An Analysis of the Impact of Market Segmentation on Energy Efficiency: A Spatial Econometric Model Applied in China

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Abstract: China’s recent development has been nothing short of remarkable, but energy-saving, and environmental protection is still a serious problem. The improvement of energy efficiency (EE) is an important factor for China to better follow the path of energy conservation, sustainable development, and environmental protection. Meanwhile, market segmentation is a unique phenomenon in the process of China’s economic development. Hence, studying market segmentation on energy efficiency has positive significance for improving energy efficiency. The major objective of this study is to investigate the relationship between EE and market segmentation. This paper measures market segmentation by the price-based approach, calculating EE by super slack-based measure (super-SBM), and integrated spatial Durbin model and geographically weighted regression model. Based on the panel data of 30 provinces in China from 1995 to 2018, this paper finds that: (1) Regional market segmentation has a significant negative effect on EE. Moreover, in terms of spatial effect, market segmentation has a positive spatial spillover on EE estimated by 0-1 matrix suggesting that market segmentation in the surrounding area has a positive impact on local EE. (2) The negative effect of Market segmentation on EE demonstrates the obvious regional difference: Eastern region > central region > western region. In addition, geographically weighted regression results show that the impact of market segmentation on EE shows that in regional spatial distribution, Shanghai, Jiangsu, Zhejiang, and Anhui have the strongest negative effect, second in Fujian, Jiangxi, Shandong, Henan, Hubei, Beijing, Tianjin, and Hebei. (3) This paper confirms that market segmentation can affect EE through local protectionism, technological difference, and scale effect. Finally, through the above research basis, put forward the corresponding policy suggestions.

Keywords: energy efficiency; market segmentation; spatial econometric model; super-SBM; Price-Based Approach

1. Introduction

Energy is a significant material basis for social and economic development [1]. With the rapid development of the economy, energy consumption has gradually emerged [2]. In 2009, the world’s primary energy consumption per capita was 70.2 gigajoules per capita, but it reached 75.7 gigajoules per capita in 2009. Moreover, the carbon dioxide emission is 29,745.2 million tons in 2009, but rapidly grew to 34,169 million tons in 2019. (Statistical Review of World Energy 2020). The growth of energy consumption has brought greater challenges to environmental protection and sustainable economic development in China. From 2009 to 2020, China’s energy consumption nearly 1.5 times. China’s “14th Five-Year Plan” also puts forward the requirements for green development and promoting a comprehensive economic green transformation. Energy is an essential component in the economic system, and plays a key role in developing a green economy, sustainable economic development, and environmental protection. Much research has focused on energy efficiency (EE). Energy efficiency is an important topic in economic development
research; improving energy efficiency had has become a vital way to ensure energy security and promote sustainable economic development [3].

Scholars have achieved rich results in the study of energy efficiency. For instance, from the perspective of the industry. In the Chinese paper industry, under the constant efficiency improvement, China’s paper industry has a huge energy-saving potential [4]. In the Chinese transport sector, energy efficiency shows a ladder-like distribution in a different region, per GDP, industrial structure, transport structure, and energy price had a significant influence on energy efficiency [5]. In addition, it accounts for more than 16% of Chinese energy consumption in China’s iron and steel industry. [6], which has a vital influence on Chinese sustainable development. A previous study about firm-level survey data reported that the national energy efficiency program made a vital contribution to the growth of total factor productivity in participating firms [7]. In addition to the above-mentioned industries, energy efficiency issues in the mining industry, coal industry, construction industry, etc., have been studied too [8–10].

Recently, there has been an increasing amount of research about the social and economic factors affecting energy efficiency. First, in energy policy, energy efficiency standard plays a crucial role in reducing the energy consumption of room air conditioners (RACs). The improvement of RACs is an important measure for environmental promotion and energy conservation, that the environmental influence of the energy efficiency standards for RACs with refrigerants is a vital direction for the enhancement of future RACs standards [11]. Meanwhile, it has a nonlinear relationship between environmental regulation and green total factor energy efficiency (GTFEE), with the advancement of environmental regulation decentralization. Environmental regulations had a negative impact on GTFEE, owing to the improvement of local governmental autonomous choices in pollution management [12]. On the other hand, command-control and market-based environmental regulation have a positive influence on total factor energy efficiency (TFEE) [13]. In addition, producer services agglomeration can improve the energy efficiency under environmental constraints in the local and surrounding regions, on a national level [14]. Moreover, energy efficiency can be improved by financial agglomeration through scale economy effect, innovation driving effect, information spillover effect, and structural adjustment effect [15]. At the same time, agricultural industrial agglomeration can promote local agricultural energy efficiency by promoting technology and acknowledge spillover, enhancing industrial completion, and optimizing energy structures [16]. Another aspect of the market-base electricity price has a positive impact on energy efficiency with the improvement of the marketization degree [17]; the increasing investment in basic research can improve energy efficiency by promoting innovative energy technologies [18].

On the other hand, energy efficiency has spatial heterogeneity in China, due to the imbalance development of the Chinese region [19]. For example, the industry sector’s TFEE had an overall downward from 2004 to 2016, and technical change is the major engine in TEFF’s growth in the research of Pear River Delta (PRD) urban agglomeration. The degree of openness, local government spending, foreign direct investment, factor input structure, environmental regulation strength, and GDP per capita have positive impacts on the TFEE, while enterprise-scale and energy consumption structure had a negative effect [20]. Apart from PRD, in small cities, Smart-city-policy can improve small city’s energy efficiency during 2003–2016 [21]. More generally, Chinese energy efficiency has spatial spillover effect [22], provincial energy efficiency had a significant spatial imbalance and showing an olive-shaped distribution [23]. Besides, energy efficiency has significant regional heterogeneity, with the highest in the eastern region, the lowest in the western region, and the second in the central region [24,25].

In addition, some studies about market segmentation had reported that market segmentation could weaken market competition mechanism and reduced market vitality, causing the stagnation of economic development when the market was saturated [26,27], reducing regional resource space allocation efficiency [28], hindering foreign direct investment in high-productivity and private enterprises [29]. For the overall economy,
market segmentation has a negative relationship with economic growth, presenting a heterogeneous impact on different economic developmental stages [30]. Besides, market segmentation can cause heterogeneous suppression in innovation efficiency [31]; moreover, inhibiting technological progress, had a negative impact on green total factor productivity and regional economic development, increasing environmental pollution [32].

We summarize, from the existing literature, that the research objects of energy efficiency have extensive results, including research on the national, city, and enterprise levels, as well as specific industries, such as the paper industry, the steel industry, and the transportation industry. At the same time, scholars have also studied energy efficiency’s impact factors, such as environmental regulation, basic research, enterprise size, and city policies. In addition, in recent years, there are notable papers that studies the influence of industrial agglomeration in energy efficiency, such as service industry agglomeration, financial agglomeration, agricultural agglomeration, and urban agglomeration. Furthermore, market factors, such as electricity prices and openness, have been considered. From a market perspective, analyzing the effect of market factors on energy efficiency is a vital aspect in improving energy efficiency. However, there are certain deficiencies in the existing research. First, a lot of the literature focuses on the research of energy efficiency, market segmentation, and the impacting factors on energy efficiency. Some literature discuss the causation between energy efficiency and market segmentation. Second, market factors are regarded as controlled variables, and the research on market factors is not in-depth. Third, the selection of indicators is single. Generally, energy prices and degree of openness (the ratio of total import and export to GDP) are used as market indicators. Last, the mechanism of market factors on energy efficiency is simple, lacking theoretical framework. Therefore, from a market perspective, this paper measures market factors by market segmentation index, studying the impact of regional market segmentation on energy efficiency. Hence, our paper contributes to three broad pieces of literature. First, literature linking market segmentation with energy efficiency, enriching the market affecting factors on energy efficiency, and provide a new idea for energy efficiency research. Second, indicators selection is a more specialized, market segmentation index used to study energy efficiency. Thirdly, considering the economic spatial and structural effects, deeply analyzing the influence of market segmentation on energy efficiency.

