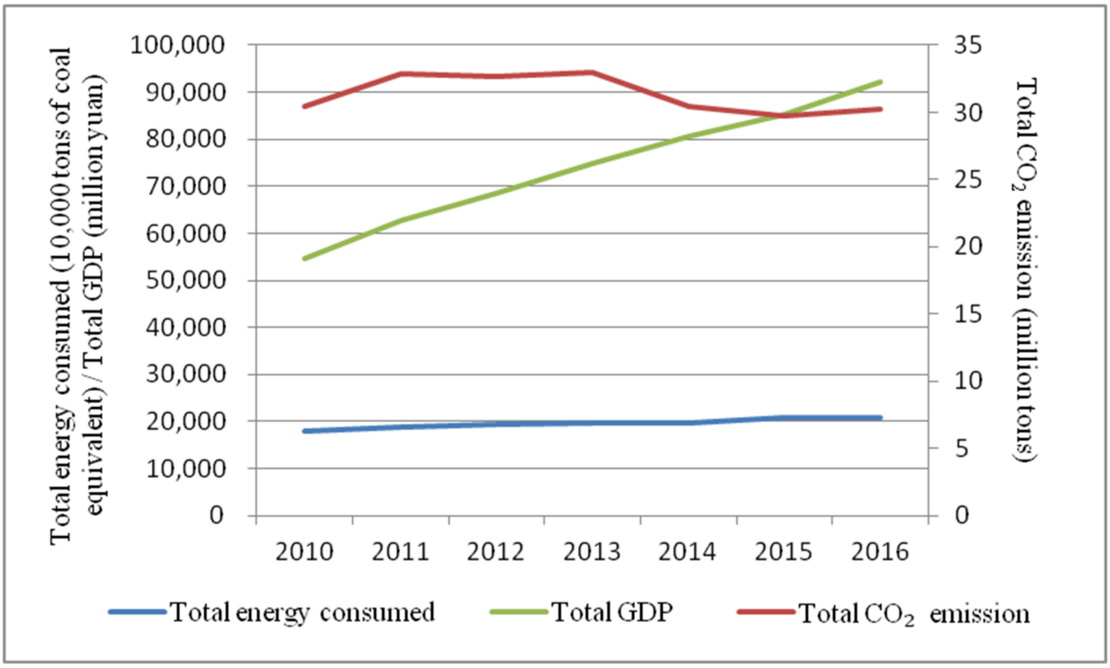

Figure 1. Total energy consumption, total CO_2 emission and total GDP of the GBA cities from 2010–2016. (Data Source: International Energy Agency, 2021).

Improving energy efficiency and considering undesirable output concurrently is one of the mainstreams in achieving the goal of sustainable development. However, most of the existing research literature is divided by provincial level or only includes 9 cities in Guangdong Province, China (Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, and Zhongshan), and few studies include Hong Kong SAR and Macau SAR, but GBA is a complete regional concept, so this study hopes to include data from Hong Kong SAR and Macau SAR by using the three-stage SBM-DEA model to study the complete DBA energy efficiency data for a total of 11 cities in GBA, the better usage of energy consumption toward green sustainable development can be investigated and use the data from these studies to provide better policy recommendations for those inefficient GBA cities, and eventually build an efficient and green GBA.

The followings are the research's main contributions: (1) This paper, with the best of my knowledge, is the first three-stage SBM-DEA model to be applied to discuss energy consumption and unfavorable CO_2 emissions on sustainable development from the various violated aspects, like industrial structure, energy structure etc. (2) When applying the model, previous researches focus on provincial or industrial analysis, while this study focuses on city-level evaluation, especially on GBA. (3) According to the UNEP Governing Council's definition of sustainable development, this research applies Hong Kong SAR and Macao SAR as decision-making units (DMUs) and then compare with other mainland cities. It is very important view of this research.

2. Literature Review

With the growing concern about adverse climate conditions and extreme weather due to global warming, a lot of efforts have been made to maintain the environmental sustainability. The GBA is considered one of the most economically dynamic regions in China since the reform and opening up. The development of GBA is of strategic importance in the development of China. In the early stages of development, most cities in the GBA achieved economic growth through labor- and energy-intensive industries, leading to over-exploitation of resources and environmental pollution. However, with the introduction of green and energy reforms in the Guangdong-Hong Kong-Macao Greater Bay Area in recent years, especially since the area consists of the cities of Guangdong as well as Hong Kong and Macao SARs, the study of the region has become representative. In February 2019, the state promulgated the Outline of the Development Plan of the Guangdong-Hong Kong-Macao Greater Bay Area, which states that priority is given to resource conservation, environmental protection, and natural restoration [3]. Therefore, how the government can improve the ecological environment and protect existing natural resources through various policies has become an important issue. Among them, controlling energy consumption is one of the keys to sustainable development, and this paper hopes to improve the energy efficiency of cities in the Guangdong-Hong Kong-Macao Greater Bay Area through policy recommendations, so as to achieve green and low-carbon development in the Guangdong-Hong Kong-Macao Greater Bay Area.

2.1. Sustainable Development

The IUCN initially established the notion of sustainable development in the World Conservation Strategy in 1980. This document states, "Sustainable development emphasizes the human use of the biosphere to manage it in order to meet the maximum sustainable interests of current generation while preserving its potential for the needs and desires of future generations" [4]. In 1989, the Governing Council of the United Nations Environment Program provided a more specific definition of sustainable development in its Statement on Sustainable Development: "It is defined as development that meets current demands without jeopardizing future generations' ability to meet their own needs, and it does not imply any violation of national sovereignty. According to the UNEP Governing Council, achieving sustainable development involves both domestic and international cooperation, include providing aid to developing nations in line with their national development programs' aims and development objectives. Furthermore, sustainable development entails a favorable international economic environment that promotes long-term economic growth and development in all countries, particularly in developing countries, which is critical for good environmental management. The maintenance, rational use, and enhancement of the natural resource base that promotes ecological stress tolerance and economic growth is also part of sustainable development. Furthermore, sustainable development refers to the integration of environmental concerns and considerations into development plans and policies, rather than a new kind of aid or development financing conditionality" [5].

In the above specific definition of sustainable development, it can be found that it encompasses various elements such as natural resources, economic growth, and the environment, which can be summarized as ecological development, economic development, and social development. Because of its central position in the sustainable development system, economic sustainable development has its unique definition. The British economist Barbier defines sustainable development from an economic perspective as "the maximization of net economic benefits while preserving natural resource quality and service provision" [6]. The British economist Pierce defines it as "economic development on the premise that natural capital remains unchanged, or that the use of resources today should not reduce real income in the future" [7]. The difference between the two is whether economic development is at the expense of resources and the environment. Barbier believes in maximizing economic benefits while preserving natural resource quality and using the money gained from environmental pollution and ecological damage as compensation for environmental and ecological construction. Pierce, on the other hand, believes that economic development should be done without destroying the world's natural resource base, and should not destroy before repairing. Yang (2002) defines sustainable economic development as "the continuous improvement of the economic welfare of the present generation on the basis of certain resources and environment, while being able to ensure that the economic welfare received by future generations is not less than the economic welfare enjoyed by the present generation" [8]. In addition to emphasizing the protection of natural resources, this definition also proposes another provision: emphasizing intergenerational equality.

The Greater Bay Area is an excellent object study for studying China's sustainable growth. The GBA includes the nine cities of Guangzhou, Shenzhen, Foshan, Zhuhai, Dongguan, Huizhou, Zhongshan, Jiangmen and Zhaoqing of the Guangdong Province, the Hong Kong Special Administrative Region (Hong Kong SAR) and the Macao Special Administrative Region (Macao SAR). GBA is considered as one of the most economically vibrant regions in China since the reformation. With a population of around 86 million, a total area of 56,000 km^2 and a GDP of USD 1669 billion in 2020 [9], the development of GBA has also its strategic importance in the development of China. In the early stage of development, most GBA cities achieved economic growth through labor and energy-intensive industries, resulting in over-exploitation of resources and pollution of the environment. However, with the introduction of green and energy reform in the GBA recently, especially with the GBA comprising of Guangdong municipalities as well as the Macao SAR and the Hong Kong SAR, the study on this area becomes representative. According to the February 2019 "Guangdong-Hong Kong-Macao Greater Bay Area Outline Development Plan" [3], priority is given to resource conservation, environmental protection and restoration of nature. Thus, efforts should be made to improve ecological and environmental quality, and then a greener and low-carbon development of GBA can be achieved.

