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Does Price Distortion Affect Energy Efficiency? Evidence from Dynamic Spatial Analytics of China

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Abstract: Despite market-oriented reforms, China's energy sector is subject to energy price distortions, which are believed to be a crucial determinants of energy efficiency in China. This paper investigates the impact of energy price distortions on energy efficiency in China from the perspective of spatial correlation. Using the nonradial directional distance function approach, we first estimate the provincial-level energy efficiency in China. Paying attention to spatial correlation among the provinces of China, in stage two, we identify the determinants of energy efficiency. Our empirical results suggest that price distortions have a significant impact on energy efficiency in China. This impact holds when the cross-region effect is considered, i.e., besides its own energy price distortion, a region's energy efficiency is also correlated to the adjacent provinces' energy price distortions. Furthermore, we found that the levels of energy efficiencies in adjacent provinces are highly correlated. This spatial relationship can be decomposed into the 'spillover effect' and 'warning effect'. These two effects work together, determining the spatial relationship among the province-level energy efficiencies.

Keywords: energy efficiency; energy price distortion; spatial panel models

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1. Introduction

Energy has played an important role in China's economic development. As the world's largest energy consumer, China has been giving a high priority to energy efficiency, especially with sustainable development getting increasing attention from policy makers. The Chinese government has taken a number of steps to improve energy efficiency. As a result, China's energy intensity (i.e., units per energy per unit of GDP) declined by approximately seventy per cent over the 1980 to 2010 period [1]. While improvement has been made in reducing energy consumption per unit output in overall terms, energy efficiency remains a serious concern in China. According to Xi Jinping's report to the 19th CPC National Congress, which is recognized as China's development blueprint, market-based systems for green technology innovation, developing green finance, and spurring the development of energy-saving and environmental-protection industries have been set as the targets for 'promoting green development' in China. The task of improving energy efficiency is becoming urgent since President Xi Jinping declared that China would aim to have CO_2 emissions peak before 2030 and achieve carbon neutrality before 2060. Though the central government is pushing for the promotion of energy efficiency, economic growth and energy conservation are viewed as somewhat contradictory targets by the local governments who are responsible for implementing the energy policies designed by the central government.

In this research, we attempt to estimate the energy efficiency and its determinants in regions of China from the perspective of provinces. Using data from 29 provinces in China over the period of 2002–2014 and employing the nonradial directional distance function

(NDDF) estimation approach, we first estimate the province-level energy efficiency. Based on the estimated province-level energy efficiency, we then focus on the determinants of energy efficiency in China. We pay special attention to energy price distortions because a decrease in the level of price distortion can lead to the better allocation of resources. In order to acquire a better understanding about energy efficiency, we estimate the dynamic spatial relationship between energy efficiency and price distortion. That is, in addition to the time-lag effect, we also consider the spatial-lag effect among the provinces of China. We will estimate (i) the impact of last year's energy efficiency on this year's energy efficiency, (ii) the impact of a neighboring province's energy efficiency, and (iii) how the neighboring province's energy efficiency from last year has impacted a province's energy efficiency this year.

While a number of studies have considered the issues of energy efficiency in China, few have considered the question of how price distortions affect energy efficiency [2,3]. This question is important because it offers a theoretical justification for market-oriented reforms in China's energy sector. By focusing on the link between price distortion and energy price in China, this paper makes some important contributions to the existing literature. First, we use a nonparametric NDDF approach to measure the province-level energy efficiency in China, which appropriately locates our work within the framework of the production with byproduct. That is, we take a holistic view, which takes into consideration and incorporates good outputs, such as GDP, as well as bad outputs, such as pollution, in estimating efficiency. The introduction of both good- and bad- outputs provides a more comprehensive measure of energy efficiency. In addition, unlike the total-factor productivity (TFP) approach that estimates the general level of productivity manifest in the production, the NDDF approach has the advantage of estimating the productivity of each input. It therefore allows us to focus on the energy efficiency while the impacts of other inputs (labor and capital) are controlled for. Second, this paper attempts to identify the determinants of energy efficiency from both time and spatial dimensions. Conventional time-series analysis focuses on the autocorrelation effect, i.e., how the energy efficiency of a region is determined by its own energy performance from the previous time periods. The spatial effects, i.e., how the energy efficiency of a region is affected by its neighboring regions, has long been ignored. In this paper, we use a spatial econometric model to estimate the determinants of energy efficiency, where time–space effects are also considered. Third, we attempt to examine the impact of energy price distortions on energy efficiency from the perspective of provinces. Most existing studies focus on energy price distortions at the national level, ignoring the large differences in economic development levels across the Chinese provinces. This paper provides a comprehensive analysis of the effects of energy price distortions using province-level data.

The remainder of this paper is organized as follows. Section 2 reviews the related studies on China's energy efficiency and price distortions. Section 3 discusses the dataset and the spatial econometric panel model that is used to identify the determinants of energy efficiency in China. The empirical results are reported and discussed in Section 4. Section 5 contains some concluding remarks and policy implications.

2. Literature Review

Energy efficiency has received a fair share of attention since the energy crisis of the 1970s [4,5]. Improving energy efficiency is regarded as being a promising way to maintain or lift living standards under energy conservation policies and rising energy prices. The so-called 'energy-efficiency gap' is defined as the difference between the amount of energy that is actually consumed and the amount that should be consumed [6]. Allcott and Greenstone [7] provided a comprehensive review on the theory of the energy-efficiency gap.

