

## Article

# An Analysis of Energy Use Efficiency in China by Applying Stochastic Frontier Panel Data Models

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**Abstract:** This paper investigates energy use efficiency at the province level in China using the stochastic frontier panel data model approach. The stochastic frontier model is a parametric model which allows for the modeling of the relationship between energy use and its determinants using different control variables. The main control variables in this paper are energy policy and environmental and regulatory variables. This paper uses province level data from all provinces in China for the period 2010–2017. Three different models are estimated accounting for the panel nature of the data; province-specific heterogeneity and province-specific energy inefficiency effects are separated. The models differ because of their underlying assumptions, but they also complement each other. The paper also explains the degree of inefficiency in energy use by its possible determinants, including those related to the public energy policy and environmental regulations. This research supplements existing research from the perspective of energy policy and regional heterogeneity. The paper identifies potential areas for improving energy efficiency in the western and northeastern regions of China. Its findings provide new empirical evidence for estimating and evaluating China's energy efficiency and a transition to cleaner energy sources and production.

**Keywords:** energy efficiency; time-variant efficiency; true fixed-effects model; four components stochastic frontier model; determinants of inefficiency; Chinese provinces

## 1. Introduction

After the 2008 economic crisis, the situation in the world stabilized in 2010. According to the yearly China Economic Report [1], China's annual GDP increased from 6.066 trillion US dollars in 2010 to 8.271 trillion US dollars in 2017, with a total growth rate of 36.35 percent showing the highest growth among the top 15 large global economies. But the China Energy Statistics Yearbook 2018 [2] shows that the GDP growth rate gradually decreased from 10.7 percent in 2010 to 6.9 percent in 2017. In 2017, the global primary energy consumption was 13.5 billion tons of oil equivalent. The annual consumption growth rate in 2010–2017 was 1.4 percent. The economic growth rate slowed down in China.

According to the BP World Energy Statistics Yearbook [3] during 2010–2017, the gap between China's energy demand and energy supply increased over time. As China continues to promote urbanization and industrialization and gradually upgrades its consumer energy consumption structure, inequalities between China's energy supply and energy demand will remain severe until 2020. This gap will play an increasingly important role in energy security. In the face of rigid growth in energy demand, China's energy supply is expected to face severe challenges with increased supply pressures.

The BP Energy Outlook [4] predicts a radical energy transition. The ongoing transition to a lower-carbon fuel mix is led by renewables and natural gas which account for 85 percent of the growth

in energy and are gaining in importance relative to traditional primary sources of oil and coal. It is forecast that the consumption of liquid fuels will grow over the next decade, but it will plateau as efficiency improvements in the transport sector are realized. A reduced use of the abundant global oil resources is likely to lead to a more competitive market and lower oil prices that will boost oil demand. The use of natural gas has grown dramatically and this growth is driven by its use in industry and power generation. Europe and China are two of the largest importers of gas. The growth in renewable energy is faster than that in oil and dominated by the developing world with China, India, and other Asian countries accounting for almost half the growth in global renewables. China and India drive global economic growth and together with other developing countries account for over 80 percent of the expansion in world output. Improvements in living standards in developing countries lead to an increase in energy demand.

The BP Energy Outlook [4] further suggests that the pattern of energy used within industry is expected to shift as a result of China's changing economic role. The process leading to the growth in energy used in industry will shift from China to other developing countries. By 2040, renewables are expected to overtake coal as the largest source of power generation. Global coal demand flatlines, with the fall in China and the OECD, but will be offset by gains in India and other emerging Asian countries; however, the growth in coal consumption will still slow down. By the mid-2020s, India will be the world's largest economic growth market. China and India both started with relatively coal-intensive fuel mixes. In a scenario of energy transition, China's coal share will fall from 60 percent in 2017 to around 35 percent in 2040 and will be offset by increasing shares of renewables, natural gas, and nuclear energy to match the growth in Chinese energy demand over the Energy Outlook's period, which is 2017–2040.

Two transition scenarios are predicted—evolving and rapid transition. According to the evolving transition scenario, the energy consumption for 1995, 2017, and 2040 is estimated at 891, 3132 and 4017 Mtoe (million tons of oil equivalent). The transition (from 1995 to 2017 and from 2017 to 2040) will lead to changes in consumption estimated at 2241 and 885 Mtoe. This corresponds to a 252 and 28 percent change which, on an annual basis, is 5.9 and 1.1 percent, respectively. In a rapid transition scenario, the estimated energy consumption is 891, 3132, and 3700 Mtoe. The changes are estimated to reach 2241 and 568 Mtoe with 252 and 18 percent total changes or 5.9 and 0.7 percent changes annually (BP Energy Outlook [4] pp. 135–137).

China's energy consumption per unit of GDP is twice that of the world average and four times that of developed countries. In recent decades, industrialized countries have invested in and developed energy saving and alternative energy technologies. It is difficult to meet the fast-growing energy demand simply by increasing energy supply. Saving energy and improving energy efficiency are extremely important and effective ways for China to meet its energy related challenges and the challenges of climate change. In such a situation one can ask, what is the status of energy efficiency in China specifically at the province level?

The Chinese government's interventions in energy use and energy efficiency mainly include government investments in the energy industry and the enforcement of energy policies targeting the energy industry. However, from the perspective of energy utilization and environmental protection, government interventions should also consider such incentives as encouraging and punishing different energy consumption industries. These include various programs such as tax incentives and subsidies for the introduction of environmentally friendly energy-saving products.

In 2013, the State Council of China issued the 'Action Plan for Air Pollution Prevention and Control' called 'Atmosphere Ten' which clearly states that the overall improvement in air quality in the country in five years led to a reduction in heavy air pollution in Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta of 15–25 percent. In 2017, the government's work report proposed to win the 'blue sky defense war' and speed up the resolution on coal-fired air pollution. As a relatively efficient and clean energy source, natural gas is favored by the government and the market. The policy of 'coal to gas' is an important substitution measure for improving air quality and it has been widely

promoted in the past. This requires Beijing, Tianjin, Hebei, Shanxi, Shandong, and Henan provinces and other cities to complete 3.55 million units of ‘coal to gas’ and ‘coal to electricity’ transformations in energy technology.