In China, which is in the middle of industrialization, the most important factors hindering the implementation of sustainable development strategy are the significant share of high-energy-consumption industries, the unbalanced industrial structure, the backward technology and equipment, the large population base, the large number of poor people, and the generally low living standard of the people. Increasing industrial restructuring efforts, accelerating technology and equipment replacement, and actively advocating energy-saving production and lifestyle are the primary solutions to promote sustainable development in China.

Then, it is essential to do research on energy consumption efficiency for sustainable development, for the 11 cities of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) during 2010–2016, by going through various violated factors including investment, human capital, and environmental protection. Especially, compared with the high economic growth rate at the current stage, the low growth rate might lower the consumption of energy resources and other environmental aspects of nature, which play a catalytic role in the global process of sustainable development [10].

2.2. The Relationship between Energy Consumption, Environmental Protection, and Sustainable Development

Early Western mainstream economists fully recognized the role of capital, technological progress, labor, and institutions on economic growth, but did not pay attention to the impact of natural resources and environmental factors on economic growth. During the oil crisis in the 1970s, when economies suffered from economic growth difficulties of different degrees due to the scarcity of energy resources, natural resources and environmental factors began to be noticed by economists. The concept of sustainable development was introduced in the 1980s, and natural resources and environmental factors became important indicators for the analysis of sustainable development [11].

2.2.1. The Relationship between Sustainable Development and Energy Consumption

Energy is the material basis of social production and human survival, and is inextricably linked to the development of a country's economy. Sustainable development emphasizes the integrated and coordinated development of economy, resources, environment and population. Therefore, sustainable development of the energy economy means that the use and development of energy meet the needs of economic development without causing serious or irreversible damage to the ecosystem. It addresses the current generations' energy needs without posing a danger to the future generations' ability to satisfy their demands.

The original concept of a sustainable energy economy dates back to 1972, when the book Limits to Growth was published, which introduced the concept that social development and economic growth cannot be supported without energy, causing a heated controversy at that time [12]. Rashe and Tatom (1977) first introduced energy into the Douglas production function, hoping to uncover a fundamental pattern between economic growth and energy consumption [13]. Stem (1993) used a vector autoregressive (VAR) pattern with four variants (capital, energy consumption, labor, and GDP) and applied Granger multivariate causality tests to find a one-way Granger causality from energy consumption to GDP in the United States for 1947–1990 [14]. Willem et al., (2010) presented an explicit model of energy economic growth using a historical deductive approach in 2010, concluding that the current socio-economic model is unsustainable and that energy security is critical [15]. Zhang et al., (2011) examined the relationship between economic growth and energy consumption using the error correction model, cointegration test, and Granger causality test. They found that there is a significant one-way Granger causality of economic growth on energy consumption and that the two are in a long-term equilibrium relationship. [16]. Li et al., (2018) constructed a VAR model of the energy-economy-environment in Henan Province based on the statistical data of total energy consumption, GDP and industrial emissions from 2000–2014. Through impulse response function and variance decomposition, a long-term stable cointegration relationship between energy consumption, economic growth and environmental pollution in Henan Province is obtained, while energy consumption plays a certain positive impact on economic growth [17]. He et al., (2018) analyzed the relationship between energy consumption and economic growth in China since the 1950s by means of the elastic decoupling index and the generalized LMDI method and concluded that both total energy consumption and GDP growth exhibit an exponential growth curve [18]. Zhang and Wang (2018) examined the spatial variation of total factor energy efficiency in 30 provincial and municipal regions of China from 2006 to 2015 based on the haze constraint and concluded that economic development has significantly contributed to the improvement of energy efficiency [19]. Wang and Li (2019) studied Chinese coal cities and found a significant positive correlation between coal resources and economic growth in the sample cities [20]. Previous literature suggests a close relationship between energy consumption and sustainable economic development.

2.2.2. The Relationship between Sustainable Development and Environmental Protection

Environmental protection is the general term for human actions to ensure sustainable social and economic development and to solve real or potential environmental problems. Environmental sustainability is the goal of sustainable development that satisfies future generations' demands by protecting the environment and reducing ecological burdens through measures such as reducing pollutant emissions.

The most representative early study of the relationship between economic sustainability and environmental protection was the empirical verification of the environmental Kuznets curve by American economists Grossman and Kruger in 1990, which demonstrated the relationship between environmental pollution and economic growth is inverted U-shaped [21]. Subsequently, more studies demonstrated this curve. Shafik et al., (1992) found that the water quality of rivers in cities was deteriorating because of the fast growth of the economy; the concentration of suspended solids and sulfur dioxide in the atmosphere in cities showed an inverted U-shaped relationship with per capita income level; and sulfur dioxide emissions in cities increased with per capita income climbed [22]. Sherry and David (2008) studied the inverted U-shaped relationship between environmental pollution and economic growth from the perspective of theoretical analysis [23]. Salvador et al., (2010) used differential dynamics models to simulate the association between economic growth, CO_2 emissions and population, etc. [24]. Liang, et al., (2011) calculated the ecological environment index of 31 Chinese provinces and cities using entropy weight method and fuzzy comprehensive evaluation method, and analyzed the ecological environment status of different locations in the Yangtze River region, and carried out a study on the ecological environment sustainability with the Yangtze River basin as an example [25]. Feng et al., (2018) established a VAR model to analyze qualitatively and quantitatively the factors influencing carbon emissions in Beijing during 1996–2016, and the study found that carbon emissions per capita showed a positive relationship with GDP per capita [26]. Wang et al., (2018) studied the relationship between carbon emissions and GDP per capita in 27 provinces in China based on EKC theory. It was found that the relationship between carbon dioxide emissions and economic development of the 27 provinces as a whole, or geographically divided into eastern, central, and western provinces, met the inverted "U" curve of the EKC hypothesis [27]. According to Xu et al., (2019), green development is an expression of sustainable development, which is essentially a balanced relationship between the environment and the economy to promote economic development and ecological protection, so that the two complement each other [28]. Previous literature shows a close link between environmental protection and sustainable economic development, and it is mostly presented in an inverted U-shape.

2.2.3. Other Impacts on Sustainable Development

In addition to energy consumption and environmental protection factors, there are many external environmental factors that affect sustainable development, such as: industrial structure, energy structure, government financial expenditure, etc.

Tian (2007) proposed that the restructuring of industry forms a structural consumption of resources and thus leads to environmental changes, which largely affect the sustainable development of the economy [29]. Based on data from Shanxi Province, Wang and Gao (2018) used a double difference model to conclude that the increase in the degree of fiscal decentralization is conducive to the upgrading of industrial structure and thus has a positive impact on the ecological environment [30]. Yang (2000) analyzed the causal link between consumption of various energy sources and GDP (electricity, natural gas, oil, and coal) using the cointegration technique using sample data from 1954–1997 in Taiwan and found that there is a two-way Granger causality between GDP and coal and electricity and a one-way Granger causality from GDP to oil and natural gas to GDP [31]. Tian (2014) found that the fiscal expenditure policy has an indirect effect through influencing the economy and thus the ecological environment is significantly based on the analysis of fiscal revenue and expenditure data of Chinese provinces from 2008 to 2011 [32]. Jiang (2018) based on the analysis of data from 2007–2015 concluded that environmental spending has both economic and environmental nature and has a significant positive correlation with economic growth [33]. Hoff and Stiglitz (2001) argue that fiscal expenditure policies should focus on the updating and application of pollution treatment technologies to reduce pollution emission levels through technological innovation in order to enhance ecological protection and promote economic development [34]. Shi (2002) in "Recommendations on China's energy consumption decreased" proposed that opening up to the outside world has a significant role in improving the efficiency of energy use [35]. Xu (2004) selected Shandong Province as a sample to analyze the supply and demand of human capital in Shandong Province and made a qualitative and quantitative analysis study respectively calculated that the support capacity of human capital to sustainable development reached 66.65% [36].