Some existing studies have attempted to explore energy efficiency in China. For example, Wu et al. [8] estimated the impact of environmental regulation on green total-factor energy efficiency of China by introducing environmental decentralization as a moderating variable. They found that there is a U-shape relationship between environmental regulation and green total-factor energy efficiency. Based on the data of the Chinese renewable-energy industry, Qiao et al. [9] found that the marketization of factor price is a decisive factor for innovation efficiency. Similar studies include [10,11]. In order to study the impact of market-oriented reforms on energy efficiency, Sheng et al. [12] used a nonparametric input distance function. Within the context of an energy shadow price framework, they estimated the energy efficiency of Chinese provinces. Lin and Du [13] used an NDDF approach to estimate the regional energy consumption and carbon emission performance of China from 1997 to 2009, finding evidence of regional imbalance. Lai et al. [14] developed a macro-energy-efficiency index for China, which indicated a decrease in energy efficiency in recent years. Considering the impact of heterogeneity, Zhang et al. [15] assessed the energy efficiency of Chinese cities by conducting a stochastic frontier analysis. Li et al. [16] adopted a hybrid methodology to evaluate and forecast the regional energy efficiency of China. In general, alternative empirical approaches have been adopted to estimate China's energy efficiency; however, different conclusions have been drawn, depending on the methodologies and data used.

Among all the explanations of energy efficiency in China, price distortion has received special attention for two reasons: (i) the market-oriented reforms of energy policies play a crucial role in China's economy and (ii) the imbalance of development in different regions across China produces different patterns of price distortion. Energy price is believed to be crucial in the context of lagging energy marketization levels in the process of China's transition from a planned economy to a market economy [17]. The studies about energy price distortions in China can be divided into two main categories. The first category focus on energy price distortions produced by price regulations, such as subsidies from the government, and define energy price distortion as the gap between the energy price in China and the international energy price. Within this set of studies, Shi and Sun [2] developed a two-sector general equilibrium (GE) model showing that regulatory price distortions have a negative effect on the economy. Hou [3] examined the relationship between energy price and energy efficiency by using linear and nonlinear effect analyses. They found that the impact of energy price on energy efficiency in China is positive in general.

The second category of studies identified in the literature dealing with energy price distortions focus on production and efficiency. Within this group, an efficient energy price is estimated by the value of the marginal output of energy. This approach corresponds to the 'efficient price' defined by Lin and Jiang [18], i.e., the efficient price of a good is the price at which the good is traded in a competitive international market or long-run marginal production cost (LRMC).

It is notable that some studies on energy have suggested the potential spillover effects among sectors. For example, Sadik-Zada et al. [19] addressed the production-linkage effect of the petroleum sector and found that the energy sector could backward- and forward-link to the rest of economy. Ziolo et al. [20] investigated the link between energy efficiency and sustainable economy in OECD countries. To address the possible link effects, we hypothesize that, besides the time-lag effect, there are also spatial-lag effects of energy efficiency. Since our study aims to understand the role of price distortion on energy efficiency, we will adopt the second approach—that is, we will gauge energy price distortions from the perspective of efficiency from a production-function-based approach. The estimation of energy efficiency and price distortion is discussed in the following sections.

3. Data and Methodology

In this section, we discuss the data and methodology adopted to investigate the determinants of energy efficiency in China. We first estimate the energy efficiency of China, then discuss the energy price distortion along with other factors that may have an impact on energy efficiency. Finally, a spatial econometric approach will be introduced.

3.1. Energy Efficiency

In most of the literature, energy efficiency has been calculated by the production function approach. The existing studies only considered the desirable output, i.e., the good output. However, the consumption of energy in production is almost always accompanied by pollutant emissions, i.e., the bad output. An environmental directional distance function (DDF) approach was developed to take into account both the desirable and undesirable outputs [21,22]. The main criticism of the DDF approach is the perceived likelihood that efficiency will be overestimated. Liu et al. [23] found that when undesirable outputs are included, energy efficiency is generally lower. Zhou et al. [24] developed a nonradial directional distance function (NDDF) approach, which relaxed the assumption about the radial efficiency measure in instances where slack exists. Another merit of the NDDF approach is that it allows one to estimate the productivity of each input, instead of a general productivity of all the inputs. Following Zhou et al. [24], we consider the production function as follows:

$$\mathrm{P} = \{(x, y, b) \mid x \geq X\lambda, y \leq Y\lambda, b \geq B\lambda, \lambda \geq 0\} \tag{1}$$

where $X = (x_1, \cdots x_n) \in R^{m\times n}$ are inputs, $Y = (y_1, \cdots y_n) \in R^{s\times n}$ are desirable outputs, and $B = (b_1, \cdots y_n) \in R^{k\times n}$ are undesirable outputs. λ_{n*1} is a vector of constants. Using the production function, as shown in Equation (1), the NDDF is defined as:

$$\vec{\mathrm{D}}(x, y, b; g) = \sup\{\mathrm{w}^T\beta\colon\ (x, y, b) + g\cdot diag(\beta) \in P\Big\} \tag{2}$$

where $diag$ is the diagonal matrices; g denotes the directional vector; $\mathrm{w}^T = (w_k, w_l, w_E, w_{gdp}, w_{SO_2}, w_{NO_X}, w_{solid})^T$ is the normalized weight vector of capital (k), labor (l), energy (E), output (GDP), industrial sulfur dioxide emission (so_2), industrial nitrogen oxide emission (NO_X), and industrial solid-waste emission ($solid$), in which capital, labor, and energy are the basic inputs in the production. GDP indicates the good output, while the three emissions represent the bad output (Unlike country-level studies that focus on greenhouse gas, in this study, we adopted industrial sulfur dioxide emissions, industrial nitrogen oxides emissions, and industrial solid waste emissions to measure the bad outputs of local energy consumption). $\beta^T = (\beta_k, \beta_l, \beta_E, \beta_{gdp}, \beta_{SO_2}, \beta_{NO_X}, \beta_{solid})^T \geq 0$ indicates the inefficiency measures of the inputs.