However, due to China’s large regional heterogeneity as compared to other countries, the feedback on energy efficiency policies in its regions is different. Therefore, energy market reforms conducive with environmental policy must be actively promoted, and, in parallel, reduce government interventions in the energy market. Regional heterogeneity in energy consumption is evident in the demand for energy and its impact on economic growth. Giving full flexibility to the endowment of energy factors improving energy efficiency can effectively promote economic development. Given these conditions it will be interesting to know whether China’s energy efficiency has improved with technological innovations, and what kind of typical regional heterogeneity exists in China’s energy efficiency.

Based on existing research, the methods for measuring efficiency mainly include the data envelopment analysis (DEA) and the stochastic frontier analysis (SFA). The former does not need to estimate the specific production function form, thus avoiding the problems caused by the choice of a wrong functional form. DEA uses information on inputs and outputs, but it does not describe the production process fully. Conversely, SFA describes individual producers’ production processes by estimating the production function, thus controlling efficiency estimates. In addition to inputs and outputs, SFA also uses production and market environmental factors. Thus, this approach assumes a functional form.

At present, most scholars adopt the DEA method for efficiency analyses, while the SFA method is less frequently used. Only a few scholars have used it for empirical research related to energy use efficiency. The simple Cobb-Douglas production function is also a commonly used functional form for describing a regional economy. Considering the heterogeneity of China’s economic regions, it is appropriate to use the SFA approach for measuring regional energy efficiency. Unlike DEA, SFA is a parametric method which allows for modeling the relation between energy use and its determinants and in addition to the inputs and outputs that one can control for firm, industry, province, and other environmental and policy characteristics. Further, the importance of extra information can be tested statistically.

Literature and evidence on inefficiencies and differences in regional level energy use in China is vast. By analyzing panel data for 30 provinces in 2005–2014 using the DEA efficiency model to measure total factor energy efficiency in China, [5] showed that total factor energy efficiency was high in the East and low in the West of the country. The eastern region had higher total factor energy efficiency and characteristics of lack of energy resources. However, the western region had the characteristics of lower total factor energy efficiency while it was rich in energy resources. The allocation of production elements of ‘more input and less output’ also existed in the central region, leading to an enormous waste of energy resources in these areas.

Ref [6] points out that the government should and can solve the problems and inefficiencies of energy allocation in the market and enforce these using mandatory energy policies. By studying the relationship between government interventions, natural resources, and economic growth, [7] found that appropriate government interventions can reduce the negative impact of pollution of natural resources on economic growth. One can ask, what are the energy policies that China has adopted for improving energy efficiency during the development process?

It is evident that production in China is very energy intensive. Energy sources are mainly fossil fuel based with extremely negative health, environmental, and climate effects. This paper evaluates energy use efficiency as a tool for reducing energy consumption and air emissions. This research does a panel data analysis of energy use efficiency in China at the province level. The method is at the forefront of research and allows for accounting province heterogeneity and temporal changes in energy use efficiency, making the results informative and useful.

In analyzing energy use efficiency, this paper uses three different models—[8], the true fixed-effects model [9,10], and four components of the stochastic frontier model. The stochastic frontier panel

model approach is parametric and allows for modeling the relationship between energy use and its determinants conditioned on different control variables. The main control variables are energy policy, and environmental and regulatory variables. The data is from the province level and covers all provinces in China (except Tibet due to lack of data availability) observed over the period 2010–2017. Three different models are estimated accounting for the panel nature of the data; province-specific heterogeneity and province-specific energy use inefficiency effects are separated. The models differ because of their underlying assumptions but also complement each other considering the directions that literature has developed in, namely assumptions about the distribution of inefficiency effects, estimation methods, and time-variance of inefficiency and its separation from province heterogeneity. The degree of inefficiency in the use of energy is also explained by its possible determinants including those related to public energy policy and environmental regulations. This research supplements existing research from the perspective of energy policy and regional heterogeneity. It shows that there is enormous potential for improving energy efficiency in the western and northeastern regions of China. These findings provide new empirical evidence for estimating and evaluating China's energy use efficiency and transition to cleaner energy sources.

The rest of the paper is organized as follows. After this brief introduction, Section 2 presents a literature review on energy efficiency. The evolution of methods for estimating energy efficiency and the approaches used are also discussed in this section. Section 3 outlines the methodologies of the three different models used. Section 4 describes the data and the specifications of the empirical model. Section 5 discusses the results both by comparing the models and by distinguishing between regional heterogeneity in China. Section 6 gives the conclusion and implications of the findings of the study.

## 2. Literature Review

This section is divided into two sub-sections elaborating on the significance, concept, meaning, and evolution of the methods of measuring and estimating energy efficiency.

### 2.1. Significance and Concepts of Energy Efficiency

Energy experts and research scholars in China and elsewhere have reached a general consensus about the important role that energy plays in an economy and in society. It is believed that improvements in energy efficiency can significantly reduce energy consumption and environmental pollution and help in gradually achieving sustained and steady economic growth. In 1995, the World Energy Commission defined energy efficiency as reducing energy inputs to provide equal energy services interpreted as producing the same amount of goods and services. However, this definition is broad and does not accurately define the concept of energy efficiency.

Ref [11] defines energy efficiency on the basis of its traditional meaning, that is, the production of the same amount of services or desirable outputs but with less energy inputs and undesirable outputs. [12] define and separate energy efficiency through economic and technical perspectives. By summarizing and analyzing existing energy efficiency measurement indicators, [13] divide energy efficiency into a number of categories—energy macro efficiency, energy physical efficiency, energy factor utilization efficiency, energy element allocation efficiency, energy value efficiency, and energy economic efficiency. Similarly, [14] point out that energy efficiency means producing the same amount of effective outputs or services with less energy. They believe that the key to defining energy efficiency is scientifically identifying effective outputs and inputs.

Based on different research fields, energy efficiency uses various quantitative indicators. Based on an analysis of the theoretical framework, energy efficiency in this paper is defined as the overall efficacy of energy economic efficiency and energy environmental efficiency.

