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Spatial Effects of Urban Agglomeration on Energy Efficiency: Evidence from China

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Abstract: The rapid expansion of large cities in China has substantially increased energy consumption. With ever stringent environmental policy in force, energy efficiency becomes an important issue. As the emergence of these urban agglomerations (UAs) is usually due to externality effects of spatially concentrated factors, this paper investigates how these factors can affect energy efficiency. Based on mono index, which is used to describe the spatial location information, we have constructed the spatial-structure index of UAs. Using panel data on ten major UAs in China from 2008 to 2017, we find that, in the whole sample, there is an inverse relationship between the spatial structure of UAs and energy efficiency: The higher the concentration degree of factors of UAs, the lower the energy efficiency. Across different regions, however, the relationship between spatial structure and energy efficiency is heterogeneous. The concentration degree of factors in the eastern and central regions of China is relatively high, and the spatial structure there does lead to a decrease in energy efficiency. By contrast, UAs in China's western region are in a period of factor concentration, with spatial structure playing, in that region, a positive role in improving energy efficiency.

Keywords: spatial structure; urban agglomeration; energy efficiency; mono index

1. Introduction

During the period of China's "13th National Five-Year Plan," 18 urban agglomerations (UAs) and two urban circles were planned and established. With UAs becoming the major engine of urbanization in China (Form National New Urbanization Plan (2014–2020)), the Plan treated them as the primary way to promote China's new urbanization initiative. Nowadays, with the construction and progress of UAs, per capita energy consumption of urban families is 50% higher than that of rural households [1]. However, developing the green economy involves complex system engineering, and the trend in the current international community is for energy efficiency to play a key role [2]. To build the green economy, China needs to promote energy conservation, emission reduction, and the exploitation, as well as utilization, of renewable energy [3], which promotes the sustainable and high-quality development of the Chinese economy. Hence, scholars, as well as policy makers, have identified a vital concern: How to improve energy efficiency so as to alleviate energy wastage and the pressure of environmental pollution on ecology. At the same time, it needs to investigate how UAs affect the energy efficiency of cities. This has important theoretical and practical implications for improving the efficiency of urban operation and promoting the sustainable and high-quality development of cities.

At present, domestic and foreign scholars have implemented considerable in-depth research on UAs or energy efficiency from multiple perspectives. These existing studies facing to energy efficiency are mostly concerned with influence factors [4–6], the relationship between energy efficiency

and economic growth [7–9], sustainable development [10–12], and so on. Fernando, Y. and Hor, W. L. found that manufacturing enterprises have a stronger energy-cost awareness and more effective measures of energy management, which not only improve energy efficiency, but also reduce the emission of carbon [13]. Li, H. and Shi, J. F. found that energy efficiency varies with different industrial structures, and light industry has the highest energy efficiency in China [14]. After examining five major energy consumption industries in 23 countries of the European Union, Makridou, G. et al. concluded that the difference in energy efficiency is mainly due to the characteristics of the industry, and countries with energy production markets that are competitive have higher energy efficiency [15]. There are ever-increasing studies on UAs, including definitions of its concepts [16–19], its ecological environment [20–22], its coordinated development [23–25], regional economy [26–28], and so on. By using semi-parametric models to study the productivity of UAs in the United States, Melo, P. C. et al. found that employment density has a clearly positive effect on the labor productivity of UAs [29]. Gu, Q. et al. researched the Yangtze River Delta UAs of China and found that, with population growth, the ecological environment has shown a “deficit,” and the biological carrying capacity has shown a downward trend [30]. Garcia-López, M. À. and Muñoz, I. found that the spatial structure of cities is crucial to the economic development of the entire metropolitan area [31]. Lee, B. found that the spatial structure of UAs has a distinct characteristic: The trend of development is from a single center to multiple centers [32]. The studies of other scholars have produced the same results and support this point [33,34]. Fang, C. et al. concluded that the stability of the spatial structures of China’s UAs is at a relatively low level, and varies greatly from one structure to another [35]. Tan, R. et al. found that the influence of spatial interaction is the only socio-economic factor that contributed to the growth of Wuhan UA from 2005 to 2010 [36]. Zheng, Z. and Bohong, Z. found that an optimal spatial structure exists, a single-core and multi-center model, that is most suitable for the development of the Yangtze River Delta UA [37]. Therefore, spatial structure is one of the main characteristics of UAs. Simultaneously, the effect of the spatial structure of UAs on the social economy cannot be ignored, and energy efficiency as well as economic output are inextricably linked [31,38]. What can be said is that the spatial structure of UAs plays an important role in energy efficiency. Yet few studies have explored the relationship between UAs and energy efficiency from the perspective of the spatial structure of UAs.