Since capital and labor inputs do not lead directly to emissions, we therefore set $w_k = 0$ and $w_l = 0$. In addition, the sum of the weight vectors equals a unit; therefore, we have $g = (0, 0, -g_E, g_{gdp}, -g_{SO_2}, -g_{NO_X}, -g_{solid})$ and $\mathrm{w}^T = (0, 0, 1/5, 1/5, 1/5, 1/5, 1/5)^T$. The NDDF values for the provinces are calculated by solving the DEA problem as follows:

$$\vec{\mathrm{D}}(x, y, b; g) = \max\ w_E\beta_E + w_{gdp}\beta_{gdp} + w_{SO_2}\beta_{SO_2} + w_{NO_X}\beta_{NO_X} + w_{solid}\beta_{solid} \tag{3}$$

$$
\begin{aligned}
s.t. \quad & \sum_{n=1}^{N} \lambda_n K_n \leq K_{n'} \\
& \sum_{n=1}^{N} \lambda_n labor_n \leq labor_{n'} \\
& \sum_{n=1}^{N} \lambda_n E_n \leq E_{n'} - \beta_E g_E \\
& \sum_{n=1}^{N} \lambda_n gdp_n \geq gdp_{n'} + \beta_{gdp} g_{gdp} \\
& \sum_{n=1}^{N} \lambda_n SO2_n \leq SO2_{n'} - \beta_{SO_2} g_{SO_2} \\
& \sum_{n=1}^{N} \lambda_n NO_{Xn} \leq NO_{Xn'} - \beta_{NO_X} g_{NO_X} \\
& \sum_{n=1}^{N} \lambda_n solid_n \leq solid_{n'} - \beta_{solid} g_{solid} \\
& \lambda_n \geq 0, n = 1, 2, \cdots, N; \quad \beta_E, \beta_{gdp}, \beta_{SO_2}, \beta_{NO_X}, \beta_{solid} \geq 0
\end{aligned}
$$

Following Cheng and Zervopoulos [25], we assume $\sum w_i = 1$, in which $w_i \subset w^T$.

The most efficient production takes place when $\vec{D}(x, y, b; g) = 0$. We denote the optimal solution for the most efficient production by $\beta^*{}_E$ and $\beta^*{}_{gdp}$. Therefore, $\beta^*{}_{it,E}$ and $\beta^*{}_{it,gdp}$ are used to denote the optimal solution for the most efficient production of province i in year t. Similar to Zhou et al. [24] and Cheng and Zervopoulos [25], the energy efficiency of the provinces is calculated as follows:

$$
Effi_{it} = \frac{(E_{it} - \beta^*{}_{it,E} E_{it}) / (GDP_{it} + \beta^*{}_{gdp} GDP_{it})}{E_{it} / GDP_{it}} = \frac{1 - \beta^*{}_{it,E}}{1 + \beta^*{}_{it,gdp}} \tag{4}
$$

In Equation (4), energy efficiency is mainly calculated by the estimated $\beta^*{}_{it,E}$ and $\beta^*{}_{it,gdp}$ in Equation (3), in which $\beta^*{}_{it,E}$ is the optimal solution for the most efficient production of energy. Specifically, $\beta^*{}_{it,E}$ and $\beta^*{}_{it,gdp}$ are calculated by solving the maximization problem, as described by Equation (3), and a DEA window model is adopted in the calculation. Xu et al. [26] had a comprehensive review on the literature regarding energy efficiency evaluation based on DEA approach. In our paper, adopt DEA window model which concerns the panel data comparison [24,27]). In other words, energy efficiency is estimated by the shadow cost of energy, while the good and bad outputs are both considered. This measure is similar to the estimation of the energy intensity improvement achievement ratio. Due to missing data and their small economic scale, some provinces such as Hainan, Tibet are dropped from our sample. We collected data for twenty-nine provinces of China from 2002 to 2014, one by one, and calculated the energy efficiency using the NDDF approach. The data on capital and labor inputs, as well as GDP, were collected from the China Statistical Yearbook. The data on energy consumption and pollution were collected from the China Energy Statistical Yearbook and the China Environmental Statistical Yearbook, respectively.

3.2. Energy Price Distortions and Other Determinants

This study attempts to investigate how energy price distortions impact energy efficiency. Therefore, the estimation of energy price distortions is a critical task. Energy price distortions are estimated by establishing the discrepancy between the real and nominal return on energy input. The basic idea is that the real return on energy input should equal the value of its marginal productivity. However, the nominal return on energy, i.e., the price of energy, is determined by other factors as well, for example, by subsidies, taxes, and so on. Therefore, the price distortion (*dist*) is measured by the ratio of the real return to the nominal return. When *dist* is equal to one, the market return is equal to the real return, which simply means that there is no distortion in the energy price. When *dist* is less than or greater than one, it means that the real return is either lower or higher, respectively, than the market price of energy. In other words, a price distortion exists.