2.3. SBM-DEA Model

Data Envelopment Analysis (DEA) is a non-parametric approach applied to obtain the efficiency of multiple Decision-Making Units (DMUs). It is like a peer group comparison using a frontier to determine efficient and inefficient units relatively. DEA has been widely used as a method in DMUs' efficiency analysis since the production function is not necessary for evaluation.

DEA was first introduced by Charnes, Cooper and Rhodes in 1978, and numerous researches have been done on methodological developments, practical applications, the status of variables and data variation, etc [37]. Since the first issued paper on using DEA in energy efficiency by Färe, Grosskopf and Logan (1983) on the relative efficiency of Illinois electric utilities, there are more and more researches on energy efficiency evaluation using DEA thereafter [38]. Bian and Yang (2010) used DEA models for estimating the aggregated efficiency of resources and the environment of the 30 provinces in China [39]. Guo et al., (2017) studied the dynamic DEA model to evaluate efficiencies based on fossil-fuel CO_2 emissions in OECD countries and China [40]. Iftikhar et al., (2018) applied the network DEA model under the free disability assumption for all undesirable outputs in 19 major economies to assess the energy and CO_2 emissions efficiency [41]. Mardani et al., (2017) also conducted an extensive review which indicated that DEA has shown to be a great evaluation tool for future analysis on energy efficiency issues, indicating that DEA is a common tool for energy and environmental efficiency researches [42].

Traditional DEA models include the CCR model and BBC model that deal with multiple inputs and multiple outputs to calculate efficiency. However, with the consideration of undesirable outputs such as atmospheric pollutants such as CO_2 emission, traditional DEA models do not perform well in increasing desirable outputs while decreasing undesirable outputs at the same time. Thus, Tone (2001) proposed a non-radial, non-angled slacks-based measure (SBM) model, which can improve radial models like the CCR model and BBC model that do not consider the slacks of inputs and outputs [43]. Du et al., (2016) constructed an SBM-DEA model to evaluate the total factor energy efficiency of 29 provincial-administrative regions of China during 1997–2011 and the influential factors [44]. Huang and Wang (2017) studied the total-factor energy efficiency of 276 cities in China during 2000–2012 by using a three-stage SBM model, with consideration of influential factors and undesirable output [45]. Shang et al., (2020) conducted a study using the SBM-DEA model to calculate the total factor energy efficiency including 30 provinces and municipalities of China from 2005 to 2016 [46]. Through previous literature, it is shown that SBM-DEA Model is a commonly used tool for assessing energy efficiency and can bring effective calculations for the energy efficiency assessment of DBA in this paper.

3. Methodological Framework

Various methods can be used to examine the energy efficiency regarding sustainability. One of the most direct ways is to evaluate the economic output in terms of energy input, i.e., GDP/energy consumption. In this study, however, a production possibility frontier theory is chosen as the method to examine energy efficiency. Instead of using only one input and one output to calculate efficiency, a nonparametric approach (DEA) is used, which has the advantage of measuring the relative energy efficiency of DMUs with multiple inputs and outputs. In addition, by application of a DEA method for efficiency analysis, the influences of external factors and stochastic disturbances can be removed.

Charles, Cooper and Rhodes are famous scholars in operation research who have developed a new systematic analysis approach known as Data Envelopment Analysis (DEA). During these years, different elaborations on DEA have been carried out by numerous researchers to tackle different situations and scenarios.

In a DEA model, each decision-making unit (DMU) is assumed to contain inputs $x \in R^n$, $y^g \in R^{S1}$ desirable inputs and $y^b \in R^{S2}$ undesirable outputs. The production possibility sets are thus defined as follows:

$$P = \left\{ \left(x, y^g,\ y^b \right) \quad \middle| x \geq X\lambda,\ y^g \leq Y^g\lambda,\ y^b \geq Y^b\lambda, \lambda \geq 0 \right\} \tag{1}$$

which $\lambda \in R^n$ is the vector of intensity.

Based on the above production possibility set, a classic DEA model, known as a CCR model, can be obtained as follows:

$$
\begin{aligned}
&\theta^* = \min\left[\theta - \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right)\right] \\
&\text{s.t. } \textstyle\sum_{j=1}^{n} X_{ij}\lambda_j + S_i^- = \theta X_{ij}\,, \quad i = 1,2,\cdots,m \\
&\sum_{j=1}^{n} Y_{rj}\lambda_j - S_r^+ = Y_{rj}\,, \quad r = 1,2,\cdots,s \\
&\theta, \lambda, S_i^-, S_r^+ \geq 0\,; \qquad j = 1,2,\cdots,n
\end{aligned}
\tag{2}
$$

where S_i^- is the excess variable and S_r^+ is the insufficient variable respectively, making effective frontiers to expand horizontally or vertically to form the envelope. The variable θ represents the efficiency of the DMU.

Besides CCR, BCC model is another classic DEA model and is described as follow:

$$
\begin{aligned}
&\min\theta_0 \\
&\text{s.t. } \sum_{j=1}^{n} \lambda_j x_{rj} \leq \theta_0 x_{i0}, \qquad i = 1,2,\cdots,m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} \leq y_{rj}, \qquad r = 1,2,\cdots,s \\
&\sum_{j=1_j}^{n} = 1\,_j \geq 0, \qquad j = 1,2,\cdots,n
\end{aligned}
\tag{3}
$$

BBC model refers to pure technical efficiency, whereas CCR model refers to both scale efficiency and technical efficiency.

In this research, a three-stage DEA method is proposed to calculate energy consumption efficiency on sustainable development. The idea is to determine the comprehensive energy efficiency in phase 1, then eliminate the influence of stochastic disturbances and external environmental influences in the second stage, so as to enable the real efficiency to be evaluated in the third stage. The three-stage DEA methodology framework for the efficiency in the GBA cities is described in Figure 2.

3.1. The Initial Phase DEA: The Undesirable-SBM Pattern with Original Inputs

In comparison to CCR and BCC models, the undesirable-SBM model deals with input excess and output shortfall, according to Tone (2001) [43]. The formula is written as:

$$
\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{s_{i0}}}{1 + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1} \frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{S_r^b}{y_{r0}^b}\right)}
\tag{4}
$$

$$
\text{s.t.} \begin{cases}
x_0 = X\lambda + S^- \\
y_0^g = Y^g\lambda - S^g \\
y_0^b = Y^b\lambda - S^b \\
\lambda \geq 0,\ S^- \geq 0,\ S^g \geq 0,\ S^b \geq 0
\end{cases}
\tag{5}
$$

From the above definitions, each DMU has m inputs, S_1 desirable outputs and S_2 undesirable outputs. The slacks of inputs, desirable outputs and undesirable outputs are S^-, S^g and S^b respectively. When a DMU is efficient, S^- = 0, S^g = 0 and S^b = 0. If either S^-, S^g and S^b is not equal to 0, then the objective function ρ^* is not 1, $0 \leq \rho^*$ <1, and this DMU is described as inefficient.