2. Mechanism Description

This article combines existing research and economic theory to propose a core influencing mechanism, and explains the transmission mechanism from three perspectives: Protectionism, technological differences, and scale effects. Interpret the path and form of the impact of market segmentation on energy efficiency from these four aspects.

2.1. Core Influence Mechanism

For the causes of market segmentation, administrative decentralization is the major reason. With local economic development stimulated by administration, it will also cause the phenomenon of “duke economy” [33], which leads to the market segmentation’s emergence and the formation of regional administrative barriers. Administrative barriers and “duke economy” are market segmentation’s concrete manifestations. Market segmentation is a unique phenomenon in the process of economic transition, emerging from the implementation of “delegation of power and profit” and administrative decentralization in the early 1980s, and basically did not appear in the past centralized planned economy [34]. Administrative decentralization is the origin and foundation of local market segmentation. On the whole, the formation and evolution of the administrative decentralization system, traditional industrial layout, unbalanced economic development, and the assessment and evaluation of local governments are the major causes for market segmentation [35]. Market segmentation has a negative influence on economic development [26–28,30]. At the same time, as a key part of economic development, energy is vital for economic development.
Thus, the imperfect decentralization system, the uncoordinated industrial layout, and economic development will lead to waste of energy consumption and energy industry uncoordinated distribution. Consequently, market segmentation will have a negative impact on energy efficiency. Therefore, this paper proposes Hypothesis 1:

**Hypothesis 1.** Market segmentation has a negative impact on energy efficiency.

### 2.2. Local Protectionism

The occurrence of strong market segmentation, it has caused serious protectionism. There is little cooperation space between different local officials because of the competitive nature of the official promotion, and officials will implement local protection to achieve their own promotion needs [36]. Under the protectionism, with the regional development strategy and industrial policy implemented by local officials, it has brought about the phenomenon of repeated investment and homogeneous industrial layout, due to these achievements in pursuit of promotion in the short term. At the same time, the government has stronger market power and control over the economy powerfully. However, regional economic development requires the flow and optimal allocation of elements in different regional spaces, improving the economic system’s efficiency. Market segmentation may hinder the free flow of different elements in regional space through protectionism, especially the layout of industries. On the other hand, administrative barriers will hinder the flow of energy resources in different regions. Clean energy flows in different regions are subject to the block of local governments, and quality energy resources cannot replace traditional energy. Therefore, this also results in a decrease in energy efficiency. Under the government’s facility protectionist policy, the inefficiency of economic operation and a huge waste of energy consumption have had caused by repeated investment and industrial homogeneity. Therefore, protectionism might distort market competition mechanism, and low-efficiency companies can continue to exist, which causes the increase of energy consumption and environmental degradation, therefore, leading to a decline in energy efficiency. Thus, the second hypothesis is that:

**Hypothesis 2.** Market segmentation has a negative impact on energy efficiency through local protectionism.

### 2.3. Technical Difference

Economic development is inseparable from technological progress. Enterprises can reduce pollution, save costs, and optimize industrial structure through technological innovation. However, the technology level in developed areas is higher than in developing areas [37], it is difficult to form effective competition between developed and developing areas in the current period. Thereby, developing areas may promote regional industrial upgrading and technological innovation through market segmentation, to support a more favorable market position in the future. So, it is impossible to eliminate technologically backward enterprises in the short term, and the economic efficiency is lower than in developed areas. Market segmentation can hinder the exchange and development of technology, leading to a decline of technology progress on energy efficiency. Moreover, due to market segmentation, the competition among enterprises in the region is weak, and low-tech enterprises can survive without technological innovation. However, when the local market becomes saturated, enterprises need a new market because of the advantage brought by technological innovation. Nevertheless, there is an increased difficulty for enterprises to open new markets owing to market segmentation, thereby decrease enterprise’s expectations for technological innovation. Meanwhile, Low-tech enterprises have no power to improve energy consumption; therefore, the backward technology brings about the reduction of regional energy efficiency. The third hypothesis is that:

**Hypothesis 3.** Market segmentation has a negative impact on energy efficiency by restraining regional technological innovation.
2.4. Scale Effect

National integration market can give full play to market’s competitiveness, improving resource flow, raising the allocative efficiency of energy resource, and promote energy efficiency. There are two major paths on scale effect. On the one hand, the integration market can stimulate the economic scale effect, reducing production costs, improving product competitiveness in domestic and international markets. Highly market segmentation may benefit regional economic growth, economic aggregate, and the survival of enterprises in the short term. However, market segmentation can decrease regional investment scale and hinder capital accumulation, causing a negative impact on inter-regional capital flow and investment. From the perspective of enterprise development, with the increase of company size, it is beneficial to the reducing cost and improving internal-operation efficiency. Under the limitations of market segmentation, companies are less likely to achieve ideal scale, and internal efficiency is hard to achieve an optimal state. On the other hand, segmented markets can inhibit developing inter-regional industries, hinder the optimization of industry structure. Finally, the obstruction of the capital flows and industry structure’s optimization can reduce enterprises’ efficiency, leading to the loss of energy efficiency. The last hypothesis is that:

Hypothesis 4. Market segmentation can inhibit energy efficiency by hindering the scale effect.

3. Methodology and Data

This paper measures market segmentation by the price-based approach, calculating EE by super slack-based measure (super-SBM). Researching the relationship between market segmentation and energy efficiency by spatial Durbin model. Using the geographically weighted regression to analysis the spatial heterogeneity of market segmentation.

3.1. Energy Efficiency

For the calculation of energy efficiency, it can be expressed simply by the ratio of energy consumption (EC) to output (GDP/EC) [38–42]. However, it is difficult to describe the economic situation of multi-input and multi-output by this single indicator measurement method, and the data envelopment analysis (DEA) has become a commonly used method in the study of energy efficiency [43–47]. Nowadays, they are many DEA models had been developed, such as two-stage bootstrap DEA [48], SBM-DEA [49], stochastic frontier SBM-undesirable method [9], stochastic frontier DEA [50], etc. Generally speaking, DEA is a key method of efficiency research, for instance, China’s agricultural total factor productivity [44], airline energy efficiency [51], regional energy efficiency [52], and other aspects of economy and society [53–55]. For the traditional DEA model, it is impossible to distinguish the difference between the evaluation objects in the efficiency value of 1. However, the Spur-SBM model is the combined of the super-efficiency DEA model and the SBM model; compared with the general SBM model and traditional DEA model, the super-SBM model can achieve a further distinguish the difference between the effective evaluation units at the efficiency value of 1, which widely used by scholars in various fields of social sciences [56–59]. Specifically, this paper uses the super-slack based measure (super-SBM) model to measure energy efficiency, and the specific formula is shown in Equation (1).

\[
\min \theta - \epsilon (\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^- + \sum_{r=1}^{s} s_r^+) \\
\text{s.t. } \sum_{i=1}^{m} x_{ij} \lambda_i + s_i^- = \theta x_{ij0}, i = 1, 2, \ldots, m, \!
\sum_{r=1}^{s} y_{ij} \lambda_r - s_r^- = y_{ij0}, r = 1, 2, \ldots, s, \!
\lambda_i, s_i^- , s_r^+ \geq 0, \!
j = 0, 1, 2, \ldots, j_0 - 1, j_0 + 1, \ldots, n. \!
\] (1)

where \(\theta\) is the efficiency value; The vectors \(s^-\) and \(s^+\) refer to slack variables of input and output, and \(\lambda\) is the weight vector; \(X\) is the input variables, \(y\) is the output variables; \(\lambda_j\) defines the intensity of the \(j\)th unit. The input variables include capital input (K), labor
input (L), and energy consumption (E), the output variable is GDP (Y). The capital stock is calculated by the perpetual inventory method.

\[ K_{i,t} = (1 - \sigma)K_{i,t-1} + \frac{I_{i,t}}{P_{i,t}} \]  

(2)

\( K \) represents the capital stock of region \( i \) in year \( t \); \( P \) donates the fixed asset investment price index; \( I \) represents the nominal fixed asset investment; \( \sigma \) is the capital depreciation rate, and this paper set depreciation rate as 10.96% [5, 12, 19, 60].