Unlike the estimation of energy efficiency, where pollution is considered as a joint output in the estimation of value return on the input, we use a Cobb–Douglas (C-D) production function approach [28] to estimate the price distortion of energy. Capital (k), labor (l), and energy (E) are employed in the production:

$$Y_{it} = A_{it} k_{it}^{\alpha_{it}} l_{it}^{\beta_{it}} E_{it}^{\gamma_{it}} \tag{5}$$

where i and t represent province and time, respectively. A is production technique, and α, β, and γ are the output elasticity of each input. Taking the logarithm form, we get

$$\ln Y_{it} = c + \alpha_{it} \ln k_{it} + \beta_{it} \ln l_{it} + \gamma_{it} \ln E_{it} + \mu_{it} \tag{6}$$

The estimated results of Equation (6) are used to calculate the value of the marginal product of energy:

$$\mathrm{MP}_{it} = c\overline{\gamma}_{it} k_{it}^{\overline{\alpha}_{it}} l_{it}^{\overline{\beta}_{it}} E_{it}^{\overline{\gamma}_{it}-1} = \overline{\gamma}_{it} Y_{it} / E_{it} \tag{7}$$

where the superscript represents the estimated coefficient. In addition to the data on capital, labor, and output, as discussed, we also use data on energy consumption, which is measured by 10 tCEs (ton of coal equivalent).

The energy price distortion is calculated as

$$dist_{it} = MP_{it} / e_{it} \tag{8}$$

where e_{it} is the market price of energy of province i in year t.

In order to estimate the price distortion, we collect the prices of main energy sources, including coal, coke, fuel oil, gasoline, diesel fuel, natural gas, and electricity, as well as the fuel and power purchasing price from 36 major Chinese cities. Because the prices of the main energy sources are only available for 2003, and the data on the fuel and power purchasing prices are available for other years, we adopted the following steps to manage this: first, the year's average prices for the main energy products of 2003 were standardized; we then obtain the baseline year's (2003) weighted-average price of energy by taking the share of each energy product as weights; the final step was to calculate the energy price of other years by taking the base year's energy price index, as well as the fuel and power purchasing price, and the other years' fuel and power purchasing prices.

Besides energy price distortion, energy efficiency also depends on a number of other factors. For example, with economic development, more advanced technologies will be introduced, which may change the energy efficiency. Meanwhile, the changing economic structure will alter the energy consumption of different sectors, which leads to the change in energy efficiency on an aggregated level. In addition, market-oriented reforms in China are believed be to a key factor in improving efficiency via the reallocation of resources. Therefore, we also consider the impact of (i) the level of economic development, (ii) the structure of economy, and (iii) the market-oriented determinations of energy efficiency.

As economic development across the provinces of China is not uniform, the level of development may influence the technologies and consumption of energy. Economic development is measured by GDP per capita (GDP_pp). In addition, technological development ($tech$) is believed to have a direct impact on energy efficiency. We used the number of patents authorized by the government in each province as a proxy for the technological development of that province. Then, we considered the structure of the economy by including the industrial structure ($stru$), market openness ($open$), and level of urbanization ($urban$) in our estimations. Industrial structure ($stru$) is measured by the share of the output of tertiary industry in the total output. Since tertiary industry mainly provides service, it is sensible to conjecture that tertiary industry leads to high energy efficiency. Market openness ($open$) is measured by the share of international trade in the GDP because empirical studies suggest that, as the economy becomes more open, technique spillover effects and international competition will lead firms to operate more efficiently [29]. The level of urbanization ($urban$), which is measured by the share of urban population in each province, is also included as a control variable. Some recent studies have indeed found that there is a correlation between energy efficiency and market-oriented reforms in China [18]. Following in this vein, we also included the share of labor employed by state-owned enterprises (*SOE_l*) in the total population and the fiscal expenditure in local output ($fiscal$) to depict the strength of the local governments' interventions in the markets. Data are collected from the China Statistical Yearbooks and the statistical yearbooks of the provinces during the sample period. Data are deflated to real values. The descriptive statistics are presented in Table 1.

Table 1. Descriptive Statistics.

	n	Mean	SD	Min	p25	p50	p75	Max
Effi	377	0.771	0.205	0.321	0.609	0.759	1.000	1.000
dist	377	0.241	0.143	0.043	0.137	0.203	0.304	0.838
SOE_l	377	0.608	0.124	0.269	0.517	0.609	0.716	0.837
open	377	0.308	0.492	0.001	0.021	0.077	0.367	2.358
stru	377	0.393	0.077	0.274	0.349	0.383	0.411	0.779
GDP_pp	377	9.324	0.817	7.169	8.666	9.306	9.910	11.278
tech	377	8.683	1.557	4.248	7.635	8.622	9.808	12.506
fiscal	377	0.215	0.162	0.079	0.135	0.174	0.228	1.287
urban	377	0.486	0.152	0.226	0.387	0.452	0.560	0.898

Data are collected and organized by authors. All variables are presented in logarithmic form, except the variables in percent form.

3.3. Methodology

The existing studies suggest a possible spatial connection between the regions of China for energy consumption [30]. Hence, we used a spatial correlation test to identify the existence of spatial autocorrelation of energy efficiency among provinces. Global Moran's I is a widely used index to gauge the spatial correlation. The result of a simple OLS estimation (Moran's I = 0.180) suggests that there is a positive spatial correlation for energy efficiency among the provinces of China, that is, one region's energy efficiency has an impact on the neighboring regions' energy efficiency, and vice versa. We therefore adopt a spatial econometric model in both static and dynamic forms.