Based on the analysis above, this paper studied the energy efficiency of UAs from the perspective of spatial structure. Spatial structure can measure the geographical features of cities and reflects the degree of concentration of various elements of UAs, reflecting the relationship between cities in UA [39,40]. This spatial structure can be measured by the concentration degree of factors between cities in a UA and the concentration degree of the cities themselves. In general, when most of the elements contributing to UAs are controlled by only one or two cities, those elements will be more concentrated. However, the distribution of factors between cities will not reflect the concentration degree of regionally based factors. In order to more fully measure this other concentration degree, the concentration degree of cities themselves should be considered, especially central cities. Generally speaking, the closer the distance between cities, the higher the degree of concentration of those cities, and, in turn, the higher the degree of concentration of those factors contributing to UAs. Meijers, E. J. and Burger, M. J. found that multi-center spatial structures can improve labor productivity, but with the increase of population, this promotion effect will be weakened [39]. In researching the relationship between spatial structure and economic growth, Lee, B. and Gordon, P. found that the higher the dispersion of elements of UAs, the faster the economic growth [40]. What’s more, based on the data of 19 Chinese UAs, Liu, C. et al. found that the concentration degree of factors in eastern UAs was higher than that in western UAs [41], which is similar to the conclusion reached by Fang, C. et al [42]. Therefore, it can be inferred that the degree of factor concentration in the spatial structure of UAs plays a vital role in the development of UAs.

In the process of studying the effect of UAs on energy efficiency from the perspective of spatial structure, there are two problems that authors have to think about: Firstly, the relationship between the

concentration degree of factors of UA and the energy efficiency of UAs; secondly, due to the differences in economic development in the eastern, central, and western regions of China's UAs, the effect of different degrees of concentration on energy efficiency may be different.

Existing studies on the degree of concentration and energy efficiency of UAs mainly discuss it from two aspects. One aspect the size of the concentration degree of factors of UA. Han, F. et al. found that whether it is a high-end technology industry or a low-end technology industry, the agglomeration of industry will reduce the energy efficiency of UAs [43]. Liu, B. et al. found that there is a big gap in the carbon emission efficiency of UAs in China, and the more developed and mature the UA, the higher its carbon emission efficiency [44]. The other aspect is the structure of the factor concentration of UAs. Through the study of 23 UAs in China, Fang, C. et al. found that increasing the amount of spending on science and technology and upgrading industrial institutions can help increase the rate of input–output [42]. Ouyang, X. et al. found that the structure of factors input into the production can significantly affect the industrial energy efficiency of Pearl River Delta UA [45]. Rongdi, G. et al. found that for the Yangtze River Delta UA, the relationship between factor structure and energy efficiency is very close, and the industrial structure, investment scale, as well as foreign trade, is positively correlated with energy efficiency [46]. All the above indicates that the heterogeneity of the spatial structure of UAs will affect energy efficiency. However, the influence of the geographical location between cities is often neglected in the existing studies on spatial structure, which leads to the deviation in results. This is because in a multi-center UA, the closer the central city, the higher the concentration degree of factors.

With these issues in mind, this study has two innovations relating to existing research in this area. Firstly, the energy efficiency of UAs is studied comprehensively from two aspects: Spatial structure and its difference. Secondly, the geographical distance between central cities is considered in the study of spatial structure when exploring the impact of spatial structure on energy efficiency. Based on the theory above, this study proposes two hypotheses:

Hypothesis H1. *The higher the concentration degree of factors of UA, the lower the energy efficiency.*

Hypothesis H2. *Owing to the differences in regional space in China, the spatial structure of the eastern, central, and western UAs has different effects on energy efficiency.*

The rest of this paper is arranged as follows: In Section 2, based on the mono index, the spatial-structure index, which is the key explanatory variables affecting energy efficiency in this study, can be defined. By comparing the mono index and the spatial-structure index, the significance of spatial information for research on energy efficiency and UAs can be demonstrated. Section 3 then formulates the relevant econometric equation, introducing each variable in detail and calculating the results according to the equation and the available data. In Section 4, the results of specific regression analysis are provided, and then the influence of spatial-structure of UAs on energy efficiency is discussed in detail. Finally, in Section 5, we draw conclusions and explore policy implications.