In order to intuitively present the dynamic changes and provincial differences in Chinese energy efficiency, this paper uses R-packages of tmap, open-source software, to show the results in the form of Chinese maps. Due to space constraints, this paper only lists the energy efficiency in 1995, 2000, 2005, 2010, 2015, and 2018. The distribution of energy efficiency shows in Figure 1. According to the EE distribution map, Figure 1 shows that from 1995 to 2018, energy efficiency has significant regional difference and high-value areas are mainly distributed in Beijing, Jiangsu, Shanghai, Guangdong, and eastern coastal areas, however, EE in western areas is lower, especially EE in Xinjiang, Qinghai, Gansu, and Inner Mongolia, showing a falling trend-moving from the eastern areas to the central and western areas. In Figure 1, we can also see that the darker the color, the higher the efficiency. From 1995 to 2018, there was a gradual decrease in the quantity of blued regions, such as Fujian, Jiangxi, Shandon, Hunan, and Chongqing. The dynamic changes reflect a downward trend in EE. This can be attributed to the fact that with the rapid growth of the economy, great achievements have been made in the economy with the huge consumption of energy and resources, leading to a downward trend in energy efficiency.

3.2. Market Segmentation

There is a certain fluctuation range of commodity prices among different regions. If the fluctuation of relative price converges, it means the decrease in transaction cost and market segmentation, otherwise, it means the increase in transaction cost and market segmentation.

Figure 1. Spatial distribution of Chinese energy efficiency.
Many scholars adopt the price-based approach, studied by Paresley and Wei [61–63], to measure goods market segmentation [64–66]. The specific process is as follows.

First, calculate the absolute value of the relative price of goods. The first-order difference of the retail price ratio’s logarithm is used to measure price change.

\[
\Delta Q_{ijt} = \ln \left( \frac{p_k^{it}}{p_k^{jt}} \right) - \ln \left( \frac{p_k^{it-1}}{p_k^{jt-1}} \right) = \ln \left( \frac{p_k^{it}}{p_k^{it-1}} \right) - \ln \left( \frac{p_k^{jt}}{p_k^{jt-1}} \right)
\]

(3)

where \( p_k^{it} \) is the price of commodity \( k \) in year \( t \) and province \( i \).

Second, eliminate commodity’s difference through the method of removing the average value. For a specific commodity \( k \), obtain \( \left| \Delta Q^k_{ijt} \right| \) that is the average value of \( \left| \Delta Q^k_{ijt} \right| \), including 120 pairs of provincial data in year \( t \), then \( \left| \Delta Q^k_{ijt} \right| \) subtract the average value to obtain \( q^k_{ijt} \).

\[
q^k_{ijt} = \left| \Delta Q^k_{ijt} \right| - \left| \Delta Q^k_{ijt} \right|
\]

(4)

Third, the variance of \( q^k_{ijt} \) is used to represent market segmentation. The market segmentation at time \( t \) in region \( i \) can be expressed as:

\[
\text{Segmentation}^i_t = \text{var} \left( q_{ijt} \right)
\]

(5)

where \( q_{ijt} = \{ q_{ijt}^1, q_{ijt}^2, q_{ijt}^3, \ldots, q_{ijt}^k, q_{ijt}^{k+1}, \ldots, q_{ijt}^s \}, s = 14. \)

Researchers can free to choose different types of commodity prices to measure market segmentation, such as 8 and 11 types of products to analyze market segmentation [67–70]. This paper uses 13 types of commodity prices to measure market segmentation.

Figure 2 summarizes the characteristics of market segmentation in China. From Figure 2a, we can find that Beijing, Tianjin, Heilongjiang, Xinjiang, and Hainan have stronger market segmentation and the lower market segmentation regions distribute in Anhui, Zhejiang, Fujian, Jiangxi. Except for Hainan, the regions with stronger market segmentation are generally northern regions, which indicates that the market conditions in the southern areas are better than in northern areas. Then, in the whole country, market segmentation in China has presented a downward trend, suggesting that the degree of regional market integration has increased. However, market segmentation might affect by emergencies. For example, the market segmentation increased significantly in 2001, mainly due to the impact of SARS. In 2008, shocking by the financial crisis, market segmentation also rose obviously. Overall, the volatility of market segmentation will be affected by emergencies. After emergencies, different administrative entities will reduce the degree of openness to restore the impacted economy, thus leading to an increase in market segmentation.
where $\overline{q}_{ij}$ = $[q_{ij1}, q_{ij2}, q_{ij3}, \ldots, q_{ij14}, \ldots, q_{ij30}]^T$, $s = 14$.

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Figure 2. (a) The trend graph of market segmentation by province; (b) The trend graph of market segmentation from 1995–2018.

3.3. Econometric Model

3.3.1. Spatial Weight Matrix

In this paper, the geographic weight matrix, 0-1 spatial weight matrix, economy weight matrix, and population weight matrix are used to measure the spatial spillover effect. The economy weight matrix and population weight matrix are defined as Equation (6):

$$W_x(ij) = 1 \left| x_i - x_j \right| W_q(ij)$$

(6)

where $\left| x_i - x_j \right|$ is the population or GDP gap between $i$ and $j$, $W_q$ is the 0-1 weight matrix or geographic weight matrix.

3.3.2. Spatial Autocorrelation

Considering energy efficiency’s spatial spillover effects, Moran’s I is used to test energy efficiency’s spatial correlation, the formula is as follows Equation (7):

$$I_{morans} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}}$$

(7)

In Formula (7), the spatial autocorrelation is calculated by Moran’s I. $x_i$ is the Energy efficiency of province $i$ in certain year, and $n$ is the total number of provinces (in this article is 30). $\overline{x}$ is the average of $x_i$ in certain year, and the $S^2$ presents the variance of energy efficiency.

3.3.3. Spatial Durbin Model

To study the impact of market segmentation on energy efficiency, the basic model can be designed as:

$$EE_{it} = \beta_0 + \beta_1 Lnseg_{it} + \sum_{j=1}^{n} a_i x_{j1} + \mu_i + v_t + \mu_{it}$$

(8)
If there is a spatial relationship between energy efficiency, this paper constructs a spatial Durbin model (SDM) as follow:

\[
EE_{it} = \beta_0 + \rho WEE_{it} + \beta_1 \ln \text{seg}_{it} + \sum_{j=1}^{m} \alpha_i X_{it} + \beta_2 W \ln \text{seg}_{it} + \sum_{j=1}^{m} \theta_i W X_{ij} + u_i + v_t + \mu_{it}
\]  

(9)

where \(EE\) indicates energy efficiency; \(\ln \text{seg}\) is the logarithm of the market segmentation index; \(X\) is a serial of covariates; \(u_i, v_t, \varepsilon_{it}\) represent time effect, state effect, and random disturbance term; \(W\) is spatial weight matrix; \(m\) is the number of the covariates.

3.3.4. Geographically Weighted Regression

To consider the changes of parameters with geographic location, this paper uses geographically weighted regression (GWR) model for further analysis.

\[
EE_i = \beta_{(u_i,v_i)} \ln \text{seg}_i + \sum_{j=1}^{n} \alpha_{ij(u_i,v_i)} X_{ij} + \mu_i
\]  

(10)

where the meaning of \(EE, \ln \text{seg}, X\) and \(\mu\) are consistent with Equation (9). \((u_i, v_i)\) is the longitude and latitude in region \(i\). \(n\) is the number of control variables.