Over the last decades spatial econometric models have become widely used tools for measuring spatial spillover effects [31–33]. As pointed out by LeSage and Pace [31], compared with the spatial-lag model (SLM) and the spatial-error model (SEM), the static Durbin model (SDM) performs better in obtaining the unbiased estimates, even if the true data-generating process fits SLM or SEM. Therefore, we started analyzing the determinants of energy efficiency for 29 provinces in China by adopting a static spatial Durbin model (SDM). Specifically, we conducted the estimation by regressing the energy efficiency of Chinese provinces with a set of explanatory variables from the current period, including both of the key factors of concern, i.e., the energy price distortion and the control variables. Besides the self-effect, the spatial-lag effect was also considered. That is, we conjecture that the energy efficiency of an individual province is not only determined by its own, but also by the adjacent regions, due to the economic and geographic connection. The SDM specification can be estimated in the vector form as:

$$\begin{aligned} Effi_{it} = \ & \delta \mathbf{W}_{ij} Effi_{it} + \beta \mathbf{dist}_{it} + \theta \mathbf{W}_{ij} \mathbf{dist}_{it} + \psi \mathbf{X}_{it} \\ & + \chi \mathbf{W}_{ij} \mathbf{X}_{it} + \boldsymbol{\mu}_i + \boldsymbol{\lambda}_t + \mathbf{v}_{it}, \\ \mathbf{v}_{it} = \ & \gamma \mathbf{W}_{ij} \mathbf{v}_{jt} + \varepsilon_{it} \end{aligned} \tag{9}$$

where $Effi_{it}$ is an $N * 1$ vector that consists of energy efficiency in each province ($i = 1, 2, \ldots, N$) in year t ($t = 1, 2, \ldots, T$). That is, there are t elements in $Effi_{it}$ and each element is a vector that contains n elements $Effi_{it}$. It allows us to estimate the spatial spillover effects among individuals at the same time, along with the time-lag effect among individuals. Similarly, $\mathbf{dist}_{it}$ is an $N * 1$ vector that consists of the energy price distortions in each province. $\mathbf{W}$ is an $N * N$ matrix that indicates the spatial relationship between provinces; its factor W_{ij} measures the geographical relationship between provinces i and j, where $W_{ij} = 1$ means that provinces i and j are adjacent, otherwise, $W_{ij} = 0$. $\mathbf{X_t}$ is an $N * K$ vector representing the value of the K control variable (The details of the vector setting [34]).

The above regression equation takes the spatial-lag effect into account. However, in real economies, in addition to the spatial-lag effect, a time-lag effect, along with a time–space interaction effect, may also exist. In the second step, the spatial-lag specification is then extended to a time–space-lag specification, i.e., dynamic spatial Durbin model [34], as follows:

$$\begin{aligned} Effi_{it} = \tau Effi_{i,t-1} + \delta \mathbf{W} \tau Effi_{it} + \eta \mathbf{W} Effi_{i,t-1} + \beta \mathbf{dist}_{it} \\ + \theta \mathbf{W} \mathbf{dist}_{it} + \psi \mathbf{X}_{it} + \chi \mathbf{W} \mathbf{X}_{it} + \boldsymbol{\mu}_i + \boldsymbol{\lambda}_t + \boldsymbol{\nu}_{it}, \end{aligned} \tag{10}$$

The main differences between Equations (10) and (9) are the terms $\tau Effi_{i,t-1}$ and $\eta \mathbf{W} \tau Effi_{i,t-1}$. $\tau Effi_{i,t-1}$ captures the time-lag effect of energy efficiency, that is, last year's energy efficiency's impact on this year's. $\eta \mathbf{W} Effi_{i,t-1}$ denotes the interaction of time- and spatial-lag effects, that is, the energy efficiencies of the neighboring provinces from last year also have an impact on those provinces' energy efficiencies this year. This extension allows us to estimate the dynamics of energy efficiency, with which we are concerned. It is notable that alternative estimation approaches, such as the nonlinear panel approach and the ARDL-based approach, which consider pooled mean groups or dynamic fixed effects, could be used in the estimation [35–37]. Sadik-Zada [38] used the pooled mean group and nonparametric panel analyses to investigate the drivers of carbon emissions in fossil-fuel-abundant settings. In our study, we used the general penal estimations. The estimation results appear in the following section.

4. Estimation Results and Discussion

4.1. Static Spatial Model

The estimation results of the static spatial model, as specified in Equation (9), are reported in Table 2. Four specifications have been estimated, using the pooled ordinary least (POLS) model as a baseline model. Elhorst [39] indicated, for adjacent observations in an unbroken area, a fixed-effects (FE) specification is more appropriate than a random-effects (RE) specification. In this study, the samples almost cover all the provinces in China. In addition, the results of the Hausman test confirm that an FE model fits better than an RE model. Therefore, we adopted an FE specification by taking the spatial FE, time FE, as well as these two together into consideration, respectively.

Comparing the estimation results reported in Table 2, the results of the log-likelihood test suggest the best performance of a space–time FE model among all the four specifications. At the same time, the results of the Wald and LR tests indicate that the spatial Durbin model (SDM) cannot be reduced to spatial-lag or spatial-error models [34]. Based on the estimation of the space–time FE model, energy price distortions (*dist*) appear to have a positive and significant impact on energy efficiency. This result is somewhat surprising since it implies that a high price distortion in a province leads to high energy efficiency. At the same time, an energy price distortion (**W***dist*) in an adjacent province has a negative effect on energy efficiency, but this effect is not very significant. Another noteworthy finding is that, although most of the control variables have insignificant effects on a province's energy efficiency, other provinces' control variables appear to have a significant impact on their energy efficiency. This result suggests the presence of a positive spillover effect.

Table 2. Estimation results of the static spatial model.