### 2.2. Evolution of Methods for Estimating Energy Efficiency

Looking at relevant literature on energy use efficiency, we see that the research methods used for analyzing energy use efficiency are mainly divided into two types: 'single factor efficiency' without

considering other factors and ‘all-factor energy efficiency’ with multiple inputs and multiple outputs. The former’s results only consider the proportional relationship between energy input and production output, while the latter adds the results of all other input factors including energy in the calculation.

Because the method of measuring single factor energy efficiency is simple and intuitive and it has strong operability, it has been favored by many scholars both in China and elsewhere, and it has been the main method for studying energy efficiency problems over time. However, with the continuous progress in research in the area of energy efficiency, the traditional single factor energy efficiency measurement method has been questioned and replaced with multi-factors energy efficiency measurement methods.

Ref [15] evaluated various indicators of traditional energy efficiency and maintained that traditional indicators did not describe the essence of ‘energy efficiency’ because they have many defects. Using a single-factor approach and three full-factor methods, [16] compared the energy efficiency of various regions in China based on data for 2005. They found that the total factor approach was promising, as it revealed the impact of a regional factor endowment structure on energy efficiency.

Because of the shortcomings and limitations of single factor efficiency research, scholars started investigating more systematic and scientific methods for evaluating and studying energy efficiency. [17] proposed the concept of total factor energy efficiency based on the total factor productivity framework and measured the total factor energy efficiency of 29 provinces in China. Their results showed that total factor energy efficiency was a more realistic measure of energy use efficiency. The approach used in this research differs from the single factor efficiency approach, by conditioning the model on other factors such as GDP, exports, education investments, R&D investments, environmental protection, population, and urbanization, all of which influence energy use. Thus, the derived demand for energy is conditional on other factors accounting for the multiple factor nature of energy use.

Researchers agree that two papers by [18] and [19] mark the birth of the stochastic frontier methodology. Subsequently, [20] proposed a new method for effectively dividing the error terms of the production and cost functions into technical inefficiency terms and random error terms and using these for measuring enterprises’ technical efficiency. However, these methods are based on cross-sectional data and cannot be technically efficient for multiple production unit observations. In short, the measure of energy efficiency is time-invariant and restrictive. [21] applied the fixed-effects model and the random-effects model for estimating enterprises’ technical efficiency. However, their model assumed that the technical efficiency of each enterprise was fixed or time-invariant. To make up for this shortcoming, [22] and [8] developed different models for estimating the time-varying technical efficiency of enterprises.

### 3. Methodology

The stochastic frontier (SF) approach for estimating technical efficiency is based on the idea that an economic unit may operate below its production potential or frontier due to low performance, errors, and some uncontrollable factors. A study of the frontier approach started with Farrell [23] who suggested that efficiency could be measured by comparing realized or actual output with the maximum or potential attainable output. Other than comparing output, we can also compare the actual input use with the minimum required input use. The two methods are called output oriented and input oriented approaches. Their aim is maximizing output with available inputs and technology or minimizing costs for given outputs and technology. The former is more adaptable for industry/firm data and the latter for services data. The empirical part of this study is based on three different models— [8], the true fixed-effects model [9,10], and four error components of the SF model with determinants of inefficiency (following [24] and [25]).

Most theoretical stochastic frontier production functions have not explicitly formulated a model for technical inefficiency effects in terms of appropriate determinants. By using panel data, one can remove the limitations of depending on the distributional assumption of noise and inefficiency components and observing each unit at several different points of time. However, the extended dimension in time



adds to the complexity, as it requires the modeler to take into account some heterogeneity effects that may exist beyond what is possible to control using a cross-sectional approach, which lumps individual effects with random errors. This can be achieved by introducing an ‘individual (unobservable) effect,’ say,  $\alpha$ , that is time-invariant but individual-specific. The limitation of such a model is eliminated when using panel data methods.

We can examine whether inefficiency has been persistent over time or whether a unit’s inefficiency is time-varying since we have information about units over time. One component of inefficiency may have been persistent over time while another may have varied over time. Regarding time-invariant individual effects, we also need to consider whether an individual effect represents persistent inefficiency or persistent unobserved heterogeneity, as well as whether individual effects are fixed parameters or are they realizations of a random variable [26]. Thus, it is important that policies promote an efficient use of resources that are scarce, and it can serve as an effective policy tool by separating unobserved heterogeneity and inefficiency components.

This study outlines three panel data models which differ in terms of the underlying assumptions made for the temporal behavior of the inefficiency components. All the models treat inefficiency as being individual-specific. This is consistent with the notion of measuring the efficiency of decision-making units. Model 1 allows for inefficiency to be both individual-specific and time-varying and explains the determinants of inefficiency. Model 2 separates inefficiency effects from unobserved individual non-inefficiency heterogeneity effects. Model 3 separates persistent inefficiency and time-varying inefficiency from unobservable individual heterogeneity effects. Thus, the three models are complementary and jointly provide information on province heterogeneity, province inefficiency, the random error term, and the variations in inefficiency in energy use. The three models are now outlined.

### 3.1. Model 1: The Time-Variant Efficiency Model

Ref [8] considered a production model wherein technical inefficiency effects were modeled in a stochastic frontier function for panel data. In this paper, we specify a factor demand version of the model. The objective is to minimize the use of a factor in the production of a given output, factor price, and technology. This is similar to [27] who analyzed labor use efficiency in the banking industry. Here we use the same approach but in the context of energy use. Separability between energy and other inputs is assumed. The assumption is supported by the fact that we use aggregate output and aggregate individual inputs. A cost function is appropriate for the current case as energy use is cost for producing a given output, which is desirable to be minimized. Provided the inefficiency effects are stochastic, the model permits the estimation of both technical change or a shift in function over time and time-varying technical inefficiencies. The model is estimated using the maximum likelihood method which allows for estimating the effects of inefficiency’s determinants. In this case inefficiency is a function of time.