3.4. Control Variables and Data Sources

Besides market segmentation, this study also introduces other control variables. (1) Industrial structure (IS): In the process of economic development, it is accompanied by the adjustment of industrial structure. This paper uses the ratio of added value in the industry to GDP to donate industrial structure [5,13,17,18]. (2) Open level (OPEN): Using the ratio of total import and export to GDP to represent the open level [71,72]. (3) Economic development: With the continuous development of the economy, the demand for energy will also continue to expand. Existing studies use per capita GDP [73,74] to represent economic development. We use the ratio of real GDP to labor (LY) and GDP growth rate (RY) to measure regional economic development. (4) Social factor (SF): In addition, this paper takes the unemployment rate as a social factor into the control variable.

The study area includes 30 of China’s provinces (Tibet, Taiwan, Hong Kong, and Macao are excluded, due to poor data accessibility) over the period from 1995 to 2018. Data calculation is based on 2004. Energy consumption data from 1995 to 2017 was obtained from the EPS database, and data for 2018 was obtained from the National Bureau of Statistics of the “2018 Sub-province (autonomous region, city) energy consumption reduction rate of 10,000 yuan of regional GDP and other indicators” Bulletin. Other data sources are China’s Economic and Social Big Data Statistics Platform (https://data.cnki.net/) (accessed on 21 September 2020). The descriptive statistics of the variables involved in this paper are reported in Table 1.
Table 1. The statistic description of variables.

| Variable | Definition | Obs | Mean   | Std.    | Min     | Max     |
|----------|------------|-----|--------|---------|---------|---------|
| EE       | Energy efficiency | 720 | 0.7276516 | 0.2408073 | 0.2655402 | 1.523454 |
| Lnseg    | The logarithm of market segmentation | 720 | -8.109698 | 0.778534 | -9.837727 | -4.122805 |
| IS       | The ratio of add value in industry to GDP | 720 | 0.4447086 | 0.0797084 | 0.165449 | 0.5904543 |
| RY       | GDP growth rate | 720 | 0.107156 | 0.0287319 | -0.025 | 0.238 |
| OPEN     | The ratio of total import and export to GDP | 720 | 0.2967834 | 0.3725913 | 0.0167815 | 2.056174 |
| LY       | The ratio of real GDP to labor | 720 | 0.8763742 | 0.5090759 | -0.3228071 | 2.239312 |
| SF       | Unemployment rate | 720 | 3.408167 | 0.7990114 | 0.46 | 6.5 |

4. Empirical Analyses

4.1. Spatial Tests

This paper tests spatial autocorrelation by Moran’s I. The calculation results are shown in Table 2.

Generally speaking, from Table 2 it can be seen that during the period from 1995 to 2018, the Moran’s I indexes of provincial energy efficiency are all positive, and all are significant at the 5% level, estimated by W_dis, W_01, Wp-01, and W_pdis. For instance, the Moran-I in 1995 estimated by W_01 is 0.199 and significant at the 1% level, which indicates that energy efficiency has a positive spillover effect. Connecting with Moran-I in 2018 is 0.135 and significant at the 5% level estimates by W_01, it is obvious that energy efficiency has a significant spatial spillover effect. The significance of the results estimated by We_01 and We_dis have decreased to a certain extent; however, the whole results support that the spatial autocorrection effect of energy efficiency in Chinese provinces is significant. Consequently, taking the spatial characteristics of energy efficiency into the model setting is reasonable.

4.2. Spatial Model Result

First, the basic model results are shown in Table 3. The result of OLS shows that Lnseg has a positive effect on EE, which contrary to theoretical analysis. The possible reason is that OLS estimation has serious endogenous problems. Considering the possible endogeneity problem in the model, the fixed effect is adopted. Finally, the results of model (5) and model (6) show that market segmentation has a negative effect on energy efficiency with the controlling of time-fixed effect and space-fixed effect, and have passed the significance of 1%. The Moran MI, Geary GC, and Getis-Ords GO all have passed the significant test of 1%, meaning that spatial effect should be considered in the EE model. In model (5), the LM lag is 83.5388 higher than LM error (62.2505), the LM lag (robust) is 156.5929 higher than LM error (robust). The LM test [75] results show that the value of LM Lag and LM lag (robust) is higher than LM error and LM error (robust), which indicates that the spatial lag model (SAR) is more reasonable than the spatial error model (SEM), as a consequence, the SDM is adopted.
Table 2. Calculation results of Moran's I.

| Year | W-dis t-stat | W-01 t-stat | Wp-01 t-stat | Wp-dis t-stat | t-stat | Moran-I |
|------|--------------|--------------|--------------|--------------|--------|---------|
| 1995 | 0.199 *** | 2.440 0.358 *** | 3.294 0.314 ** | 2.435 0.136 | 1.468 | 0.382 *** |
| 1996 | 0.191 ** | 2.487 0.343 ** | 3.082 0.301 ** | 2.281 0.193 ** | 1.913 | 0.355 *** |
| 1997 | 0.187 ** | 2.440 0.304 ** | 2.759 0.266 ** | 2.039 0.209 ** | 2.046 | 0.303 ** |
| 1998 | 0.202 ** | 2.998 0.300 ** | 2.715 0.281 ** | 2.132 0.277 ** | 2.598 | 0.291 ** |
| 1999 | 0.225 ** | 2.839 0.325 ** | 2.907 0.302 ** | 2.266 0.293 ** | 2.720 | 0.399 ** |
| 2000 | 0.214 ** | 2.718 0.297 ** | 2.683 0.256 ** | 1.956 0.315 ** | 2.913 | 0.295 ** |
| 2001 | 0.249 ** | 3.101 0.317 ** | 2.842 0.265 | 2.019 0.341 | 3.124 | 0.322 |
| 2002 | 0.238 ** | 2.989 0.315 ** | 2.832 0.244 * | 1.883 0.350 ** | 3.207 | 0.280 ** |
| 2003 | 0.286 ** | 3.530 0.387 ** | 3.439 0.318 ** | 2.396 0.425 ** | 3.855 | 0.320 ** |
| 2004 | 0.282 ** | 3.504 0.392 ** | 3.488 0.366 ** | 2.728 0.411 ** | 3.750 | 0.320 ** |
| 2005 | 0.272 ** | 3.402 0.374 ** | 3.353 0.382 ** | 2.849 0.381 ** | 3.506 | 0.335 ** |
| 2006 | 0.228 ** | 2.934 0.343 ** | 3.123 0.384 ** | 2.882 0.322 ** | 3.033 | 0.330 ** |
| 2007 | 0.180 ** | 2.424 0.3 ** | 2.794 0.341 ** | 2.606 0.342 ** | 2.285 | 0.300 ** |
| 2008 | 0.189 ** | 1.967 0.256 ** | 2.459 0.298 ** | 2.340 0.176 | 1.831 | 0.283 ** |
| 2009 | 0.102 * | 1.598 0.228 ** | 2.267 0.250 ** | 2.047 0.104 | 1.232 | 0.254 * |
| 2010 | 0.064 | 1.157 0.195 ** | 1.992 0.189 | 1.617 0.038 | 0.651 | 0.225 * |
| 2011 | 0.050 | 1.012 0.161 | 1.733 0.161 | 1.440 0.029 | 0.583 | 0.195 |
| 2012 | 0.062 | 1.193 0.158 ** | 1.748 0.177 | 1.602 0.066 | 0.944 | 0.194 |
| 2013 | 0.079 | 1.473 0.139 ** | 1.656 0.183 | 1.733 0.117 | 1.494 | 0.174 |
| 2014 | 0.138 ** | 2.227 0.175 ** | 1.992 0.259 | 2.325 0.207 ** | 2.369 | 0.399 ** |
| 2015 | 0.133 ** | 2.191 0.170 ** | 1.980 0.251 | 2.295 0.194 | 2.280 | 0.195 |
| 2016 | 0.135 ** | 2.223 0.191 ** | 2.191 0.267 | 2.434 0.194 | 2.281 | 0.204 |
| 2017 | 0.137 ** | 2.257 0.199 | 2.279 0.275 | 2.513 0.197 | 2.319 | 0.2038 |
| 2018 | 0.135 ** | 2.233 0.188 ** | 2.166 0.257 | 2.360 0.193 | 2.272 | 0.193 * |