Dependent Variable: *Effi* (Energy Efficiency)				
	POLS	**Spatial FE**	**Time FE**	**Spatial and Time FE**
dist	0.567 ***	0.309 **	0.581 ***	0.316 **
SOE_l	−0.040	−0.019	0.054	0.034
open	0.045 *	0.072	0.02	0.074
stru	0.327 ***	−0.177	0.561 ***	−0.029
GDP_pp	0.007	0.006	0.009	0.004
tech	0.034 ***	0.004	0.040 ***	0.007
fiscal	−0.061	0.014	−0.071	0.016
urban	−0.110	0.148	−0.168	0.083
W*dist*	0.203	−0.653 ***	0.21	−0.214
W*SOE_l*	0.841 ***	0.148	0.991 ***	0.330
W*open*	−0.056	−0.279 ***	−0.167 ***	−0.258 ***
W*stru*	0.725 ***	0.414 **	1.198 ***	0.894 ***
W*lnGDP_pp*	−0.031 **	0.057 ***	−0.030	0.055 ***
W*lntech*	−0.066 ***	−0.055 **	−0.036 **	−0.033 **
W*fiscal*	0.065	0.026	0.059	0.029
W*urban*	−0.000	−0.031	0.014	−0.631
W*Effi*	0.324 ***	0.151 **	0.153 **	0.092
R-squared	0.545	0.853	0.578	0.863
Log-likelihood	206.570	423.246	224.727	438.106
Wald_spatial_lag	49.796 ***	32.117 ***	53.137 ***	29.916 ***
LR_spatial_lag	46.814 ***	30.499 ***	50.292 ***	32.614 ***
Wald_spatial_error	44.730 ***	32.048 ***	57.010 ***	29.800 ***
LR_spatial_error	44.978 ***	31.975 ***	53.561 ***	32.682 ***

* significant at the 10% level; ** significant at the 5% level; *** significant at 1% the level.

4.2. Dynamic Spatial Model

While the estimations from a static model yield some interesting results, such a model may suffer from potential endogeneity arising from the omitted variables and/or model mis-specification. In order to solve the potential endogeneity problem, we also used a dynamic specification. This involves introducing the dependent variable lagged in time ($Effi_{t-1}$) along with the dependent variable lagged in space and time ($\mathbf{W}Effi_{t-1}$) as explanatory variables. In addition, we employed the bias-corrected quasi-maximum-likelihood (BCQML) approach developed by Lee and Yu [40] for dynamic spatial panels to estimate the dynamic spatial Durbin model (DSDM). The estimation results are reported in Table 3.

First, a higher log-likelihood ratio of dynamic specification indicates that the dynamic specification fits better than the static specification. The sum of the estimated parameters of the dependent variables lagged in time (τ), in space (δ), and in time with space (η) is 0.599, indicating the stability of the model. As reported in the first column of Table 3, the positive and significant coefficient of the dependent variable lagged in time ($Effi_{t-1}$) confirms the autocorrelation of energy efficiency in China. That is, for a province with high energy efficiency last year, it is quite possible to maintain its high energy efficiency this year. In contrast to the static model estimation results, with the introduction of the self-lag effect into the estimation, the dynamic model estimation suggests that energy price distortions (*dist*) have a negative impact on energy efficiency in China. This implies that provinces where the energy price distortion is small are likely to have a higher level of energy efficiency, which suggests that market-oriented reforms have helped to improve energy efficiency in China. This result validates the general idea that lower energy price distortions, i.e., the higher marketization, will lead to higher efficiency, which can be explained by the fact that the low price distortion of energy encourages firms to use energy efficiently. This result is important from a policy perspective. For this sense, the dynamic model has a better explanatory power than the static specification.

Table 3. Estimation results of the dynamic model.

Dependent Variable: *Effi* (Energy Efficiency)								
			Short Run			Long Run		
	Coefficient	Neighbors' Estimates (*WX*)	Direct Effect	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
dist	−0.299 ***	0.676 ***	−0.319 ***	0.685 ***	0.367	−1.318	2.144 *	0.827
SOE_1	0.004	0.479 ***	−0.012	0.585 **	0.574 **	−0.234	1.511 ***	1.277 *
open	−0.009	−0.110 *	−0.028	−0.138	−0.166 **	−0.076	−0.305	−0.381 *
stru	−0.141	0.618 ***	−0.089	0.622 *	0.534	−0.502	1.671 *	1.169
GDP_pp	0.004	0.032 **	0.008	0.037	0.045	0.009	0.080	0.089 *
tech	−0.014	0.050	−0.016	0.038	0.022	−0.080	0.134	0.054
fiscal	0.009	−0.008	0.011	0.003	0.014	0.027	−0.011	0.016
urban	0.312	−0.481	0.25	−0.556	−0.306	1.039	−1.726 *	−0.687
$Effi_{t-1}$ (τ)	0.648 ***							
$\mathbf{W}Effi_t$ (δ)	0.165 **							
$\mathbf{W}Effi_{t-1}$ (η)	−0.214 *							
R-squared	0.911							
Log-likelihood	478.923							
Wald_spatial_lag	23.793 ***							
Wald_spatial_error	25.740 ***							
($\tau + \delta + \eta$)	0.599							

* Significant at the 10% level; ** significant at the 5% level; *** significant at 1% the level.

As for the spatial effect, the positive and significant effect of the spatial-lag term ($\mathbf{W}Effi$) suggests a spillover effect, i.e., the provinces that are adjacent to highly energy-efficient provinces tend to use energy efficiently in the same period. The spillover effect could be caused by the technique spillover, etc. However, there exists a negative spatial dependence of the time-lag term ($\mathbf{W}Effi_{t-1}$), that is, a province's intent to have high energy efficiency if its neighboring province consumed energy with low efficiency last year. We interpret this phenomenon by a 'warning effect', that is, if a province observed its neighbor having low energy efficiency last year, it is warned and learns from the experience by trying to improve its own efficiency the following year.