In Model 1 we use the following generic formulation to discuss the various components in a unifying network:

$$ENE_{it} = f(x_{it}, \beta) + \epsilon_{it}, \quad \epsilon_{it} = v_{it} + u_{it}, \\ u_{it} = G(t)u_i, \quad v_{it} \sim N(0, \sigma_v^2), \quad u_{it} \sim N^+(\mu, \sigma_u^2), \quad G(t) = [1 + \exp(\gamma_1 t + \gamma_2 t^2)]^{-1}$$

where  $ENE$  is energy use and  $G(t) > 0$  is a function of time ( $t$ ); in this model, inefficiency ( $u_{it}$ ) is not fixed for a given individual, instead it both changes over time and across individuals. Inefficiency is composed of two distinct components: the nonstochastic time component,  $G(t)$  and a stochastic individual component,  $u_i$ . The stochastic component,  $u_{it}$ , uses the panel structure of the data in this model. The  $u_i$  component is individual-specific and the  $G(t)$  component is time-varying and is common for all the individuals. We consider some specific forms of  $G(t)$  used in [28] model which assumes  $G(t) > 0$ , given that  $u_i > 0$ , and thus  $u_{it} \geq 0$  is ensured by having a non-negative  $G(t)$ .  $G(t)$  can be monotonically increasing (decreasing) or concave (convex) depending on the signs and magnitude of

$\gamma_1$  and  $\gamma_2$ . Inefficiency changes in this model are time driven and a nonlinear exponential function of time. However, the trend pattern is similar for all individuals; the differences in performance among individuals are due to the  $u_i$  component. The random and nonlinear nature of the model requires iterative estimation by the maximum likelihood (ML) estimation method. Cost efficiency is estimated assuming truncated normal distribution using the product of the individual specific  $u_i$  and the time variant  $G(t)$ . The product of the two is in the interval between 0 and 100 where 100 represents a full cost-efficient unit.

### 3.2. Model 2: The True Fixed-Effects Model

Model 1 is a standard panel data model where  $\alpha_i$  is an unobservable individual effect. The model can be estimated using the standard panel data fixed and random-effects estimators to estimate the model's parameters to obtain the estimated value of  $u_i$ . The highest estimated value of  $\hat{\alpha}_i$ , namely  $\hat{u}_i$ , is used as a reference for the frontier.

However, there is a notable drawback in Model 1's approach as it does not allow individual heterogeneity to be distinguished from inefficiency. In other words, all time-invariant heterogeneity such as enterprise infrastructure that is not necessarily inefficient is included as inefficiency [9,29]. Also, the time-invariant assumption of inefficiency is a potential issue with Model 1. If T is large, it seems implausible that the inefficiency in energy use will stay constant for an extended period of time, since the technological progress will eventually replace less efficient technologies. So, should one view the time-invariant component as persistent inefficiency or as individual heterogeneity? The optimal choice lies somewhere in between, that is, a part of the inefficiency might be persistent, while another part may be transitory.

To solve the problem that the two parts cannot be separated from time-invariant individual heterogeneity effects, we have to choose either a model wherein  $\alpha_i$  represents persistent inefficiency, or a model wherein  $\alpha_i$  represents an individual-specific heterogeneity effect.

Following Kumbhakar and Heshmati [29] we consider both specifications in this paper. Thus, the models we examine can be written as:

$$ENE_{it} = \alpha_i + x'_{it}\beta + \epsilon_{it}, \quad \epsilon_{it} = v_{it} + u_{it}, \\ v_{it} \sim N(0, \sigma_v^2), \quad u_{it} = h_{it}u_i, \quad h_{it} = f(z'_{it}\delta), \quad u_i \sim N^+(\mu, \sigma_u^2),$$

The key feature that allows for the model's transformation is the multiplicative form of inefficiency effects,  $u_{it}$ , in which individual-specific effects,  $u_i$ , appear in multiplicative forms with individual and time-specific effects,  $h_{it}$ . As  $u_i^*$  does not change with time, the within and first-difference transformations leave this stochastic term intact. Thus, the difference between Model 1 and Model 2 is that inefficiency in Model 2 is explained by its observable determinants (z), while in the former, the time patterns of inefficiency are explained by a trend, but inefficiency is not explained by any determinants. Thus, cost efficiency is obtained based on the separated  $u_{it}$  components of the residual.

### 3.3. Model 3: Four Components of the Model with Determinants of Inefficiency

To fully satisfy the assumptions made in the model, we introduce a final model by [24] and [25] that overcomes some of the limitations of the earlier models. In this model, the error term is split into four components. The four components in this paper's context capture:

- Provinces' latent heterogeneity [9], which has to be disentangled from provinces' persistent inefficiency effects;
- Short-run time-varying transitory inefficiency;
- Persistent or time-invariant inefficiency as in [30,31] and [29]; and Random shocks.

Then, our final model based on these characteristics is the Kumbhakar et al. [25] model which is specified as:

$$ENE_{it} = \alpha_0 + f(x_{it};\beta) + \mu_i + v_{it} + \eta_i + u_{it}$$

where  $\mu_i$  is two-sided individual province heterogeneity,  $v_{it}$  is a two-sided random error term,  $\eta_i$  is one-sided time-invariant individual inefficiency, and  $u_{it}$  is one-sided time-variant inefficiency. In production models, the signs on the front of the inefficiency components are negative, reflecting production below the frontier output, while in cost or energy use models they are positive, suggesting higher cost or energy use above the minimum or frontier.

Instead of using a single stage ML estimation method based on the distributional assumption of the four components ([32], a simpler multi-step procedure is considered and we write the model as:

$$ENE_{it} = \alpha_0^* + f(x_{it}; \beta) + \alpha_i + \epsilon_{it}$$

where  $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$ ; and  $\alpha_i = \mu - \eta_i + E(\eta_i)$ .

This model can be estimated in three steps. In the first step, we use the standard random-effects panel regression to estimate  $\hat{\beta}$ . This procedure also gives predicted values of  $\alpha_i$  and  $\epsilon_{it}$ , which we denote by  $\hat{\alpha}_i$  and  $\hat{\epsilon}_{it}$ . In the second step, we estimate the time-varying technical inefficiency,  $u_{it}$ , and in the final step, we estimate  $\eta_i$  following a procedure similar to that in Step 2. Lastly, we estimate the persistent efficiency, PE, as  $PE = -\exp(\eta_i)$ . The residual efficiency, RE, is obtained as in Models 1 and 2, assuming a half normal distribution or truncated normal distribution  $u_{it}$ . The overall efficiency, OE, following Kumbhakar et al. [28], is obtained from the product of PE and RE, that is,  $OE = PE \times RE$ .