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Regression results of the basic model.

| | OLS | RE | FE_State | FE_Both | FE_Both |
|---|-----|-----|---------|---------|---------|
| | (1) | (2) | (3) | (4) | (5) |
| Lnseg | 0.0778 *** | 0.105 *** | 0.104 *** | −0.0242 *** | −0.0549 *** |
| OPEN | 0.205 *** | 0.116 *** | 0.0513 | (2.99) | (8.12) |
| LY | 0.0312 *** | 0.0334 *** | −0.0579 *** | −0.00104 | 0.0487 *** |
| RY | 1.683 *** | 1.876 *** | 2.166 *** | 1.405 *** | 1.122 *** |
| SF | −0.0096 | 0.000181 | 0.00568 | (1.09) | 0.00410 |
| IS | −0.500 *** | −0.877 *** | −0.842 *** | −0.535 *** | −0.554 *** |
| Moran MI | 0.4157 *** | 0.4157 *** | 0.4157 *** | 0.2463 *** | 0.2160 *** |
| Geary GC | 0.5471 *** | 0.5471 *** | 0.5471 *** | 0.7435 *** | 0.7323 *** |
| Getis-Ords GO | −0.4157 *** | −0.4157 *** | −0.4157 *** | −0.2463 *** | −0.2160 *** |
| LM Error | 231.1463 *** | 231.1463 *** | 231.1463 *** | 81.3765 *** | 62.2505 *** |
| LM Lag | 1283.7907 *** | 1283.7907 *** | 1283.7907 *** | 122.7882 *** | 135.3045 *** |
| LM Lag(robust) | 373.7387 *** | 373.7387 *** | 373.7387 *** | 103.6847 *** | 83.5388 *** |
| N | 720 | 720 | 720 | 720 | 720 |

Note: *** indicate significance at the 1% levels, respectively.

Given that energy efficiency has significant spatial correlation and LM test results, SDM are employed to examine the relationship between energy efficiency and market segmentation with different spatial matrices. This paper reports the estimation results with controlling of time and space fixed effect in Table 4. The regression result estimated by W_01 shows that the coefficient of Lnseg is −0.0636 and has passed the significance of 1%. In addition, the estimation results of model (2–6), the coefficient of Lnseg is negative, and they all have passed the significance of 1%, which are roughly consistent with the fixed effect model (Table 3 model (3) and (4)). The results of Lnseg estimated by differ
weight matrix, for the direct effect, we can find that market segmentation will bring about a significant negative effect on energy efficiency, indicating that market segmentation will increase the inefficiency of energy utilization, which is consistent with the Hypothesis 1.

As for the control variables, the impact of LY is positive, but model (2), model (4), and model (6) have not passed the significance test. It indicates that LY in the surrounding area can promote EE. The impact of IS is significantly positive. This may be because of the increase in industry needs more energy consumption, and it has a positive influence on energy efficiency. OPEN has a negative impact on energy efficiency, but it is not significant in model (1) and model (3). Because of the development of the economy, there has a rising trend in the opening level, but a falling trend of EE; thereby, the coefficient is negative. Finally, SF has a significant negative impact on energy efficiency. This is because the unemployment rate is a key considered factor in economic operation and national governance. An excessively high unemployment rate will have a negative impact on economic operations and EE.

In addition, there are two conclusions finding the coefficient of market segmentation’s spatial lag term in Table 4. First, under different spatial weights, the significance of \( W^* \text{Lnseg} \) has decreased to a certain extent. Specifically, regression results based on the geographic weight matrix have a certain decline in significance test (model (2), model (4), model (6)), while the results based on the spatial proximity matrix have passed the significance of 5%. One possible reason for this difference is that the spatial weight based on the geographic weight matrix comprehensively considers the influence of the whole country’s market segmentation, while the 0-1 matrix considers the influence of the surrounding area. Market segmentation in the surrounding areas might show a stronger and more significant impact on energy efficiency than the whole country’s market segmentation. Second, the sign of \( W^* \text{Lnseg} \) is positive. A stronger market segmentation in the surrounding area has a positive spatial spillover in local energy efficiency. The possible reason is that with a higher market segmentation in surrounding areas, it might have stronger administrative barriers and local protection in the local region, which will repel the entry of highly efficient foreign companies. On the contrary, a local region with lower market segmentation has a faster flow of economic factors than surrounding areas. Therefore, foreign companies will choose lower market segmentation areas, and the entry of new technologies it will improve the local region’s energy efficiency, so the market segmentation in surrounding areas has a positive effect on local energy efficiency. In summary, the hypothesis, that energy efficiency is negatively affected by market segmentation, has been verified.

4.3. Discussion

Due to the significant regional spatial heterogeneity, there are some differences in energy efficiency among east, central, and west areas [4,24,25]. Hence, this paper takes the dummy variable of west, central, and cross-terms \( \text{West} \times \text{Lnseg}, \text{Central} \times \text{Lnseg} \) into the model. For Table 5, the estimation result of model (1–6) presents that the direct effect of Lnseg is negative and have passed the significance test in 1%. The coefficients of Lnseg \( \times \) west are positive and have passed the significance test in 5% (model (1–4) and model (6)) and 10% (model 5). The impact of Lnseg \( \times \text{Mid} \) is positive, but the result estimated by \( w_01 \) and \( w\_\text{pop01} \) have not passed the significance test. For spatial effect, the coefficient of \( W^* \text{Lnseg} \) is positive, that consistent with Table 4, and has passed the significant test in 5% in model (2–4) and model (6). However, for \( W^* \text{Lnseg} \times \text{west} \), it has not passed the significance test, and the symbol is also unstable. The coefficient of \( W^* \text{Lnseg} \times \text{central} \) passes the significance test is 5% in the result of model (1), model (2), and model (5).
### Table 4. Estimation results of SDM.