2. Measuring the Spatial-Structure Index

2.1. Research Object

Based on the UAs that The State Council has approved and that have already been widely studied, ten representative UAs were selected as the sample in this study. The time span under consideration runs from 2008 to 2017. The data are taken from the China City Statistical Yearbook, the China Energy Statistics Yearbook, and the Statistical Yearbooks compiled by provinces for the period 2009–2018. The specific sample information is shown in Table 1.

Table 1. Ten urban agglomerations (UAs) and their constituent cities.

UAs	Cities (137)
Central and Southern Liaoning UA	Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Yingkou, Liaoyang, Panjin, Tieling (10)
Beijing-Tianjin-Hebei UA	Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang (10)
Shandong Peninsula UA	Jinan, Qingdao, Zibo, Dongying, Yantai, Weifang, Weihai, Rizhao (8)
Yangtze River Delta UA	Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou, Hefei, Wuhu, Ma'an Shan, Tongling, Anqing, Chuzhou, Chizhou, Xuancheng (26)
West Coast Strait UA	Fuzhou, Xiamen, Putian, Quanzhou, Zhangzhou, Ningde (6)
Pearl River Delta UA	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, Zhongshan (9)
Central Plains UA	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Hebi, Xinxiang, Jiaozuo, Xuchang, Luohe, Shangqiu, Zhoukou, Jincheng, Haozhou (13)
Middle Yangtze UA	Wuhan, Huangshi, Yichang, Xiangyang, Ezhou, Jingmen, Xiaogan, Jingzhou, Huanggang, Xianning, Changsha, Zhuzhou, Xiangtan, Hengyang, Yueyang, Changde, Yiyang, Loudi, Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ji'an, Yichun, Fuzhou, Shangrao (28)
Guan-Zhong Plain UA	Xi'an, Tongchuan, Baoji, Xianyang, Weinan, Shangluo, Yuncheng, Linfen, Tianshui, Pingliang, Qingyang (11)
Chengdu-Chongqing UA	Chongqing, Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, Ziyang (16)

2.2. Measuring Method

The spatial-structure index can be calculated by combining two other indexes: The concentration degree of factors distributed between cities, and the concentration degree of cities themselves.

On the basis of the method of Meijers, E. J. and Burger, M. J. [39], the mono index figured by the Rank-Size Rule is used to measure the concentration degree of factors distributed between cities. The econometric equation can be created as:

$$\ln POP_{ij} = C - q \ln R_{ij} + u_{ij} \quad (1)$$

where j and i separately denote the j th city and i th UA; POP_{ij} and R_{ij} respectively represent the size and the position order; u_{ij} is the random disturbance term; C is a constant; and the q is the estimated value of UA, which is also the basis for calculating the mono index. In general, the larger the absolute value of q , the more concentrated the elements of UA in only one or two cities. For specific calculations, three indicators, regional GDP, year-end total population, and the area of developed urban spaces, are selected as the original indicators, and the method of Principal Component Analysis (PCA) is applied to determine a composite score based on these three indicators. This score is used to measure the size of the city. Meanwhile, in order to avoid a negative score, all the scores are added at one point to make sure that the negative scores become positive, and the adjusted size scores are then generated. These results are values of POP_{ij} . The position order of each city, the value of R_{ij} , is reflected in Table 1. By substituting these values of POP_{ij} and R_{ij} for the second, third, and fourth cities in each UA in Equation (1), three values of q can be calculated separately. The average of these three values of q is defined as the mono index.

For another index, the spatial location of cities within the same UA should be considered, and this paper only measures the spatial location of the central cities. Further, when it comes to choosing the central cities, there are two main criteria: The size scores of cities (POP_{ij}), and the number of cities within UAs. According to the calculation results, the Guan-Zhong Plain UA, the size score of Xi'an is over 2 points, while other cities' scores are between 0.5 and 0.7. There is a huge gap between these scores, so it is reasonable to choose Xi'an as the only central city in this UA. By contrast, both the Yangtze River Delta UA and Middle Yangtze UA feature more than 25 cities each, so the top three cities in each UA can be selected as central cities. For the other UAs, the top two cities can be designated as central cities. In this study, information about the spatial location of such central cities can be measured by the ratio of the average distance between central cities to the root square of the UA's total area. This ratio corresponds to the concentration degree of cities within UAs.