Table 1 gives the main characteristics of the three different efficiency models. The characteristics are related to the underlying assumptions of the different models, decomposition of the error components, time variation patterns of inefficiency, and the estimation procedure.

**Table 1.** Main characteristics of the different models.

	Model 1	Model 2	Model 3
General firm effects are treated as:	Fixed	Fixed	Random
Energy use inefficiency components:			
Persistent inefficiency	No	No	Yes
Residual inefficiency	No	No	Yes
Overall energy use inefficiency:			
Mean	Time-inv.	Zero trunc.	Zero trunc.
Variance	Homosc.	Homosc.	Homosc.
Symmetric random error term:			
Variance	Homosc.	Homosc.	Homosc.
Estimation method:	ML	ML	Multi-step

Notes: Fixed-effects (Fixed), random-effects (Random), homoscedastic variance (Homosc.), time invariant efficiency (Time-inv.), zero truncated error term (Zero trunc.), and maximum likelihood (ML).

## 4. Data

The data used in this study are from the province level observed for the period 2010–2017. It is obtained from the National Bureau of Statistics of China [1]. The dataset is the best available and frequently used in research and planning. This section describes the data source and provides a list of key and control variables; it also gives a descriptive analysis of the data.

### 4.1. Main Variables

In this research, energy use is defined as the economic value of total energy used per capita. It covers all economic sectors. It is reflected in both the price and quantity of energy. It is also reflected in the value of production. The definition of energy used here is close to the one used by [11], who defined energy efficiency as the production of the same amount of services or desirable outputs but with less energy inputs and undesirable outputs. In the current study, the undesirable output is controlled for by environmental stringency, carbon dioxide, and fine particulate matter. Provinces' per capita GDP is used as the main explanatory variable. It reflects labor productivity, size or scale in the economy as well as opportunity for energy use or consumption.



It should be noted that one may consider income to be endogenously determined and, as such, it can induce biased estimation results. One way of endogenizing income is by using predicted income or lag income as the explanatory variable. However, the two approaches may in turn lead to a bias. Here, we ignore the issue of endogeneity with the argument that we use province level data which is average per capita income and not endogenous to private and public users. Variations in income levels within the province that could be a source of endogeneity are not observed. At the level of aggregate income there is one-to-one correspondence between income and expenditure, and work is part of social life and most people, regardless of their income per hour, work 40 h per week.

#### 4.2. Control Variables

A review of the factors affecting energy efficiency in existing literature shows that these are mainly focused on three aspects: technological progress; structural factors including industrial, economic, and energy consumption structures; and system factors including energy prices, the degree of opening up to the outside world, and the government's environmental regulations.

**Technological changes:** It is generally believed that improvements in energy efficiency are mainly through structural adjustments and technological progress. In the process of economic development, technological progress accelerates the process of eliminating backward industrial sectors, transforming the original industrial sectors, and improving the industry which also promotes establishing new industrial sectors. Progress directly improves energy efficiency through the transformation of traditional technologies, development of new technologies, and adoption of new processes. This paper uses R&D internal expenditure (in 10,000 yuan) of industrial enterprises in each province as a proxy for technological progress. Changes in product mix and manufacturing mix are partially controlled for over time through investments in R&D and education, as well as time variance efficiency.

**The government's environmental regulations or environmental protection investments:** [33] targeted 14 prefectures in Xinjiang and used three indicators of the government's environmental pollution treatment investments to characterize the government's environmental regulations. Their results showed that the policy on pollution treatment investments and resource tax both generated energy inefficiencies. [34] used Xinjiang as their research subject for measuring the intensity of environmental regulations using the entropy method. Their results showed that the government's environmental regulations had an inhibitory effect on energy efficiency, which was not only reflected in the current period, but also in three periods lagged. [35] showed that environmental protection investments had a negative impact on energy efficiency probably because pollution treatment was not effective and investments in treatment were often passive.

**Openness** defined as  $((\text{export} + \text{import})/\text{GDP})$  characterizes foreign trade. Foreign trade is an important component of economic development. The structure of foreign trade products and the structure of foreign trade itself can affect energy efficiency. [36–39] show that the degree of openness is positively related to energy efficiency. Some scholars have come to different conclusions though. [40] shows that at the national level, economic openness is significantly positively correlated with the development of electrical equipment. At the regional level, economic openness is only significantly positively related to energy efficiency in the middle Yellow River. [14] show that for every 1 percent increase in the value of imports and exports in GDP, energy efficiency will decrease by 0.18 percent, but due to its dual effect, performance will vary in different regions. [41] research on single factor energy efficiency shows that the relationship between openness and energy efficiency in typical provinces is inconsistent, and he believes that the impact of openness on energy efficiency is a sufficient condition and not a necessary condition.

**Population and urbanization:** [42] show that both endogenous innovations and human development have a positive impact on single factor energy efficiency. [43] examined the impact of urban morphology and transportation modes on national and regional energy efficiency. His results showed that the former had a significant negative impact on regional energy efficiency while the latter had no significant impact. In some previous research the impact of urban agglomeration scale density

on urban energy efficiency is examined. The former can improve the latter, but impact on energy efficiency can be heterogeneous. It should be noted that in this research all explanatory variables and determinants of energy use inefficiency are province-specific and some, such as education and R&D investments, have spillover effects. In this research, we do not account for spatial effects of investments across provinces.

#### 4.3. A descriptive Analysis of the Data

The energy consumption structure in China by sectors is very skewed (transport 8.2 percent, industry 29.0 percent, building 16.7 percent, electricity 40.1 percent, and others 6.1 percent) [44]. Concerning primary energy consumption, the problems facing China's energy use include a very high proportion of coal use, low thermal efficiency, high unit energy consumption, high growth rate of consumption, and trade disputes with the US which influence energy efficiency with an impact on industry. From a spatial perspective, the level of economic development in different regions of China is very different. While there are differences in climate, geographical environment, and resources, there are also differences in energy structures in different regions.