| Variables   | W_01          | W_dis         | W_eco01        | W_ecodis       | W_pop01       | W_popdis       |
|-------------|---------------|---------------|----------------|----------------|---------------|----------------|
|             | (1)           | (2)           | (3)            | (4)            | (5)           | (6)            |
| Lnseg       | −0.0636 ***   | −0.0415 ***   | −0.0549 ***    | −0.0425 ***    | −0.0517 ***   | −0.0377 ***    |
|             | (−5.28)       | (−3.98)       | (−4.78)        | (−3.84)        | (−4.89)       | (−3.72)        |
| LY          | 0.0300 *      | 0.0110        | 0.0412 **      | 0.0219         | 0.0369 **     | 0.0136         |
|             | (1.71)        | (0.61)        | (2.23)         | (1.19)         | (2.02)        | (0.70)         |
| OPEN        | −0.0820       | −0.0885 **    | −0.0969 *      | −0.118 **      | −0.0709 *     | −0.0802 **     |
|             | (−1.63)       | (−1.97)       | (−1.96)        | (−2.07)        | (−1.73)       | (−2.03)        |
| IS          | −0.835 ***    | −0.677 ***    | −0.772 ***     | −0.855 ***     | −0.738 ***    | −0.543 ***     |
|             | (−7.68)       | (−5.80)       | (−6.52)        | (−6.36)        | (−6.86)       | (−4.61)        |
| Ry          | −0.398 *      | −0.260        | −0.492 **      | −0.549 **      | −0.375 *      | −0.242         |
|             | (−1.73)       | (−1.05)       | (−2.10)        | (−2.16)        | (−1.65)       | (−1.04)        |
| SF          | −0.0150 *     | −0.0107       | −0.0119        | −0.0211 ***    | −0.00923      | −0.00486       |
|             | (−1.81)       | (−1.24)       | (−1.47)        | (−2.66)        | (−1.13)       | (−0.59)        |
| W*Lnseg     | 0.0769 ***    | 0.0409 *      | 0.0482 **      | 0.0147         | 0.0458 **     | 0.0212         |
|             | (3.44)        | (1.67)        | (2.98)         | (0.85)         | (2.41)        | (1.01)         |
| W*Ly        | −0.101 ***    | −0.150 ***    | −0.101 ***     | −0.0165        | −0.144 ***    | −0.171 ***     |
|             | (−2.67)       | (−3.14)       | (−3.42)        | (−0.39)        | (−4.84)       | (−4.99)        |
| W*OPEN      | −0.0895 *     | −0.246 ***    | −0.110 **      | −0.149 **      | −0.178 ***    | −0.274 ***     |
|             | (−1.86)       | (−3.60)       | (−2.47)        | (−2.37)        | (−3.84)       | (−4.20)        |
| W*IS        | −0.392 *      | 0.0965        | −0.438 ***     | 0.0790         | −0.293 *      | 0.644 ***      |
|             | (−1.76)       | (0.41)        | (−2.63)        | (0.32)         | (−1.65)       | (5.53)         |
| W*RY        | 2.132 ***     | 1.583 ***     | 1.278 ***      | 1.525 ***      | 1.636 ***     | 1.179 *        |
|             | (5.18)        | (2.06)        | (3.89)         | (3.58)         | (4.55)        | (1.93)         |
| W*SF        | 0.00993       | 0.0292        | −0.0224        | −0.0188        | −0.0142       | 0.0520 **      |
|             | (0.45)        | (1.12)        | (−1.36)        | (−1.15)        | (−0.69)       | (2.17)         |
| ρ           | −0.0216       | −0.217 ***    | −0.0135        | 0.113 **       | −0.0809       | −0.0776        |
|             | (−0.34)       | (−2.80)       | (−0.28)        | (2.04)         | (−1.58)       | (−1.62)        |
| Sigma       | 0.0878 ***    | 0.0872 ***    | 0.0880 ***     | 0.0897 ***     | 0.0849 ***    | 0.0849 ***     |
|             | (23.81)       | (26.68)       | (23.36)        | (20.51)        | (26.12)       | (28.13)        |
| N           | 720           | 720           | 720            | 720            | 720           | 720            |
| State dummy | Yes           | Yes           | Yes            | Yes            | Yes           | Yes            |
| Year dummy  | Yes           | Yes           | Yes            | Yes            | Yes           | Yes            |

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

### Table 5. Estimation results of SDM with a regional difference.

| Variables   | W_01          | W_dis         | W_eco01        | W_ecodis       | W_pop01       | W_popdis       |
|-------------|---------------|---------------|----------------|----------------|---------------|----------------|
|             | (1)           | (2)           | (3)            | (4)            | (5)           | (6)            |
| Lnseg       | −0.0862 ***   | −0.0639 ***   | −0.0849 ***    | −0.0738 ***    | −0.0759 ***   | −0.0683 ***    |
|             | (−5.31)       | (−4.36)       | (−4.77)        | (−4.03)        | (−5.10)       | (−4.64)        |
| Lnseg × west| 0.0451 **     | 0.0387 **     | 0.0465 **      | 0.0625 ***     | 0.0309 *      | 0.0408 **      |
|             | (2.40)        | (2.25)        | (2.34)         | (3.10)         | (1.69)        | (2.42)         |
| Lnseg × Mid | 0.0147        | 0.0369 ***    | 0.0368 **      | 0.0629 ***     | 0.0205        | 0.0272 **      |
|             | (0.97)        | (2.66)        | (2.33)         | (3.68)         | (1.49)        | (2.06)         |
| W * Lnseg   | 0.0647 **     | 0.0565 *      | 0.0525 **      | 0.0403         | 0.0634 ***    | 0.0591 **      |
|             | (2.50)        | (1.73)        | (2.49)         | (1.47)         | (2.75)        | (2.06)         |
| W * Lnseg × West | −0.000769 | 0.0445 | 0.0105 | −0.0325 | 0.0181 | −0.00892 |
|             | (−0.03)       | (1.15)        | (0.45)         | (−1.11)        | (0.75)        | (−0.25)        |
| W * Lnseg × Mid | 0.163 *** | 0.111 ** | 0.0147 | −0.0588 * | 0.0679 ** | 0.0613 * |
|             | (4.18)        | (2.23)        | (0.59)         | (−1.91)        | (2.43)        | (1.68)         |
| ρ           | 0.0351        | −0.146 *      | 0.0660         | 0.119 **       | 0.0204        | −0.0226        |
|             | (0.60)        | (−1.82)       | (1.51)         | (2.21)         | (0.42)        | (−0.46)        |
| Covariates  | Yes           | Yes           | Yes            | Yes            | Yes           | Yes            |
| N           | 720           | 720           | 720            | 720            | 720           | 720            |

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
The estimated results in Table 5 show that, first, the effect of market segmentation on energy efficiency is inversely proportional to the economic development of eastern, central, and western regions. Market segmentation’s direct effect is the largest in eastern China, the second in central China, and the smallest in western China, which is opposite to regional economic development level. Regression results of model (2–3) and model (6) show that $\beta_{\text{East}} > \beta_{\text{Central}} > \beta_{\text{West}}$, model (1) and model (5) show that $\beta_{\text{East}} = \beta_{\text{Central}} > \beta_{\text{West}}$, and the difference between central and west in model (4) is small so the result is that $\beta_{\text{East}} > (\beta_{\text{Central}} \approx \beta_{\text{West}})$. Overall, the estimation results support the conclusion. Secondly, the spatial lag term ($W * \text{Lnseg} \times \text{west}$, $W * \text{Lnseg} \times \text{central}$) is not significant. Market segmentation has not significant difference in spatial effect among the western, central, and eastern regions, which indicates that the spatial spillover effect of market segmentation has little influence on the regional difference.

Furthermore, considering the spatial fluctuation of parameters, taking geographic information into the model, and using geographically weighted regression (GWR) to re-estimate the model. For 30 provinces from 1995 to 2018, this paper obtains 720 estimation results of $\text{Lnseg}$ by GWR, and estimation results are shown in Figure 3. First, from the perspective of Figure 3a, the average level of $\text{Lnseg}$ has a volatility trend. From 1997 to 2001, 2002 to 2007, and 2008 to 2012, the impact of market segmentation on energy efficiency showed a strengthening trend. This may be because of the impact of SARS in 2001 and the financial crisis in 2008, causing an increase of market segmentation. On the other hand, during 1995–1997 and 2012–2018, the impact of market segmentation on energy efficiency gradually weakened, especially in 2012–2018. It represents the continuous improvement of the economic openness condition. Secondly, in Figure 3b, from the perspective of average regional effect, Shanghai, Jiangsu, Zhejiang, and Anhui in Yangtze River Delta have the strongest negative annual average effect, second in Fujian, Jiangxi, Shandong, Henan, and Jing-Jin-qi region (Beijing, Tianjin, Hebei).