The equation is:

$$2 \sum_{\substack{i, j = 1 \\ j > i}}^n d_{ij} / n(n-1) \sqrt{\sum_{k=1}^m S_k} \quad (2)$$

where n is the number of central cities; d_{ij} represents the linear distance between i th and j th central city; m is the number of cities within the same UA; and S_k measures the area of the administrative region of k th city. What can be seen from the definition is that a smaller ratio indicates that the central cities are closer, such that the elements of UAs are more concentrated. If there is only one central city in a UA, like Xi'an, this ratio of Equation (2) can be written as $\sqrt{S/\pi}$.

The higher the mono index, the higher the concentration degree of factors distributed between cities. Simultaneously, the smaller the distance between central cities, the higher the concentration degree of cities. Thus, the spatial-structure index in this study can be defined as the ratio of the mono index to the concentration degree of cities, with this ratio being used to measure the concentration degree of factors contributing to UAs. Further, the larger the spatial-structure index, the more concentrated the elements in UAs.

In line with the main research focus of this paper, the results of the mono index and spatial-structure index are presented in Tables 2 and 3, whereas the concentration degree of cities is not shown.

2.3. Results Measured

2.3.1. The Mono Index

Following the steps described above, and making use of the method of PCA, all the variables can be substituted into Equation (1) to calculate three values of q for each UA. To reiterate, the average of these three values is the mono index. The results can be found in Table 2.

Further analysis can be performed on the base of this regional division of UAs. First, from the perspective of the values for the mono index, as Table 2 shows, the mono index of eastern UAs is lower overall than central and western UAs. Among these eastern UAs, the mono index of the Beijing-Tianjin-Hebei UA and the Yangtze River Delta UA whose values are about 1 point are obviously higher than the other UAs in the region. The reason is that Beijing and Tianjin have the highest size scores of all the cities. As for the Yangtze River Delta UA, compared with the rest cities in this UA, the size score of Shanghai is dramatically higher. In short, when the development of central cities far exceeds other cities, the size scores of those central cities will be high, as will the mono index. By contrast, the values for the mono index of the Shandong Peninsula UA and the West Coast Strait UA are no more than 0.4 and are lower than those of other UAs, indicating that the progress of the cities included in these two UAs is relatively balanced. For the two central UAs, Central Plains UA and Middle Yangtze UA, the average value of each one is over 0.6. As for the western regional, the Chengdu-Chongqing UA, in which the value varies from 1.358 to 1.555, clearly presents the dual-core condition of Chongqing and Chengdu. Thus, the Chengdu-Chongqing UA is ranked first among the ten UAs. Meanwhile, the lowest value for the mono index of the Guan-Zhong Plain UA is 1.121, causing this UA to get the second-place ranking.

Table 2. The mono index of ten UAs.

UAs	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Central and Southern Liaoning	0.672	0.697	0.644	0.649	0.678	0.685	0.730	0.715	0.691	0.643
Beijing-Tianjin-Hebei	1.099	1.109	1.049	1.042	1.039	1.076	1.007	0.962	0.936	0.928
Shandong Peninsula	0.216	0.219	0.218	0.218	0.250	0.325	0.329	0.372	0.318	0.355
Yangtze River Delta	1.024	1.015	0.989	0.962	0.885	0.828	0.785	0.777	0.810	0.711
West Coast Strait	0.289	0.294	0.264	0.247	0.293	0.302	0.306	0.308	0.315	0.152
Pearl River Delta	0.574	0.626	0.637	0.637	0.639	0.649	0.476	0.577	0.553	0.549
Central Plains	0.699	0.716	0.930	0.947	0.997	0.963	0.994	0.836	0.789	0.704
Middle Yangtze	0.805	0.758	0.758	0.690	0.693	0.677	0.671	0.530	0.516	0.609
Guan-Zhong Plain	1.121	1.149	1.199	1.230	1.254	1.298	1.337	1.357	1.337	1.379
Chengdu-Chongqing	1.358	1.368	1.413	1.517	1.492	1.496	1.542	1.555	1.519	1.525

In addition, some conclusions can be drawn about the trend of the mono index over time. As Figure 1 shows, in the east, the mono index of the Beijing-Tianjin-Hebei UA and the Yangtze River Delta UA are gradually decreasing, showing that the concentration degree of factors is diminishing, while the mono index of other eastern UAs remains low and stable.