The model used in this study is parametric and it allows for modeling the relationship between energy use and its determinants conditioned on different control variables. The main control variables are energy policy (investments in environment protection) ( $x_{env}$ ); the degree of trade openness ( $x_{exp}$ ); and environmental and regulatory variables including education investments ( $x_{edu}$ ), R&D investments ( $x_{R\&D}$ ), population ( $x_{pop}$ ), and urbanization ( $x_{urb}$ ). The variables which may influence energy use efficiency are  $z_1$  (PM2.5),  $z_2$  (CO<sub>2</sub>), and (municipal solid waste treated). PM2.5 refers to atmospheric fine particulate matter (PM) that has a diameter of less than 2.5 micro-meters. We also use the log of GDP per capita ( $x_{gdp}$ ) as a main indicator. To see the variations in energy use, we use the cost function approach and the log of energy use per capita ( $ENE_{cost}$ ) as the dependent variable. The series used in this analysis is at the province level and contains all provinces in China (except Tibet due to lack of data) observed yearly from 2010 until 2017.

Table 2 shows that all the indicators are logarithmically transformed, except for investments in environment protection, which are defined as a percentage of regional GDP or gross regional product GRP ( $x_{env}$ ) and urbanization ( $x_{urb}$ ) in the production function variables. Energy use cost per capita ranges between 427.638 and 5665.779 CNY among the sample provinces, with a mean of 1556.498 and dispersion of 1039.165 CNY. The GRP per capita varies in the interval of 1350.430 and 89,705.230 CNY in the provinces. The mean value is 21,652.784 with a dispersion of 16,997.766 CNY.

**Table 2.** Summary statistics of input and output data (2010–2017) ( $30 \times 8 = 240$  observations).

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
A. Energy cost function variables:					
$ENE_{cost}$	Energy use per capita	1556.498	1039.185	427.638	5665.779
$x_{gdp}$	GRP per capita	21,652.784	16,997.766	1350.430	89,705.230
$x_{exp}$	Value of export	69,598,470.492	123,875,644.740	424,174.000	646,000,000.000
$x_{edu}$	Education investments (in 10,000)	9,596,653.987	5,952,569.714	994,671.000	36,587,681.000
$x_{R\&D}$	R&D investments	2,872,909.717	3,713,827.748	57,760.000	18,650,313.000
$x_{env}$	Investments in environmental protection, as % of GRP	2.956	0.935	1.200	6.700
$x_{pop}$	Population (10,000 people)	4522.296	2705.794	563.000	11,169.720
$x_{urb}$	Urbanization (%)	0.560	0.127	0.338	0.896

Table 2. Cont.

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
B. Determinants of energy use inefficiency:					
$z_1$	PM2.5 ( $\mu\text{g}/\text{m}^3$ )	39.903	15.703	10.487	82.379
$z_2$	CO <sub>2</sub> intensity (tons/billion yuan)	19.750	12.089	3.129	69.052
$z_3$	Municipal solid waste treated (tons/day)	17,269.510	13,961.950	931.000	78,185.000

Note: Monetary variables are in fixed Chinese yuan, CNY. Source: Based on data from the National Bureau of Statistics of China (2018).

## 5. An Analysis of the Results

The three stochastic frontier models are specified and estimated using the data described earlier, and the estimation results are given in Table 3.

Table 3. Stochastic frontier models' estimation results (NT = 240 observations).

Variable	Description	Model 1	Model 2	Model 3
$x_{\text{gdp}}$	Log GDP per capita	−0.563 **	−0.461 **	−0.583 **
$x_{\text{exp}}$	Log Exportation	0.008	−0.024	0.013
$x_{\text{edu}}$	Log Education Investments	0.016	0.053	0.016
$x_{\text{R\&D}}$	Log R&D Investments	0.144 *	0.124 *	0.143 *
$x_{\text{env}}$	Environment Protection	−0.010	0.006	−0.012
$x_{\text{pop}}$	Log Population (10,000 people)	−0.412 *	−0.954 *	−0.436 **
$x_{\text{urb}}$	Urbanization (%)	2.380 **	3.390 **	2.260 **

Note: significant at less than the 0.05 (\*) and less than the 0.01 (\*\*) percent level of significance.

In Table 3 we present the estimation results of the three energy efficiency models. In Model 1, GDP, R&D investments, and environment protection are all statistically significant predictors of energy use. In Model 2, GDP and R&D investments are predictors of energy use. However, environment protection is a statistically insignificant predictor of energy use. In Model 3, GDP and R&D investments are significant variables that predict variations in energy use. However, environment protection is not found to be a significant predictor of energy use.

Another result that can be attained from Table 3 is attributed to the use of time as a driver of efficiency, which reduces the inefficiency component of the overall residual.

The Wald test is a joint test for multiple regressors. It mainly tests how much the model changes if the variables added are removed. In other words, the distance from the coefficient of each variable to zero is measured. The test results (see Table 4) show that the independent variable contributes significantly to the model and cannot be eliminated. The  $p$ -values of the fit of the three models are all less than 0.01, indicating that the models fit the data well.

Table 4. Model fit test's results.

Model Fitted	Model 1	Model 2	Model 3
Wald test statistics	92.49	7684.93	109.70
Wald test $p$ -value	<0.001	<0.0001	<0.001

The rest of this section analyzes the results. The analysis is in the form of a comparison of the different model's estimation results and an analysis of time-variance patterns as well as regional differences in energy use efficiency.

### 5.1. A Comparative Analysis of the Models' Estimation Results

Table 5 gives the descriptive statistics for mean energy use efficiency according to the three models. Model 1 shows that province level energy use efficiency ranged from 0.091 to 0.937 with large dispersions. The energy use efficiency in Model 2 ranged from 0.387 to 1.000. In Model 3 the residual efficiency ranged from 0.013 to 0.990, the persistent efficiency ranged from 0.179 to 0.897, and the overall efficiency ranged from 0.176 to 0.876. A number of 0.80 for Province A in a given year indicates that province A is 80 percent efficient in energy use compared to the frontier reference Province B with the best energy use technology. Province A has the potential of improving its efficiency by 20 percent.