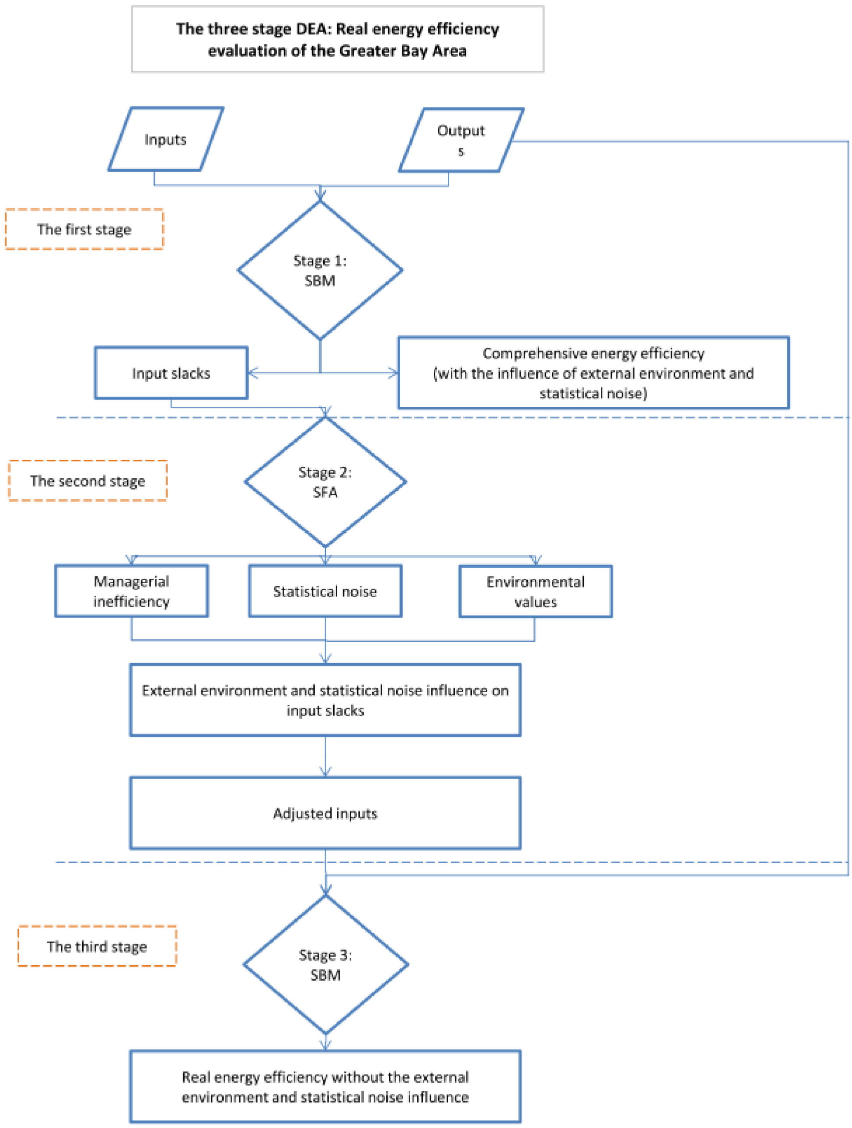

Figure 2. The three-stage DEA's methodological framework.

3.2. The Second Phase: Frontier Analysis with a Random Component

DEA is an ideal way to assess efficiency without having to know the production functions. However, as Fried et al., (2002) suggested, stochastic disturbances, environmental impacts, and managerial efficiency can all affect the efficiency calculated by DEA [47]. In order to deal with this disadvantage and to evaluate the real efficiency of each DMU, a SFA model is established to decompose the slacks in the first stage due to measurement errors in the input and output variables. To describe a SFA model, the environmental variables can be used as explanatory variables and the relaxation values in the first stage as interpreted variables:

$$S_{ni} = f^n(Z_i; \beta^n) + \nu_{ni} + \mu_{ni} \qquad n = 1, 2, \cdots N, \quad i = 1, 2 \cdots I \tag{6}$$

In Equation (4), S_{ni} stands for the relaxation value of the n-th input of the i-th DMU and $f^n(Z_i; \beta^n)$ indicates the impact of the environmental variables on the relaxation value of the input and $Z_i = (z_{1i}, z_{2i}, \cdots z_{ki}), \quad i = 1, 2, \cdots I$, and k are the external environmental variables. β^n is the coefficient of environmental variables. The term $\nu_{ni} + \mu_{ni}$ is the mixed error, in which ν_{ni} is a random error term and $\nu_{ni} \sim N(0, \sigma_\nu^2)$; μ_{ni} is the management efficiency and $\mu_{ni} \sim N^+\left(0, \sigma_\mu^2\right)$. The term ν_{ni} and μ_{ni} are independent and does not relate to each other. When $\gamma = \frac{\sigma^2_{\mu i}}{\sigma^2_{\mu i}+\sigma^2_{vi}}$ is close to 1, it means that the difference in efficiency is affected by the managerial efficiency. However, when $\gamma = \frac{\sigma^2_{\mu i}}{\sigma^2_{\mu i}+\sigma^2_{vi}}$ is near to 0, it suggests that efficiency remains primarily untouched by stochastic disruption.

The mixed error term can be further decomposed as follow [28]:

$$E[\nu_{ik}/\nu_{ik} + \mu_{ik}] = s_{ik} - f_i(z_k; \beta_i) - E[\mu_{ikik} + \mu_{ik}]$$

Then, by applying the Dengyue's approach, $\mathrm{E}[\mu_{ik}|\nu_{ik} + \mu_{ik}]$ can be solved as following [48]:

$$E[\mu_{ik}/\nu_{ik} + \mu_{ik}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\varphi\left(\frac{\varepsilon_k\lambda}{\sigma}\right)}{\varnothing\left(\frac{\varepsilon_k\lambda}{\sigma}\right)} + \frac{\varepsilon_k\lambda}{\sigma}\right]$$

with $\lambda = \frac{\sigma_u}{\sigma_v}$, $\varepsilon_k = \nu_{ik} + \mu_{ik}$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, φ, $\varnothing$ are the standard normal distribution's density and distribution functions respectively.

In order to adjust the input variables for real efficiency calculation under the same external environment, the SFA model is used to identify and exclude the associated environmental variables and stochastic disturbances. The formula for adjusted input variables X^*_{ni} is then described as:

$$\mathrm{X}^*_{ni} = \mathrm{X}_{ni} + \left[\max_i\{\mathrm{Z}_i\beta^n\} - \mathrm{Z}_i\beta^n\right] + \left[\max_i\{\nu_{ni}\} - \nu_{ni}\right] \tag{7}$$

where $n = 1, 2, \cdots N$ $i = 1, 2, \cdots I$; $\mathrm{X}^*_{\mathrm{ni}}$ denotes the adjusted input after the SFA model while X_{ni} indicates the initial input variable of the first phase; $\left[\max_i\{Z_i\beta^n\} - Z_i\beta^n\right]$ describes the external environmental variable adjustment and $\left[\max_i\{\nu_{ni}\} - \nu_{ni}\right]$ represents the adjusted stochastic disturbance value.

3.3. The Third Phase: The Undesirable-SBM Pattern with Adjusted Input Variables

During phase 3, the efficiency is once again evaluated using undesirable-SBM model but replacing the original inputs with the adjusted input variables X^*_{ni} instead. By comparing with the results of the first phase, the impact of stochastic disruption and external environmental variables have been removed as the outcomes of the third phase, indicating a real efficiency of the GBA cities.

4. Variables and Data Sources

The SBM-DEA Model's Input and Output Variables

During the examination of energy efficiency by using the SBM-DEA model, production assumptions are not necessary and multiple input and output variables can be handled at the same time. This is beneficial in cases when examining energy efficiency when details are uncertain. Table 1 shows a selection of input and output variables commonly used in DEA models.

Based on previous studies, the input variables can be justified by the total number of employees, the total investment in fixed assets and total energy consumption in this study.

Regarding output variables, both desirable output and undesirable output are included, especially with the global agenda of low carbon development. Therefore, both the environmental influence and the economic output should be considered. Hence, GDP is chosen as the desired output, while the undesirable output is CO_2 emissions based on Table 1. Table 2 presents the input and output variables that are chosen, while Table 3 demonstrates the relevant statistical descriptions.

Table 1. List of selected input and output variables commonly used in energy efficiency DEA models.