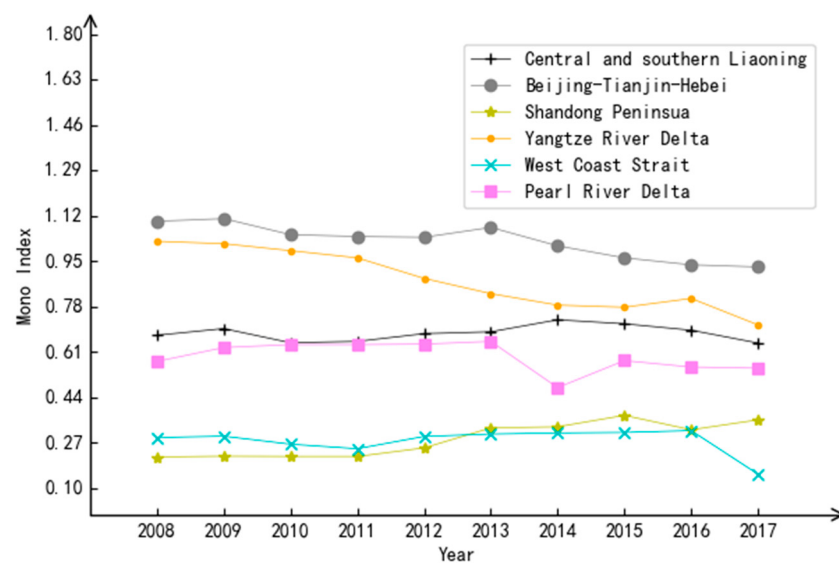


Figure 1. The trend of the mono index of the eastern UAs.

In the central area, as shown in Figure 2, the mono index of the Central Plains UA increased at first, and then continuously decreased. As for Middle Yangtze UA, the mono index shows a declining trend. The reason for the declining trend in both UAs is that the development of other cities has narrowed the gap with the central cities.

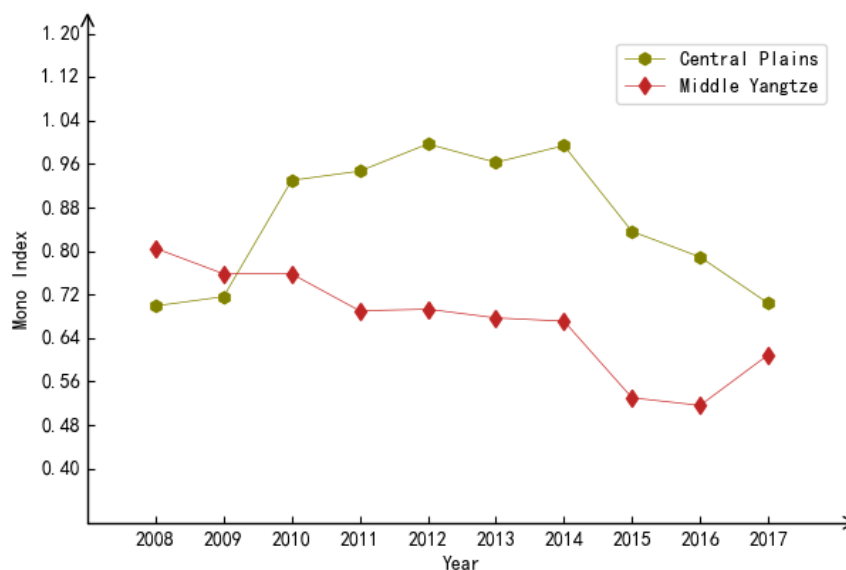


Figure 2. The trend of the mono index of the central UAs.

Finally, it is shown that mono index is high and continuously increasing of the two western UAs by Figure 3, indicating that the concentration degree of factors in the Guan-Zhong Plain UA and the Chengdu-Chongqing UA are rising, with economic factors being gathered into the central cities, such as Xi'an, Chongqing, and Chengdu.