Meanwhile, the positive and significant spatial dependence on price distortion ($\mathbf{W}dist$) confirms the 'warning effect', as discussed. According to the estimation results, if adjacent provinces suffered from high price distortions, a province would use energy more efficiently in the following year. The phenomena appear irrelevant, but as our discussion about the 'warning effect' suggests, a province's price distortion last year, which leads to its low energy efficiency last year, is a warning for its neighboring provinces this year, and leads adjacent provinces to use energy efficiently this year. Hence, last year's energy efficiency of a province will have an impact on the energy efficiency of adjacent provinces in two opposite ways: (i) by the 'warning effect', because low energy efficiency, which is accompanied by its own high price distortion, will send a warning to other provinces and encourage other provinces to use energy more efficiently in the following year; and (ii) by the 'spillover effect', because a province with low energy efficiency last year may use energy at low-efficiency levels, which will lead to low energy consumption efficiency in the adjacent province in the following year. The real impact of an energy price distortion on the neighboring province's energy efficiency next year is determined by the result of these two effects, as shown in Figure 1. As to the control variables, we found that, although most of the control variable impacts are insignificant, their spatial-lag terms are significant. This could be explained by the close economic links among regions in China.

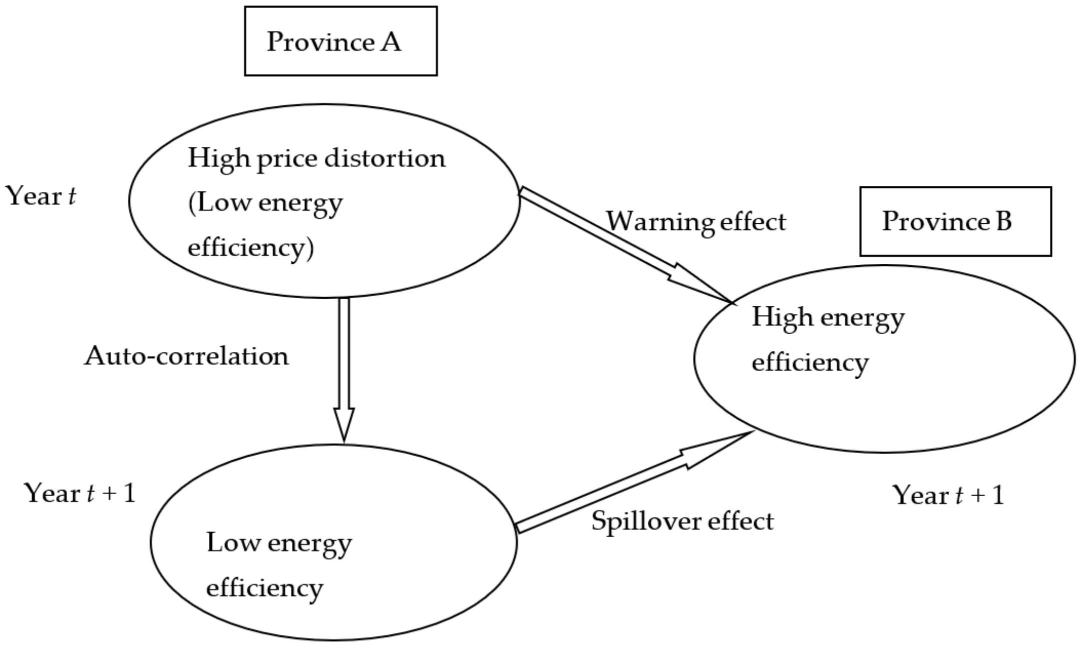

Figure 1. Time–space-lag effects, spillover effect, and warning effect.

4.3. Short- and Long-Run Effects

Our hypothesis is that spatial dependence exists among Chinese provinces and the estimation results validate the spatial-lag effects. Accordingly, the partial impact of explanatory variables should be interpreted by taking the spatial dependence into account. Following Elhorst et al. [34], the short-run effect, by taking the spatial effect into account, can be calculated by Equation (11), while the long-run effect, which also considers the time-lag effect, can be calculated by Equation (12) as follows:

$$\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y})}{\partial x_{Nk}}\right] = (\mathbf{I} - \delta \mathbf{W})^{-1}[\beta_k \mathbf{I}_N + \theta_k \mathbf{W}] \tag{11}$$

$$\left[\frac{\partial E(\mathbf{Y})}{\partial x_{1k}} \cdots \frac{\partial E(\mathbf{Y})}{\partial x_{Nk}}\right] = [(1-\tau)\mathbf{I} - (\delta + \eta)\mathbf{W}]^{-1}[\beta_k \mathbf{I}_N + \theta_k \mathbf{W}] \tag{12}$$

where the direct effects that measure own-economy effects are the diagonal elements and the indirect effects that measure cross-economy effects are the off-diagonal elements [31,34]. Following this approach, we estimate the direct and indirect short-run and long-run effects, respectively. The results are reported from columns (3) to (5) and (6) to (8) in Table 3.

First, for all the explanatory variables, the coefficient of the short-term effect is lower than the ones for the long-term. This result holds for direct, indirect, and total effects. It means in the long-run the marginal effects will accumulate. Secondly, the negative direct impact of energy price distortion on energy efficiency indicates that the provinces with low energy price distortions intend to use energy more efficiently. This result confirms the principle that, in most situations, the market is the most efficient way to allocate resources. In contrast, the positive indirect effects suggest that if a province demonstrates an energy price distortion, its adjacent provinces are likely to have high energy efficiency. This result holds for different frequencies (short- and long-run). This result also confirms the 'warning effect', as discussed above.