Third, from Figure 3c, we can find that the negative effects of market segmentation in 1995 were weaker in the southern region, but the negative effects in the northern region were stronger than in the southern region in 2018. This indicates that there is certain volatility of the negative effect of market segmentation on energy efficiency. The reason might be that the huge differences between different provinces, such as market behavior, culture, government behavior, etc. At the same time, regional policy change may be an important cause of these differences. These factors are difficult to measure, but have a significant impact on economic development. Market segmentation has significant regional differences also, so the influence of economic operation is the difference from different regions. Overall, the conclusion is consistent with the conclusion of Table 5, that market segmentation has a stronger negative impact in developed provinces. Regional economic development needs an open and free environment, especially for developed regions.
5. Mechanism and Robustness Tests

5.1. Mechanism Tests

Based on Hypothesis 2, Hypothesis 3, and Hypothesis 4, this paper uses stepwise regression to test different mechanisms (see Table 6 for the results). To avoid possible endogeneity, this paper uses the exogenous geographic weight matrix to estimate the result.
| Variables | lnfv | lnpv | Market | ED | STRU | LP | Tech | Energy Efficiency |
|-----------|------|------|--------|----|------|----|------|-------------------|
|           | (1)  | (2)  | (3)    | (4) | (5)  | (6) | (7)  | (8)               |
| Lnseg     | 0.0260 | −0.123*** | 0.00986*** | −0.0604*** | −0.0648** | −0.0223** | −0.00391*** | −0.0415*** |
|           | (1.32) | (−4.82) | (3.09)  | (−3.45) | (−1.99) | (−2.36) | (−4.16) | (−3.98) |
| lnpv      | 0.0798*** | (7.13) | −0.0584*** | (−3.18) | −1.063*** | (−6.48) | 0.0393*** | (10.69) |
| lnfv      | −0.0584*** | (−3.45) | 0.124*** | (5.30) |
| Market    | 1.060*** | (6.48) | 0.585*** | (5.01) |
| ED        | 0.393*** | (10.69) | 0.312*** | (8.71) |
| Struc     | 0.312*** | (8.71) | 0.0921*** | (2.35) |
| Tech      | 0.312*** | (8.71) | 0.129*** | (4.24) |
| LP        | 0.132*** | (3.41) | 0.175*** | (4.82) |
| W*Lnseg   | −0.179*** | (−3.81) | 0.0477 | (0.83) |
|           | (−3.81) | (−2.58) | (6.63)  | (−4.16) | (−1.57) | (0.47) | (1.67) | (1.47) |
| W*Lngv    | 0.132*** | (3.32) | 0.284*** | (7.84) |
| W*lnfv    | 0.132*** | (3.32) | 1.269*** | (3.41) |
| W*MARKET  | 0.293*** | (3.22) | −0.132*** | (−2.90) |
| W*ED      | 0.293*** | (3.22) | 0.0921*** | (2.35) |
| W*STRU    | 0.293*** | (3.22) | 0.129*** | (4.24) |
| W*TECH    | 0.293*** | (3.22) | 0.175*** | (4.82) |
| W*LP      | 0.112 | (1.57) | 0.104* | (1.90) |
| ρ         | 0.0769 | 0.354*** | 0.255*** | 0.627*** |
| Sigam     | 0.175*** | 0.252*** | 0.0140*** | 0.185*** |
| N         | 720 | 720 | 720 | 720 |
| Covariates | Yes | Yes | Yes | Yes |

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
For Hypothesis 2, this paper uses the logarithm of passenger volume (lnpv), the logarithm of freight volume (lnfv), and the ratio of state-owned economy employees to total employment (MARKET) as proxy variables for local protectionism. The estimation results of model (1) Table 5 show that the direct effect of Lnseg in model (1) is 0.026 and failed to pass the statistical significance test, but the spatial effect is −0.179 and has passed the significance test in 1%. So, we can find that market segmentation has a negative effect on lnfv through the influence of surrounding regions. In model (2), the coefficient of Lnseg is −0.123 and significant at 1%, showing that Lnseg has a directly negative in lngv. In short, Lnseg has a significant negative spatial effect on lnfv and a significant negative direct effect on lngv, indicating that market segmentation can hinder the flow and diffusion of economic factors through local protectionism. In addition, the direct effect of Lnseg on MARKET is 0.00986 and has passed the significance test in 1%, indicating that government power is stronger with severer market segmentation. For Hypothesis 3, this paper uses capital per labor (ED) stands for investment level, and the ratio of service output value to industrial output value (STRU), expressing industrial structure optimization as the proxy variables of scale effect. Estimation results of model (4–5) indicate that the coefficient of Lnseg on ED is −0.0604 and passed the significance test in 1%, the coefficient of Lnseg on SRRU is −0.0648 and passed the significance test in 5%, indicating that Lnseg has a significant negative effect on industrial structure optimization and investment level. Market segmentation will inhibit the optimization of investment level and industrial structure. For Hypothesis 4, the number of patents per 100 employees (LP) and the ratio of technology market’s turnover on GDP (TECH) is used to measure technological innovation. Model (5–6) show that the influence of Lnseg on LP and TECH is −0.0223 and −0.00391; all of them passed the significance test in 5%, suggesting that Lnseg has a significant negative effect on LP and TECH. With the increasing of market segmentation, the lack of motivation for enterprises to participate in technological transformation and innovation. The tendency of regional economic development to be closed will hinder the exchange of technologies.

The proxy variables of the three mechanisms are further added to the model, and the estimation results report in model (9–12). In summary, for the information in model (9–12), we can find that the size and significance of Lnseg’s coefficient have changed greatly, the coefficient is −0.00843, −0.0117, −0.0157, and −0.00218 in model (9–12) and failed to pass the significance test in 5%, compared with the result of model (8) that the coefficient of Lnseg is −0.0415 and passed the significance test in 1%. All the Lnseg’s coefficients have not passed the significance of 5%. However, lnfv has a negative impact on energy efficiency in model (9) and model (12), differing from the theoretical analysis. A possible explanation for this might be that the freight volume has a rapid growth, which is faster than the change of energy efficiency, causing the negative relationship between energy efficiency and lnfv. Therefore, the growth rate of freight volume (Δlnfv) is used to re-estimate the model; the estimated result reveals that Δlnfv has a significant positive spatial effect on energy efficiency, that the coefficient of Δlnfv and W * Δlnfv are 0.0148 and 0.148, and spatial effect is significant at the 5% level (the results are excluded from this paper). The increase in the flow rate across the entire region can promote the improvement of energy efficiency. In addition, the coefficient of Market in model (12) is positive, which is opposite to the sign of Equation (9). The main reason may be that market behavior (Market) has a greater impact on the economy, and there may have endogeneity in model (12). Hence, the first-order lag of Market_{t-1} is used to re-estimate model (12) (the results are excluded from this paper). The regression results show that MARKET has a negative direct effect on energy efficiency, and a positive spatial effect at the significance of 1%, which is consistent with the analysis of Hypothesis 2. Taken together, the results in this chapter indicate that the mechanisms of Hypothesis 2–4 have been proved.

5.2. Robustness Tests

First, this paper estimates regression results by a different spatial weight matrices; therefore, the robustness is guaranteed to a certain extent. On the other hand, for more
robust results, we replace the explained variable with the traditional DEA model. Estimation results are shown in Table 7A. The estimation results report that \( \text{Lnseg} \) and spatial lag \( W^* \text{Lnseg} \) are negative, and all have passed the significance test, and consistent with the sign of Table 4.