**Table 5.** Descriptive Statistics for Energy Efficiency Measures by Different Models.

Energy Efficiency		Mean	Std. Dev.	Minimum	Maximum
Model 1		0.371	0.184	0.091	0.937
Model 2		0.968	0.092	0.387	1.000
Model 3	Residual efficiency	0.973	0.013	0.092	0.990
	Persistent efficiency	0.625	0.179	0.209	0.897
	Overall efficiency	0.609	0.176	0.202	0.876

Notes: Model 1: The time-variant efficiency model. Model 2: The true fixed-effects model (Greene, 2005a). Model 3: Four components of the SF model with determinants of inefficiency.

### 5.2. An Analysis of Trends in Energy Use Efficiency

Table 6 gives the yearly mean of provincial energy use efficiency for the three models. The results show that, according to the time-variant Model 1, energy use efficiency decreased during the study period. But Models 2 and 3 show increasing energy use efficiency. However, the changes over time are extremely small.

**Table 6.** Development of mean energy efficiency over time (2010–2017).

Year	Model 1	Model 2	Model 3		
			Residual Efficiency	Persistent Efficiency	Overall Efficiency
2010	0.374	0.954	0.970	0.621	0.602
2011	0.373	0.971	0.973	0.622	0.606
2012	0.372	0.963	0.971	0.623	0.606
2013	0.372	0.970	0.976	0.626	0.611
2014	0.371	0.973	0.977	0.627	0.613
2015	0.370	0.971	0.974	0.627	0.612
2016	0.370	0.970	0.972	0.627	0.610
2017	0.369	0.974	0.976	0.628	0.613

Table 6 shows that the trends of national mean energy use efficiency over 2010–2017 were practically constant over time. Although energy demand increased constantly, there was a technological revolution and policies for improving energy efficiency were introduced continuously, there were no significant improvements in energy use efficiency throughout the country. The possible small improvements in energy use efficiency are eliminated by increased consumption of energy due to economic growth in energy intensive industries.

### 5.3. Regional Heterogeneity in Energy Efficiency

For investigating the performance of different provinces and their positions as compared to the best performing province, energy use efficiency was compared across provinces and major regions in China. In the latter case, the provinces were divided into East (Beijing, Fujian, Guangdong, Henan, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, and Zhejiang), Center (Anhui, Hubei, Henan, Hunan,

Jiangxi, and Shanxi), West (Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan), and Northeast (Heilongjiang, Jilin, and Liaoning).

Table 7 gives the summary of average energy use efficiency values by provinces for the period 2010–2017. Different models' estimated measures of efficiency show that there were differences between provinces in terms of energy use efficiency.

**Table 7.** Average energy use efficiency by provinces (2010–2017).

Provinces	Model 1	Model 2	Model 3		
			Residual Efficiency	Persistent Efficiency	Overall Efficiency
East					
Beijing	0.724	1.000	0.986	0.857	0.845
Fujian	0.365	0.998	0.972	0.684	0.665
Guangdong	0.332	1.000	0.980	0.634	0.621
Hainan	0.136	0.928	0.966	0.343	0.332
Hebei	0.313	0.998	0.975	0.599	0.583
Jiangsu	0.437	1.000	0.987	0.738	0.728
Shandong	0.145	1.000	0.988	0.341	0.337
Shanghai	0.437	0.999	0.984	0.743	0.731
Tianjing	0.520	1.000	0.989	0.795	0.786
Zhejiang	0.347	1.000	0.980	0.658	0.645
Center					
Anhui	0.478	0.999	0.982	0.772	0.758
Hubei	0.352	1.000	0.983	0.668	0.656
Henan	0.402	1.000	0.986	0.717	0.707
Hunan	0.417	1.000	0.982	0.731	0.718
Jiangxi	0.437	0.994	0.977	0.750	0.733
Shanxi	0.699	0.974	0.962	0.849	0.816
West					
Chongqing	0.937	0.997	0.980	0.892	0.875
Gansu	0.128	0.962	0.973	0.301	0.293
Guangxi	0.232	0.994	0.975	0.509	0.497
Guizhou	0.443	0.952	0.963	0.748	0.720
Inner Mongolia	0.516	0.893	0.945	0.777	0.734
Ningxia	0.281	0.537	0.940	0.555	0.522
Qinghai	0.401	0.946	0.974	0.728	0.709
Shaanxi	0.215	0.998	0.975	0.469	0.457
Sichuan	0.309	0.999	0.971	0.617	0.599
Xinjiang	0.093	0.987	0.972	0.216	0.210
Yunnan	0.383	0.932	0.959	0.702	0.674
Northeast					
Heilongjiang	0.199	0.984	0.964	0.429	0.413
Jilin	0.320	0.980	0.969	0.624	0.605
Liaoning	0.138	0.999	0.972	0.311	0.302

According to the models' results reported in Table 7, most of provinces in East China had relatively higher energy use efficiency as compared to provinces in the Center, West, and Northeast of the country. Provinces in the East such as Beijing, Chongqing, and Shanxi had high efficiency above 80 percent. Conversely, an energy use efficiency of less than 40 percent was observed in Gansu, Xinjiang, Shandong, and Liaoning provinces.

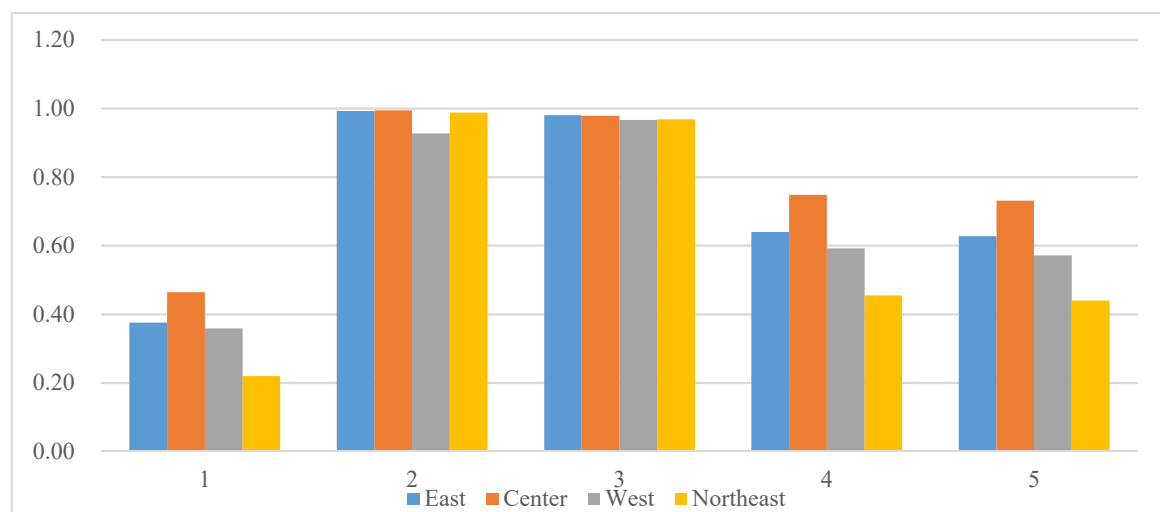
It can be seen in Table 7 that there is very obvious regional heterogeneity of energy use efficiency. Beijing, as the main energy efficiency policy implementation region, has always maintained high energy efficiency. Because of hosting a large proportion of secondary and tertiary industries, Changsha and Chongqing have also maintained high values in terms of energy efficiency.