4.4. Robustness Checks

To enhance the robustness of our empirical results, we used standardized energy consumption per GDP to measure the energy efficiency. The new measure of energy efficiency is denoted by $Effi1$ and the results for the robustness test are reported in

Appendix A (Table A1). The results of our robustness test revealed that energy efficiency, which is measured by energy consumption per unit output, has strong autocorrelation and spatial dependence. For the provinces in China, energy price distortion is negatively correlated with their own energy efficiency, which confirms our conjecture that market-oriented price reforms encourage economies to use energy more efficiently. To sum up, the results of our robustness test confirm the previous findings, in which a region's energy efficiency is determined by its own energy efficiency from last year, along with the adjacent provinces' energy efficiencies and energy price distortions.

5. Conclusions and Policy Implications

This paper attempts to examine the determinants of energy efficiency of regions in China by paying special attention to the impact of energy price distortions. Unlike the existing studies that focus on the inter-region determinants, we consider the intra-region effects, i.e., the spatial impact among the provinces in China. Specifically, using data from 29 provinces over the 2002–2014 period and employing the nonradial directional distance function (NDDF) approach, we first estimated the province-level energy efficiency in China. This was followed by the estimation of static as well as dynamic spatial-regression models that aimed to evaluate the impact of energy price distortions on energy efficiency in China. We focused on the impact of energy price distortions, while the level of economic development, technological development, and government intervention in local economies are among the control variables included in the spatial regressions.

Empirical estimation yielded some very interesting results. First, we found that energy efficiency in a province is significantly impacted by the performance of the neighboring provinces. In other words, we found evidence of energy-efficiency spillover effects, where increased energy efficiency in a province was seen to increase energy efficiency in the neighboring provinces in the same year. We also found evidence of a 'warning effect', where a decrease in energy efficiency in one province serves as a warning to its neighbors. As a result of this warning, the neighboring provinces attempt to improve their energy efficiency in the following year. Second, energy price distortions (as measured by the difference between the real and shadow price) were found to have a significant effect on energy efficiency. The dynamic model estimation results demonstrate that provinces with high energy price distortions use energy inefficiently. This result provides support for market-oriented reforms in China's energy sector. Third, we found that energy efficiency is strongly autocorrelated. This implies that energy efficiency in a province in the current period has a significant impact on energy efficiency in the next period. Finally, estimation of the spatial econometric model suggests that energy efficiency in a province is also affected by factors that affect energy efficiency in adjacent provinces (such as the level of economic development of the adjacent provinces). The main results were found to be robust and offer an alternative measure of energy efficiency.

The results presented in this paper have some important policy implications. First, it is highly desirable that policy makers acknowledge the fact that energy price distortion does have a significant impact on energy efficiency in China. For economies in transition, such as China's, the market-oriented reforms in the energy sector that aim to reduce energy price distortions should be given serious consideration when setting their energy policies. This policy implication is especially important for the central government because it is the major policy maker setting the blueprints for national energy policies.

Second, based on the results of spatial regression, provincial government policy makers, as well as the energy sector practitioners, need to pay more attention to the broader social and economic factors—i.e., there is an urgent need to think beyond one's own region (province). The empirical results show that the adjunct provinces' energy efficiency and energy price distortions have an impact on a province's energy efficiency through the 'spillover effect' and the 'warning effect'. The interaction among regions' energy performances is mainly driven by the market. Therefore, the local governments who are implementing the energy policies, should further implement market-oriented reforms while having a broader outlook.

Lastly, as energy efficiency has time-lag effects and the long-run effect is larger than the short-run effect, it is sensible to evaluate the results of policies in the long run. Meanwhile, it is suggested that the government should set more stable energy policies in the long run.

We are aware of the limitations created by being dependent on the data until 2014. Since 2015, China has formally begun implementing an updated Environmental Protection Law ("the China EPL"), which has had a significant impact on China's energy market. Future research has the opportunity to consider the role of changes in policies and compare the impact of market-oriented factors, such as price distortions, and changes in policies on energy efficiency.

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Appendix A

Table A1. Robustness test.

Dependent Variable: *Effi*1 (Energy Efficiency)			
Explanatory Variables	**Coefficient**	**Explanatory Variables**	**Coefficient**
dist	−0.689 ***	$\mathbf{W}dist$	0.671 ***
SOE_l	−0.064	$\mathbf{W}SOE\_l$	0.149
open	−0.006	$\mathbf{W}open$	0.083 *
stru	−0.089 **	$\mathbf{W}stru$	−0.238 **
GDP_pp	−0.005	$\mathbf{W}GDP\_pp$	0.002
tech	−0.010	$\mathbf{W}tech$	0.017
fiscal	0.014	$\mathbf{W}fiscal$	−0.014
urban	−0.146	$\mathbf{W}urban$	−0.344
$Effi1_{t-1}$ (τ)	0.691 ***		
$\mathbf{W}Effi1_t$ (δ)	0.398 ***		
$\mathbf{W}Effi1_{t-1}$ (η)	−0.122		
R-squared	0.993		
Log-likelihood	695.932		
Wald_spatial_lag	31.342 ***		
Wald_spatial_error	44.929 ***		
$(\tau + \delta + \eta)$	0.967		

* Significant at the 10% level; ** significant at the 5% level; *** significant at 1% the level.

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