Author	Title	Input	Output
Khalili-Damghani, K., Tavana, M., & Haji-Saami, E. (2015)	A data envelopment analysis model with interval data and undesirable output for combined cycle power plant performance assessment	Fossil fuel	Energy, CO_2, SO_2, SO_3, NO_x
Zha, Y., Zhao, L., & Bian, Y. (2016)	Measuring regional efficiency of energy and carbon dioxide emissions in China: A chance constrained DEA approach	Labor, capital, coal, oil, natural gas	GDP, CO_2
Zhao, L., Zha, Y., Liang, N., & Liang, L. (2016)	Data envelopment analysis for unified efficiency evaluation: an assessment of regional industries in China	Capital input (Investment of fixed assets), labor, energy	Industrial production value, waste gas, wastewater
Chen, L., & Jia, G. (2017)	Environmental efficiency analysis of China's regional industry: a DEA based approach	Total number of employees of industry, total energy consumption, total investment in fixed assets of industry	GDP, total emissions of SO_2, industrial solid waste
Guo, X., Lu, C., Lee, J., & Chiu, Y. (2017)	Applying the dynamic DEA model to evaluate the energy efficiency of OECD countries and China	Land area, population, and energy use, carry-over variable, energy stock	CO_2 emission and GDP
Huang, J., Du, D., & Hao, Yu. (2017)	The driving forces of the change in China's energy intensity: An empirical research using DEA-Malmquist and spatial panel estimations	Energy, capital stock, labor, economic structure and GDP	GDP
Sueyoshi, T., & Yuan, Y. (2017)	Social sustainability measured by intermediate approach for DEA environmental assessment: Chinese regional planning for economic development and pollution prevention	Capital, labor and energy	Gross regional product, CO_2, SO_2, soot (dust), wastewater, COD, ammonia nitrogen
Sueyoshi, T., Yuan, Y., Li, A., & Wang, D. (2017)	Methodological comparison among radial, non-radial and intermediate approaches for DEA environmental assessment	Capital, labor, energy	Gross Regional Product, CO_2, SO_2, Smoke and dust, wastewater, COD, ammonia nitrogen
Zhao, L., Zha, Y., Wei, K., & Liang, L. (2017)	A target-based method for energy savings and carbon emission reduction in China based on environmental data envelopment analysis	Labor, capital stock, total energy consumption	GDP, CO_2
Cayir Ervural, B., Zaim, S., & Delen D. (2018)	A two-stage analytical approach to assess sustainable energy efficiency	Total renewable energy potential, network length, total installed power of renewable energy, transformer capacity	Gross energy generation from renewable sources, number of consumers, total exports, GDP per capita, human development index, total energy production, population, area
Iftikhar, Y., Wang, Z., Zhang, B., & Wang, B. (2018)	Energy and CO_2 emissions efficiency of major economies: A network DEA approach	Labor, capital, energy, population	CO_2 emission, middle income class, high income class, low income class
Khoshroo, A., Izadikhah, M., & Emrouznejad, A. (2018)	Improving energy efficiency considering reduction of CO_2 emission of turnip production: A novel data envelopment analysis model with undesirable output approach	Amount of energy for labor, machinery, diesel fuel, chemical fertilizers, seed and water	Turnip yield, GHG

Table 1. *Cont.*

Author	Title	Input	Output
Nadimi, R., & Tokimatsu, K. (2019)	Evaluation of the energy system through data envelopment analysis: Assessment tool for Paris Agreement	Heat, FEC, oil products, IMR, LEB, MYS, P_NRE, R_NRE, RE, IWA	CO_2, electricity, GDP, GNI per capita, QoL
Piao, S., Li, J., & Ting, C. (2019)	Assessing regional environmental efficiency in China with distinguishing weak and strong disposability of undesirable outputs	Labor (number of employees), water (total domestic and industrial water consumption), energy and capital	GDP, CO_2 (previous research), SO_2, wastewater and waste
Wu, J., Li, M., Zhu, Q., Zhou, Z., & Liang, L. (2019)	Energy and environmental efficiency measurement of China's industrial sectors: A DEA model with non-homogeneous inputs and outputs	Capital, labor, coal, oil, natural gas	Gross industrial output value, volatile hydroxyl-benzene, cyanide, COD, petroleum, ammonia-nitrogen, demand, petroleum, and ammonia-nitrogen
Yang, Z., & Wei, X. (2019)	The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross-efficiency DEA	Productive capital stock	GDP, wastewater, SO_2, smoke and dust, pollutants (comprehensive index)
Zhao, H., Guo, S., & Zhao, H. (2019)	Provincial energy efficiency of China quantified by three-stage data envelopment analysis	Labor force (total amount of employees at year end), capital (total investment on fixed assets), energy consumption (total energy consumption)	GDP divided by amount of SO_2 emission
Zhou, Z., Xu, G., Wang, C., & Wu, J. (2019)	Modeling undesirable outputs with a DEA approach based on an exponential transformation: An application to measure the energy efficiency of Chinese industry	Energy, total asset	Total profit, industrial wastewater, industrial waste gas

Table 2. The choice of input and output variables.

Variable	Definition of Variables	Units
Inputs	Total number of employees	10,000 people
	Total investment in fixed assets	100 million yuan
	Total energy consumption	10,000 tons of coal equivalent
Desirable output	Gross domestic product (GDP)	100 million yuan
Undesirable output	Carbon dioxide (CO_2) emission	million tons

Table 3. The input and output variables, as well as the environmental elements, are statistically described.

Year	Variables	No. of Employees (10,000 ppl)	Investment on Fixed Assets (100 Million Yuan)	Energy Consumption (10,000 Tons of Coal Equivalent)	GDP (100 Million Yuan)	CO_2 Emission (Million Tons)	Secondary Industry GDP to Total GDP	Coal Consumption to Total Energy Consumption	R&D Investment (10,000 Yuan) to GDP	Local Fiscal Expenditure (10,000 Yuan) to GDP	Import and Export to GDP
2010	Average	359.17	1348.83	1641.30	4979.16	30.45	0.39	0.31	0.01	0.11	1.38
	Variance	60,080.56	1,152,070.33	2,032,778.57	23,002,949.16	715.36	0.05	0.06	0.00	0.00	1.13
	Maximum	758.14	3263.57	4775.60	14,928.92	99.32	0.63	0.76	0.03	0.17	3.60
	Minimum	31.48	230.10	98.35	965.12	2.13	0.05	0.00	0.00	0.06	0.23
2011	Average	373.25	1499.22	1716.27	5691.86	32.85	0.38	0.36	0.02	0.11	1.33
	Variance	68,132.36	1,390,138.24	2,205,935.34	28,291,300.48	774.88	0.05	0.07	0.00	0.00	1.13
	Maximum	828.86	3826.45	5013.40	16,257.63	103.90	0.63	0.94	0.04	0.15	3.67
	Minimum	32.76	297.09	98.00	1169.41	2.30	0.04	0.00	0.00	0.06	0.23
2012	Average	383.95	1700.31	1760.43	6223.67	32.67	0.37	0.35	0.02	0.11	1.26
	Variance	75,512.84	1,698,756.09	2,312,417.06	33,425,972.92	697.18	0.05	0.07	0.00	0.00	1.05
	Maximum	898.54	4348.50	5163.45	17,120.16	99.73	0.63	0.88	0.04	0.16	3.61
	Minimum	34.32	380.63	105.03	1279.64	2.34	0.04	0.00	0.00	0.07	0.23
2013	Average	400.43	1892.62	1799.00	6806.96	33.02	0.42	0.36	0.02	0.11	1.23
	Variance	88,584.02	1,900,441.68	2,425,523.24	38,804,566.21	700.95	0.04	0.09	0.00	0.00	1.04
	Maximum	967.14	4454.55	5333.57	17,971.06	100.18	0.62	0.98	0.04	0.15	3.56
	Minimum	36.10	448.20	98.11	1437.04	2.56	0.04	0.00	0.00	0.07	0.22
2014	Average	416.91	2062.03	1791.55	7317.69	30.41	0.42	0.35	0.02	0.12	1.17
	Variance	101,984.85	2,096,958.27	2,452,465.96	44,691,526.73	359.55	0.04	0.08	0.00	0.00	0.92
	Maximum	1034.58	4889.50	5496.46	18,993.87	66.02	0.63	0.83	0.04	0.16	3.49
	Minimum	38.81	678.07	107.66	1580.50	2.71	0.05	0.00	0.00	0.07	0.23
2015	Average	431.51	2299.13	1887.08	7758.39	29.70	0.41	0.31	0.02	0.15	1.11
	Variance	114,433.11	2,394,742.57	2,722,659.31	52,982,707.12	325.65	0.03	0.06	0.00	0.00	0.75
	Maximum	1100.80	5405.95	5688.89	20,155.98	67.33	0.62	0.74	0.04	0.22	3.19
	Minimum	39.65	726.85	117.57	1691.85	2.90	0.07	0.00	0.00	0.09	0.27
2016	Average	446.18	2496.35	1891.41	8378.46	30.22	0.40	0.31	0.02	0.14	0.97
	Variance	128,117.70	2,761,952.37	2,839,642.31	60,900,156.05	312.08	0.03	0.06	0.00	0.00	0.68
	Maximum	1165.73	5703.59	5852.60	20,930.51	65.55	0.61	0.68	0.04	0.23	3.05
	Minimum	38.97	640.43	121.83	1810.67	3.11	0.07	0.00	0.00	0.08	0.23

Note: No. of employees, investment in fixed assets and energy consumption are input variables; GDP and CO_2 emissions are output variables; the ratio of secondary industry GDP to total GDP, the ratio of coal consumption to total energy consumption, the ratio of R&D investment to GDP, the ratio of local fiscal expenditure to GDP and the ratio of import and export to GDP are environmental factors.