Table 7. Robustness text.

| Variables | A. Replace the Explained Variable by DEA-Energy Efficiency | B. Replace the Explain Variable by Lag First-Order Variables | C. Adding Covariates in Series |
|-----------|----------------------------------------------------------|----------------------------------------------------------|-------------------------------|
|           | \( W_{01} \) | \( \text{W_dis} \) | \( \text{W_eco01} \) | \( \text{W_ecodis} \) | \( \text{W_pop01} \) | \( \text{W_popdis} \) | \( W_{01} \) | \( \text{W_dis} \) | \( \text{W_eco01} \) | \( \text{W_ecodis} \) | \( \text{W_pop01} \) | \( \text{W_popdis} \) | \( \text{W}_{1} \) | \( \text{W}_{2} \) | \( \text{W}_{3} \) | \( \text{W}_{4} \) | \( \text{W}_{5} \) | \( \text{W}_{6} \) |
| Lnseg     | -0.0399 ***  | -0.0276 ***  | -0.0334 ***  | -0.0264 ***  | -0.0314 ***  | -0.0234 ***  | -0.0744 ***  | -0.0533 ***  | -0.0641 ***  | -0.0482 ***  | -0.0656 ***  | -0.0486 ***  | -0.0525 ***  | -0.0480 ***  | -0.0473 ***  | -0.0413 ***  | -0.0424 ***  | -0.0415 ***  | -0.0525 ***  | -0.0480 ***  |
| W*Lnseg   | 0.0566 ***  | 0.0430 **    | 0.0367 ***  | 0.0240 *     | 0.0342 **    | 0.0239      | 0.0573 ***  | 0.0494 ***  | 0.0286 **    | 0.0260 **    | 0.0394 ***  | 0.0252 ***  | 0.0573 ***  | 0.0519 *    | 0.0492 *     | 0.0447      | 0.0434 *     | 0.0409 *     | 0.0475       | 0.0519 *     |
| \( \rho \) | 0.134 **    | 0.0356       | 0.0908 **   | 0.229 ***    | 0.0503       | 0.0662      | 0.0289      | -0.156 **   | 0.00298     | 0.100 *      | -0.0277     | -0.00415    | 0.0289      | -0.110 **   | -0.0885 **   | -0.773 ***   | -0.756 ***   | -0.677 ***   | -0.00681     | -0.00768     |
| Covariates| YES         | YES          | YES         | YES          | YES          | YES         | YES         | YES          | YES          | YES          | YES         | YES         | YES         | YES         | YES          | YES          | YES          | YES          | YES          | YES          | YES          |

Note: *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Second, re-estimating the model with the lag value of the explanatory variable. To reduce the possible endogenous problems of mutual causality relationship, using the lagging first-order variable to re-estimate the model. The results are shown in Table 7B, indicating that statistical significance and sign of \( \text{Lnseg} \) and \( W^* \text{Lnseg} \) are consistent with the result of Table 4. Moreover, to avoid the influence of control variables, this paper gradually adds the control variables for regression using a geographic weight matrix. Estimation results are shown in Table 7C, which conclusion is consistent with Table 4 too.

6. Conclusions and Policy Implications
6.1. Conclusions

This paper uses Chinese panel data of 30 provinces from 1995 to 2018 to study the impact of regional market segmentation on energy efficiency. Measuring regional market segmentation by price-based approach, calculating regional energy efficiency by super-
SBM model. Finally, a Spatial Durbin Model (SDM) was designed to analyze the impact of market segmentation on energy efficiency. The following conclusions are drawn.

1. Market segmentation has a significant negative impact on energy efficiency. With the increasing market segmentation, energy efficiency has a stronger inhibition. Comparing with the existing studies, the negative effect on EE can be in these files, namely, environmental regulation [12], enterprise scale [20], the proportion of secondary industry [3], labor misallocation [76], and energy consumption structure [3,20]. At the same time, in terms of spatial effects, market segmentation has a positive spatial spillover on energy efficiency estimated by 0-1 matrix, while spatial effects based on the geographic weight matrix are not significant. The conclusion of energy efficiency’s spatial effect is consistent with amounts of studies, such as Wang et al. (2019) [22], Huo et al. (2020) [10] Wu et al. (2020) [16], Cheng et al. (2020) [24], etc. Market segmentation in the surrounding area has a positive impact on local energy efficiency.

2. The effect of Market segmentation on energy efficiency has spatial heterogeneity. First, the negative direct effect of market segmentation is inversely proportional to the economic development of the eastern, central, and western areas. The spatial heterogeneity of EE have proved by existing studies, for example, Cheng et al. (2020) [24], Zhu et al. (2019) [23], Zhonghua Cheng et al. (2020) [25], that energy efficiency demonstrates various regional differences: Eastern region > central region > western region. Market segmentation in the eastern region has the strongest inhibitory effect on energy efficiency, followed by the central region. Second, the result of geographically weighted regression indicates that the impact of market segmentation on energy efficiency is intensified in 1997–2001, 2002–2007, and 2008–2012. During 1995–1997 and 2012–2018, the impact of market segmentation on energy efficiency gradually weakened. From the perspective of average effects in different regions, Shanghai, Jiangsu, Zhejiang, and Anhui in the Yangtze River Delta region have the strongest annual average effects, followed by Fujian, Jiangxi, Shandong, Henan, Hubei, and Beijing, Tianjin, and Beijing-Tianjin-Hebei region. The higher level of regional development, the stronger negative effect of market segmentation. Developed regions need an open and free market environment.

3. Using the causal identification and intermediary effect model, market segmentation can impact energy efficiency through local protectionism, technological difference, and scale effect. The results indicate that, first, market segmentation can hinder economic element’s free flow in different regions, distorting the market competition mechanism, and bring about a decline in energy efficiency through local protectionism. Second, market segmentation can affect energy efficiency by restraining regional technological innovation. Third, market segmentation can also hinder capital flow and investment across regions, hindering the optimization of industrial structure from curbing energy efficiency by scale effect.

Through the research of this article, it points out the relationship between market segmentation and energy efficiency. Market segmentation is a still existing problem in China, which has a negative impact on regional development. Therefore, the research in this article proposes a new path to improve energy efficiency. By improving the market segmentation between different administrative regions, can promoted energy efficiency can and saving resource consumption. However, this article also has certain shortcomings. First, environmental factors are not considered in the study of energy efficiency. Due to the difficulty of data collection, the study of energy efficiency does not consider the constraints of pollution emissions on efficiency. Therefore, in further research, environmental-related data will be collected to measure energy efficiency. On the other hand, in terms of theoretical mechanism, the mechanism of market segmentation on energy efficiency is not deep enough and needs to be further improved and supplemented. This article is only a relatively simple design of the relevant mechanism, which needs to be further strengthened in future research. In addition, since there are few market segmentation measurement data at the national level, data from 30 provinces are used to study based on the perspective of microeconomics.
Hence, in further research, the research on China’s national-level macroeconomics is a further research direction.

6.2. Policy Implications

The following policy recommendations are proposed based on the study of this paper:

1. Breaking down government barriers, upgrading the modernization level of the energy industry chain and supply chain, forming a new form of production and consumption in the energy industry. Specifically, including:
   1. Increasing the institutional innovation and digitization level of the energy industry, promoting the establishment of the energy-internet on a whole country scale;
   2. breaking the institutional barriers of energy consumption and production through promoting new forms and new business formats of energy transactions, relying on big-clients-direct-purchase, financial instruments, such as energy forward and energy options;
   3. promoting energy sales side competition to release the benefits of energy sales;
   4. relax energy production side competition appropriately to alleviate the problem of X inefficiency;
   5. construction of pipelines and network lines that run through the large area to break the geographical barrier between energy consumption in eastern regions and energy production in western regions, forming a major artery for the geographical east-west flow of energy elements.

2. Strictly controlling government subsidies, optimizing subsidy targets, further reducing protectionism:
   1. Strictly controlling the subsidies for high energy-consuming and high-polluting industries;
   2. enhance the support for new energy technologies, such as support for hydropower, solar energy, bio-intelligent power generation, and other fields, optimizing energy structure;
   3. continuing to maintain preferential treatment for key industries, for example, new energy vehicles and green environmental protection equipment (wind power generation devices, combustible ice mining devices, etc.), promoting industrial progression.

3. Extending the energy price control period, stimulating the energy industry’s technological innovation. The period of energy price control should be appropriately relaxed to 5–8 years, allowing technological innovation companies to obtain the excess profits of cost reduction and efficiency improvement brought about by technological innovation for a longer time. During the control period, enterprises enjoy the profits of technological progress, releasing technological advantages and social welfare in the next control period. Considering their own profits and competitive advantages, enterprises will increase the motivation for technological innovation during a longer price control period, increase technological exchanges, forming an innovative competition pattern at the enterprise level, and finally, promoting energy efficiency.

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