Industrial cities such as Gansu, Shandong, and Liaoning have a very high proportion of production using coal. It can be speculated that the use of nonclean energy and the level of technology are the reasons for the low energy efficiency in these cities. As Xinjiang is a minority autonomous region that lacks resources, it has low technological levels, and slow implementation of energy efficiency policies which could have contributed to its low energy efficiency levels.

In looking at average energy use efficiency by provinces it is noted that Models 1 and 3 have similar trend calculation results, while Model 2 shows higher results that are similar to the results of residual efficiency in Model 3, which cannot reflect regional heterogeneity well. What we are concerned with is why the cities/provinces of Fujian, Guangdong, Shandong, Zhejiang, Hubei, Gansu, Shaanxi, Heilongjiang, and Liaoning have different efficiency results across different models. The reason could be that the energy structures in these provinces are basically dominated by energy-intensive secondary industries and there is congestion in resource inputs for achieving economic growth.

Figure 1 shows the average value of energy use efficiency by regions in the three models. It can be seen in the figure that the central region has higher energy efficiency, which has much to do with the good implementation of energy efficiency policies and human resource allocation structures in this region.



**Figure 1.** Estimated energy use efficiency by regions (2010–2017).

Notes:

1. Model 1: The time-variant efficiency model.
2. Model 2: The true fixed-effects model.
3. Model 3: Four components residual efficiency.
4. Model 3: Four components persistent efficiency.
5. Model 3: Four components overall efficiency.

A table giving the full results (not reported here but available on request) shows all 30 provinces' yearly energy use efficiency for the three models. From this table, we can compare the trends of energy efficiency between provinces and regions more comprehensively, and we can also see that energy efficiency showed slow and steady growth.

Energy efficiency in the central region before 2010 was low, and its energy efficiency in 2005–2010 was lower than that in the eastern and western regions, indicating that the central region had a weak capacity to absorb production capacity, and the industrial market had not been fully developed. After 2010, as the country's 'Central Rise' policy entered the implementation phase, the central region's industrial structure was adjusted, its capacity to absorb production was continuously enhanced, and

energy resource utilization technology was improved, leading to continuous improvements in energy efficiency year by year.

Energy efficiency in the western region declined steadily. The reason for this declining pattern is that the western region has abundant energy endowments and the gradual implementation of the western development policy enhanced its economic development, expanded its market capacity, and helped achieve improved energy efficiency. However, with the country's excessive dependence on the western region's policies, this region's market could not absorb too much capacity, and energy productivity and energy consumption capacity did not match, resulting in serious overcapacity which led to energy efficiency falling for several years.

Affected by the world financial crisis in 2008, China's economic development, in particular the development of energy intensive secondary industries, was hit hard. Therefore, after experiencing a decline in energy efficiency, the Chinese government adopted a large-scale investment stimulus package to protect its high rate of economic growth. Vigorous development of infrastructural investments and construction drove the development of the secondary industries. As a result, from 2010 to 2017, energy efficiency in the eastern and central regions increased significantly and steadily. However, the improvements were far below the optimal level required by health and environmental standards.

## 6. Conclusions and Implications

This study estimated three different models accounting for the panel nature of the data and determined separate province-specific energy use inefficiency effects. It also explained the degree of inefficiency in the use of energy using its possible determinants including those related to the public energy policy and environmental regulations. This research supplements existing research from the perspective of energy policy and regional heterogeneity. We observed a large potential for improving energy use efficiency, particularly in the western and northeastern regions. This study provides new empirical evidence for evaluating China's energy efficiency and transitioning to cleaner energy sources.

Energy use efficiency in most provinces of China improved slowly after 2010 as did the trend of steady regional economic growth, but the magnitude of energy efficiency improvements was small compared to investments in technological innovations. A comparison of the results of the three stochastic frontier models shows that there was provincial and regional heterogeneity in energy use and its efficiency. The models complement each other and being based on different distributional assumptions and estimation methods together provide a picture of energy consumption in China at the province level for the period 2010–2017.

We can also see that the impact of the government's policies on energy efficiency were significant. As the country's 'Central Rise' policy entered the formal implementation phase, the central region showed improvements in energy efficiency. This also means that there is potential for improving energy efficiency in the western and northeastern regions. With the 'coal to gas' and 'coal to electricity' policy, energy efficiency in Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta showed relatively high levels of progress.

With the country's excessive dependence on policies for the western region, this region's market could not absorb as much capacity and energy productivity and energy consumption capacity did not result in production capacity, which led to decreased energy efficiency. The results of the western region's policy imply that the government's energy policy should be adjusted considering regional heterogeneity. But the low level of energy efficiency in the northeastern region still needs more empirical analysis to find out why this is the case. The 'Central Rise' policy could be modified to account for specific characteristics of the western and northeastern regions, such as resource endowments, production capacity adjustments, and infrastructure to increase their energy use efficiency. Further, the determinants of energy use (in) efficiency can be identified and the models be specified such that each model can explain possible outcomes of energy use and environmental protection.

A possible and interesting extension of this study is expanding the data period to include the period before the 2008 global economic crisis and disaggregating the province level data to the industry

level. This will help control for energy intensity and targeted energy saving policies and an evaluation of their impact.

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