For differentiation, if the chosen input and output variables are appropriate, the Spearman's Rank correlation coefficients are calculated to demonstrate the strength of the link between inputs and outputs. The relevant outcomes in Table 4 show that the coefficients between input and output variables possess a positive correlation with significant values of 1% and 5%. Thus, the input and output variables have been chosen appropriately.

Table 4. Between input and output variables, the Spearman's rank correlation coefficients.

Inputs / Outputs	Labor	Capital	Energy
GDP	0.782 *** (0.004)	0.827 *** (0.0001)	0.627 ** (0.04)
CO_2 emission	0.873 *** (0.0004)	0.927 *** (0.00004)	0.709 *** (0.01)

Note: The significance level of *** and ** are 1% and 5% respectively. The relevant *p*-value is indicated by numbers in brackets.

External environmental variables do also exert influence on efficiency as mentioned by Liu et al. [49]. In terms of selecting these environmental variables, based on existing literatures, five major factors are analyzed in this research, which include industrial structure, energy structure, technology, government intervention and openness of economy [44,50,51]. In the SFA regression, Table 5 lists the factors chosen as explanatory variables.

Table 5. The selection of external environmental variables.

Factors	Explanatory Variables
Industrial structure IS	Ratio of secondary industry GDP to total GDP
Energy structure ES	Ratio of coal consumption to the total energy consumption
Technology T	Ratio of R&D investment to total GDP
Government intervention GI	Ratio of local fiscal expenditure to total GDP
Openness of economy OE	Ratio of import and export to total GDP

Secondary industries are known to be more energy intensive industries than tertiary industries. Thus, the industrial composition of a city exerts huge difference in energy demand and its energy efficiency. Besides, the types of energy resources used also affect the performance of outputs too. Coal is known to be an inexpensive but unclean source of energy. CO_2 emission is one of the environmental concerns when coal is being combusted tremendously during development. Thus, advancement in technology is necessary to clean up air pollution or even to utilize clean energy as a replacement. In this regard, the government can intervene with fiscal incentives to incur research and development in technology. Besides, the frequency of import and export often remarks the openness of an economy, hopefully with more technology transfer of goods and services taking place at the same time.

The data used in this research is mainly comprised of variables of 11 cities, including 9 Guangdong cities (Guangzhou, Shenzhen, Foshan, Zhuhai, Dongguan, Huizhou, Zhongshan, Jiangmen and Zhaoqing), and 2 special administrative regions, namely the Hong Kong Special Administrative Region (Hong Kong SAR) and Macao Special Administrative Region (Macao SAR) from 2010 to 2016. In most of the previous literatures on sustainable development of the cities of China, data of HK SAR and Macao SAR are often excluded due to statistical caliber. Therefore, in order to fulfill the consistency of input and output variables as well as for all cities in GBA, all data were derived from the official Statistical Yearbook of each Guangdong municipality, the Census and Statistics Department of the Hong Kong SAR and the Statistics and Census Service of the Macao SAR from 2010 to 2016. Since there is no official CO_2 emission data of the GBA cities available, relevant CO_2 data from 2010 to 2016 was directly obtained from research by Zhou et al. [52]. According to the study of Zhou et al., (2018), the total CO_2 emissions is calculated based on territorial emission accounting approach of the Intergovernmental Panel on Climate Change (IPCC), with inventories consisting of 17 kinds of fossil fuels, 47 socio-economic sectors and 7 industrial processes.

5. Results and Discussion

5.1. Results

5.1.1. The First Phase Undesirable-SBM Model: The Comprehensive Efficiency Calculation Results

During the first stage, with consideration of the undesirable output CO_2 emission, the undesirable-SBM pattern stated in article 3.1 was chosen to calculate the comprehensive efficiency of the 11 GBA cities from 2010–2016. The calculation was done with MaxDEA (Beijing Realword Software Company Ltd, Beijing, China) and the outcomes were displayed in Table 6.

Table 6. Comprehensive efficiencies of the GBA cities from 2010 to 2016.

Cities	2010	2011	2012	2013	2014	2015	2016	Average
Guangzhou	0.393	0.438	0.478	0.439	0.425	0.405	0.396	0.425
Shenzhen	1	1	1	1	1	1	1	1
Zhuhai	0.307	0.302	0.309	0.300	0.348	0.333	0.294	0.313
Foshan	0.374	0.371	0.378	0.348	0.359	0.373	0.354	0.365
Jiangmen	0.194	0.207	0.228	0.228	0.288	0.269	0.223	0.234
Zhaoqing	0.265	0.264	0.269	0.259	0.315	0.300	0.276	0.278
Huizhao	0.150	0.159	0.168	0.168	0.204	0.206	0.194	0.178
Dongguan	0.318	0.356	0.359	0.322	0.376	0.452	0.422	0.372
Zhongshan	0.203	0.215	0.231	0.243	0.344	0.328	0.315	0.269
Hong Kong SAR	1	1	1	1	1	1	1	1
Macao SAR	1	1	1	1	1	1	1	1
Average	0.473	0.483	0.493	0.482	0.514	0.515	0.498	0.494

5.1.2. The Second Phase: The Analysis of Influence of External Environmental Factors on Efficiency

During phase 2, the stochastic frontier analysis (SFA) approach is applied to analyze the influence of exterior environmental elements on the relaxation variables of inputs, namely the relaxations of the total number of employees, the slacks of total investment of fixed assets and the slacks of the total energy consumption. External environmental variables are elements that will affect energy efficiency, but not in a direct and controllable way. Five factors include the ratio of secondary industry GDP to total GDP, the ratio of coal consumption to the total energy consumption, the ratio of R&D investment to total GDP, the ratio of local fiscal expenditure to total GDP and the ratio of import and export to total GDP. The explanatory factors are these external environmental variables, while the slack inputs are considered as explained variables. Frontier 4.1 software is being used to create the SFA model. Table 7 shows the empirical findings.

After conducting the second stage SFA regression model, the input data in the first stage is adjusted with the coefficient values as shown in Table 7. With this adjustment, the effects from stochastic disturbances and external environmental elements can be eliminated. Adjusted input and original output variables can be run by the undesirable SBM-model once again to obtain the real energy efficiencies. The adjusted results of energy efficiency are compared with that of the original shown in Figure 3.

Table 7. SFA model parameters and estimation results in the second stage.

Explanatory Variable	Slacks: Number of Employees	Slacks: Investment in Fixed Assets	Slacks: Energy Consumption
Constant term	6.66 (42.56) ***	6.78 (3.72) ***	9.09 (24.11) ***
The ratio of secondary industry GDP to total GDP	−0.07 (−0.90)	1.97 (2.99) ***	0.23 (1.48)
The ratio of coal consumption to total energy consumption	−0.02 (−0.46)	−0.25 (−0.73)	0.05 (0.66)
The ratio of R&D investment to GDP	0.09 (2.24) **	0.25 (0.64)	0.15 (1.70) *
The ratio of local fiscal expenditure to GDP	−0.04 (−0.69)	−1.12 (−1.66) *	−0.07 (−0.54)
Import and export to GDP	−0.20 (−3.26) ***	−1.52 (−3.39) ***	−0.30 (−2.22) **
sigma-squared	12.08 (2.34) **	6.25 (2.12) **	18.32 (3.07) ***
gamma	0.99 (11414.37) ***	0.93 (26.08) ***	0.99 (4651.11) ***
LR test of the one-sided error	411.04 *	102.42 ***	359.24 ***

Note: The significance level of ***, ** and * are 1%, 5% and 10% respectively. The matching *t*-statistics of the computed parameters are indicated by numbers in brackets 5.1.3. The third phase: the real energy efficiency calculation results.

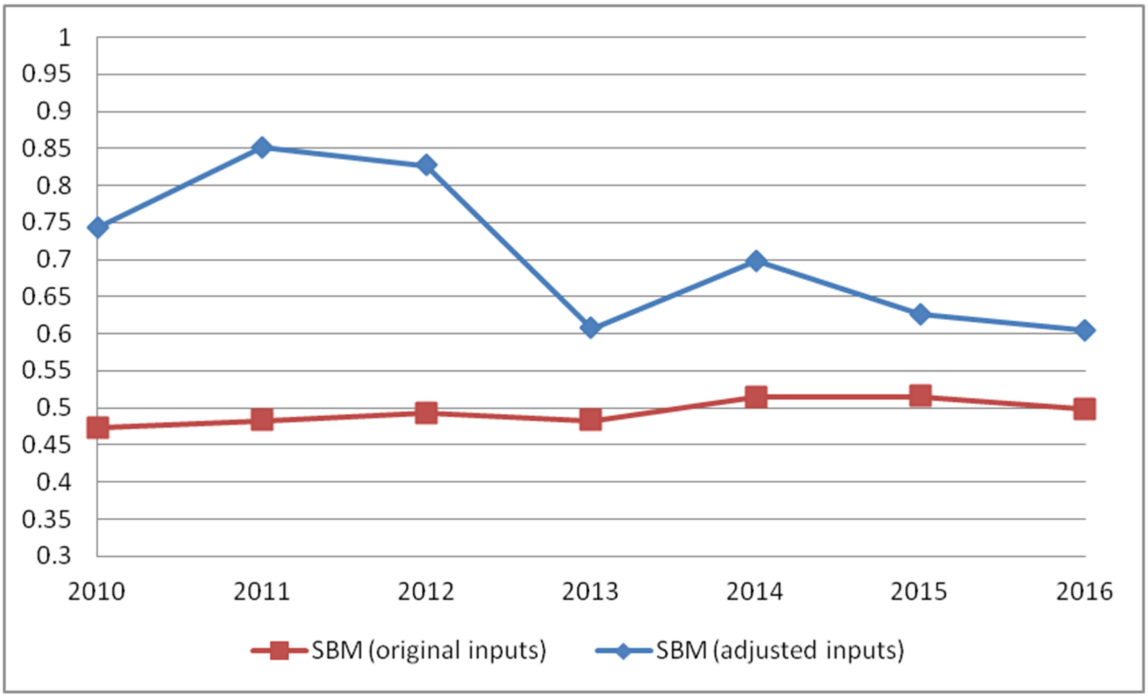

Figure 3. In the period 2010–2016, the average energy efficiency of the GBA cities' first stage (original inputs) and third stage (adjusted inputs) was compared.

5.2. Discussion

As seen in Table 5, Shenzhen, Macao SAR and Hong Kong SAR are operating at the efficient frontier from 2010–2016, with energy efficiencies equal to 1. This implies that Shenzhen, Macao SAR and Hong Kong SAR are efficient in terms of energy consumption. However, other cities such as Guangzhou, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhao, Dongguan, and Zhongshan, their efficiencies are all below the average value of 0.494

from 2010–2016. Among inefficient cities, only Guangzhou and Dongguan are close to the average value, but still, the tendency of comprehensive efficiencies is not promising and have not been increasing obviously from 2010–2016. On the contrary, the comprehensive efficiencies of Shenzhen, Hong Kong SAR and Macao SAR demonstrate better performance in efficiencies and these cities have similar economic activities, industrial structure, technology and market openness.

According to previous literature demonstrating that there is a clear one-way Granger causality between sustainable economic development and energy consumption, the energy efficiency of the eight cities Guangzhou, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan and Zhongshan has been below the average from 2010–2016, and as the cities develop year by year, the low energy efficiency will have an impact on future sustainable economic development, and an efficient and green Energy consumption policy is an important issue at this stage to ensure sustainable development in the future.

From the SFA results, certain evaluated coefficients listed in Table 6 are significant at the 1%, 5%, and 10% significance levels respectively, indicating that certain external environmental conditions do have an impact on the GBA cities' energy efficiency. Besides, the correlation coefficients calculated in the SFA regression also represent the relationship between input relaxations and external environmental conditions.

For the GDP of secondary industries as a percentage of overall GDP, it shows a positive and 1% significant correlation with the slack of investment in fixed assets. An increase in the ratio of secondary industry GDP to the total GDP will increase the slack of the investment in fixed assets, which in turn bringing unfavorable impacts on energy efficiencies. Secondary industry is known to be an energy intensive industrial category and an adjustment policy in industrial structure to less energy intensive industry may have a positive effect on energy efficiencies of the GBA cities.

Coal combustion in energy generation is the known source of CO_2 emission. Thus, in Table 6, it shows that when the ratio of coal depletion to overall energy consumption rises, the slacks of energy consumption rise as well. However, the result is not significant.

R&D investment as a percentage of GDP shows positive and significant correlation coefficients with the slacks of number of employees and energy consumption. This finding is not similar to Zhao et al. [53], as investment of R&D usually encourages technology improvement and innovation that can contribute to efficiency in production process, causing a decrease in labor and investment demand, as well as more energy saving technologies. However, Liu (2020) mentioned that technological progress affects negatively on energy efficiency in her research [54]. One of the possible reasons maybe due to rebound effect, indicating that an increase in energy efficiency triggered by technology advancement is being offset by the increase in energy consumption demand.

The ratio of local fiscal expenditure to total GDP is negatively but not significantly correlated with the input slacks. An increase in government involvement in economic activities may be interpreted as incentives or drivers in energy efficiency improvement such as energy savings technology or implementation of relevant efficiency policies. The significant relationship between the ratio of local fiscal expenditure to GDP and investment in fixed assets signals the government's part in driving energy efficiency performance.

For the empirical study, the intensity of import and export activities shows a negative relationship with all the three input variables. Any increase in import and export as a percentage of GDP will decrease the slacks of inputs. Among all other environmental factors, import and export as a percentage of GDP appears to be the only factor that is significant to all the input variables of the GBA cities. It is worthwhile to note that the average import and export to GDP value of the GBA cities has been declining from 1.38 in 2010 to 0.97 in 2016 and the average energy efficiency has also dropped since 2010.

The average energy efficiency of the third stage during 2010–2016 has increased from 0.494 to 0.708, compared with the first phase. This explains that the overall energy efficiencies may have been underestimated in the first stage and are affected by the external environmental factors and stochastic disturbances. During phase 3 calculation, the average energy efficiencies of the GBA cities range between 0.604 and 0.851 throughout the study period from 2010–2016. From the first phase calculation shown in Figure 4, the values of energy efficiencies have increased but the average energy efficiency of the GBA cities does not improve during the period 2010–2016. In fact, the average energy efficiency had reached a peak of 0.85 in 2011 and since then, it started to drop to 0.605 in 2016. By eliminating the external environmental factors and stochastic disturbances after the third stage, a decrease in energy efficiency implies a real decline in managerial efficiency of the GBA cities since 2011.

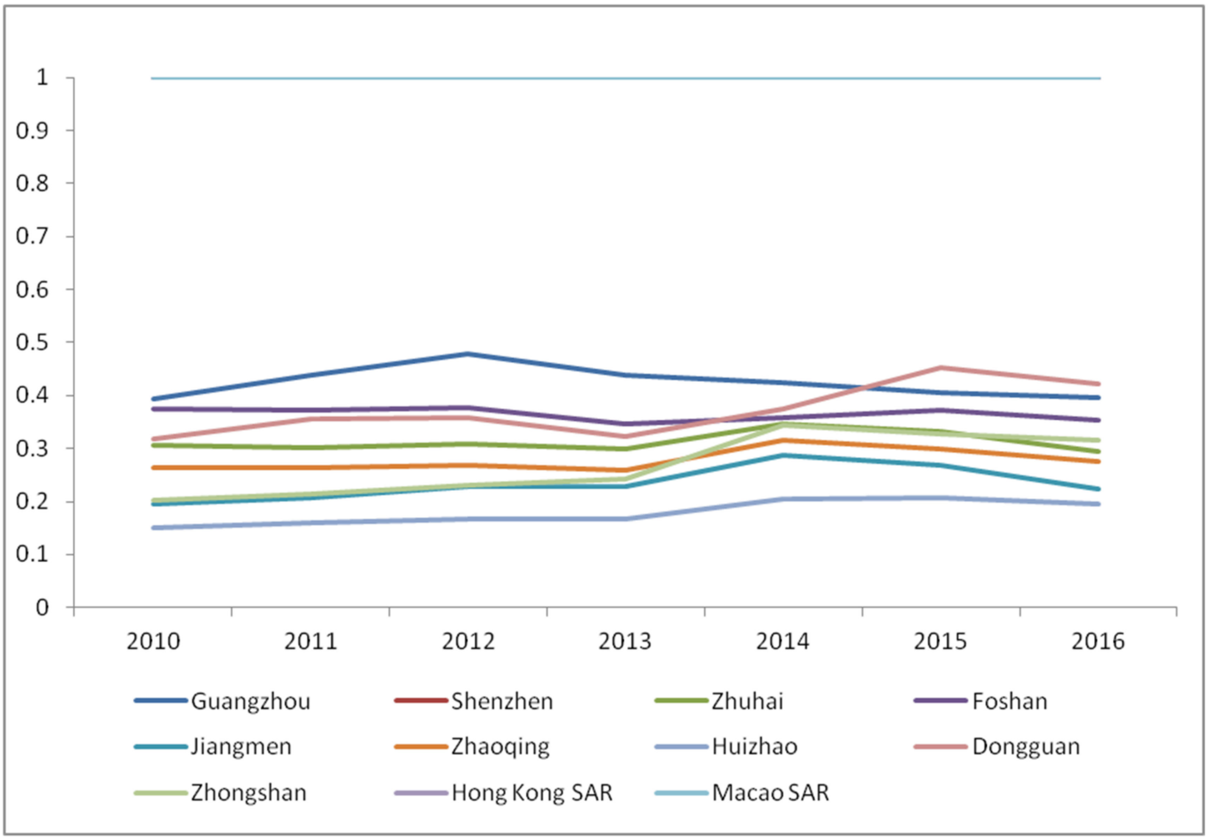

Figure 4. Energy efficiencies of the GBA cities in 2010–2016 (the first stage).

From Figure 5, it is shown that Shenzhen, Hong Kong SAR and Macao SAR are energy efficient cities, with an energy efficiency value of 1. When stochastic disturbances and external environmental elements are excluded after the SFA regression, the number of energy efficient cities varied from 4 to 7 in the studied years, including Shenzhen, Zhuhai, Zhaoqing, Zhongshan, Dongguan, Macao SAR and Hong Kong SAR. However, the number of cities with an average energy efficiency of 1 both in the first and the third stage of the SBM-DEA throughout 2010–2016 remain only 3, namely Shenzhen, Hong Kong SAR and Macao SAR.

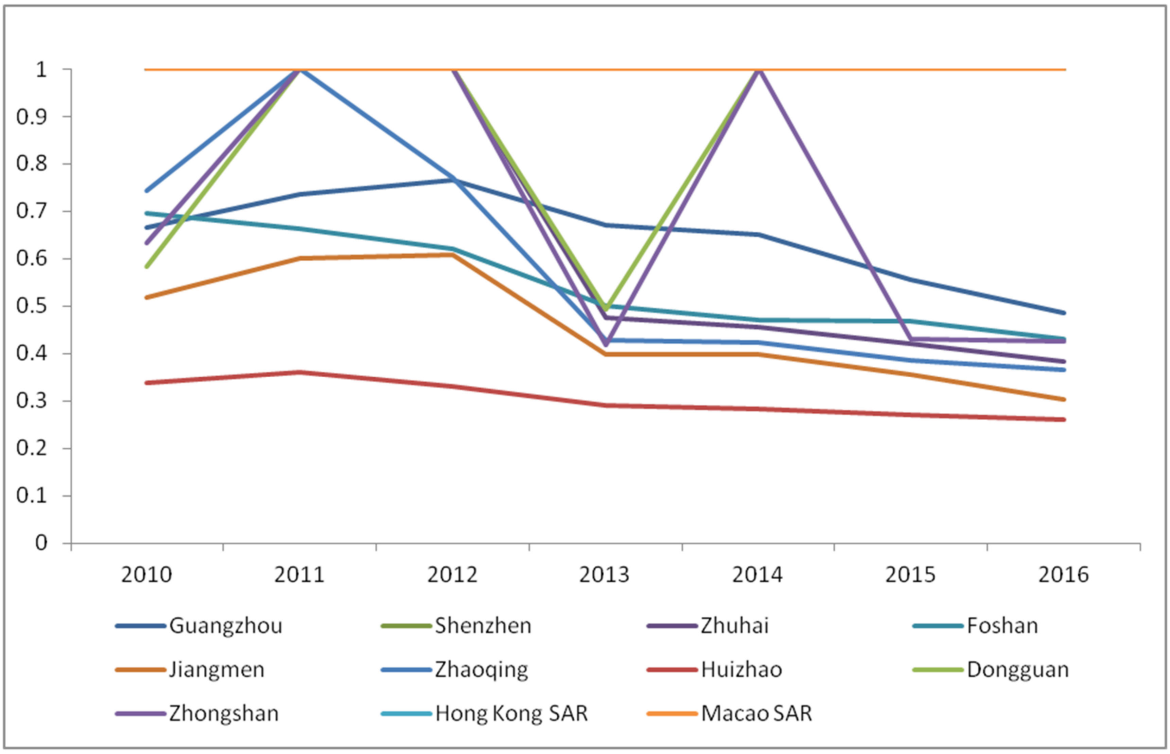

Figure 5. Energy efficiencies of the GBA cities in 2010–2016 (the third stage).

6. Conclusions and Policy Recommendations

6.1. Conclusions

The following conclusion can be obtained using a three-stage SBM-DEA model to determine energy efficiencies and investigate the influential elements of the GBA cities:

(1) Among the 11 GBA cities, only Shenzhen, Hong Kong SAR and Macao SAR have an energy efficiency of 1 from 2010–2016, both in the initial phase as well as in the third phase. This means that all these three cities operated at the efficient frontier during the study period. Other cities such as Guangzhou, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhao, Dongguan, and Zhongshan, their energy efficiencies were all below the average value of 0.494 (the first stage) from 2010–2016;

(2) By eliminating the external environmental factors and stochastic disturbances by the stochastic frontier analysis during phase 2, the GBA cities' average energy efficiency during 2010–2016 has increased from 0.494 to 0.708 during phase 3 SBM-DEA model. This explains that energy efficiency has been underestimated at the first stage. Besides, Shenzhen, Hong Kong SAR and Macao SAR, Dongguan was the other GBA city that had an average energy efficiency of 0.87, which is above the average of all GBA cities. At the same time, a decreasing trend of energy efficiency after the third phase SBM-DEA pattern since 2010 had been observed. This implies a real decline in managerial energy efficiency of the GBA cities since 2010;

(3) Through the second stage stochastic frontier analysis, the influence of external environmental factors is investigated and among all, the ratio of import and export to GDP shows a negative and significant relationship to all three input variables, meaning an increase in the ratio will cause a decline in the input slacks, which favors energy efficiency.

6.2. Policy Recommendations

Based on the empirical analysis and conclusion, several policy recommendations are proposed for energy efficiency and sustainable growth:

(1) Acceleration of economic structure transformation. Instead of achieving the sole target of GDP growth, more emphasis should be made on environmental protection such as increasing the ratio of clean fuels and minimizing the emission of atmospheric pollutants such as CO_2 emission, especially under the agenda of sustainable development.
(2) Financial support from the government. Government intervention is always an important driver in encouraging energy-efficient and low-carbon production, especially during the initial stage in fixed assets investment. Government can also promote public awareness and enforce tougher environmental protection standards.
(3) Promotion of imports and exports. When products are less energy-intensive and environmentally friendly, an increase in imports and exports will not only facilitate a higher GDP, but also indirectly boost technological innovation and living standards.

This study, however, has a few limitations. First, this is the first research of this kind with the Guangdong-Hong Kong-Macao Bay Area cities as the DMUs and using the SBM-DEA model for energy efficiency evaluation, as far as we know. Thus, it is recommended that other DEA methods should be studied to examine the energy efficiency for comparison of results. Second, the structure of statistical data of mainland China and that of HKSAR and Macao SAR are quite different and may cause uncertainties in results. Further development of a homogeneous GBA statistical data collection system would be helpful to minimize the associated uncertainties. Last, different GBA cities exhibit different energy efficiency performances and are affected by different influential factors. Investigation on other social or economic influential factors for a wider aspect of policy formulation would be helpful.

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