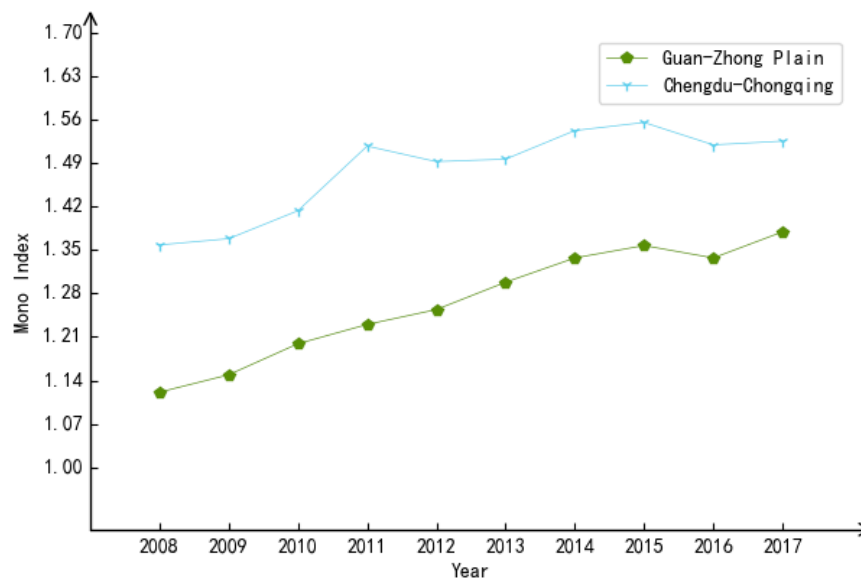


Figure 3. The trend of the mono index of the western UAs.

2.3.2. The Spatial-Structure Index

Taking into account the distance between the central cities, the spatial-structure index can be measured as a ratio of the mono index described on Table 2 and the concentration degree of cities calculated via Equation (2). The concentration degree of cities is not listed in this paper because of space limitations, but Table 3 shows the spatial-structure index.

A brief analysis reveals some key points. When the concentration degree of cities is taken into account, the spatial-structure index of several UAs has undergone considerable changes, among which the Guan-Zhong Plain UA has the largest numerical fluctuation. The average value for the spatial-structure index of the Guan-Zhong Plain UA rose from 1.266 to 14.508, surpassing the Chengdu-Chongqing UA and assuming the number-one position. This is because Xi'an, the only one central city, controls almost all elements of this UA. Similarly, for the Beijing-Tianjin-Hebei UA, the two central cities, Beijing and Tianjin, have a close association, causing the value for the spatial-structure index to be higher than 3 points, and surpassing the Chengdu-Chongqing UA as well; it occupies the number-two position. At the same time, compared with the distance between Dalian and Shenyang, or Jinan and Qingdao, the distance between Fuzhou and Xiamen is smaller. Hence, in contrast with the values for the mono index, the gap between the spatial-structure index of the West Coast Strait UA and the spatial-structure index of the Central and Southern Liaoning UA has closed, whereas the gap between that of the West Coast Strait UA and that of the Shandong Peninsula UA has expanded. Meanwhile, there is little change in the relative rankings of the other UAs.

In short, it can be clearly seen from discussion about the mono index and the spatial-structure index, which are used to describe the spatial feature of UAs, that the closer the distance between the central cities is, or the wider the regional coverage of UA is, the larger the spatial-structure index is compared with the mono index, which indeed reflects the characteristics for UAs in China.

Table 3. The spatial-structure index of UAs and the central cities of each UA.

UAs	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Central Cities
Central and Southern Liaoning	0.587	0.609	0.563	0.567	0.592	0.598	0.638	0.625	0.604	0.562	Shenyang, Dalian
Beijing-Tianjin-Hebei	3.704	3.738	3.535	3.512	3.502	3.626	3.394	3.242	3.155	3.128	Beijing, Tianjin
Shandong Peninsula	0.197	0.200	0.199	0.199	0.228	0.296	0.300	0.339	0.290	0.324	Jinan, Qingdao
Yangtze River Delta	2.092	2.074	2.021	1.966	1.808	1.692	1.604	1.588	1.655	1.453	Shanghai, Nanjing, Hangzhou
West Coast Strait	0.318	0.323	0.290	0.272	0.322	0.332	0.336	0.339	0.346	0.167	Fuzhou, Xiamen
Pearl River Delta	1.303	1.421	1.446	1.446	1.450	1.473	1.080	1.310	1.255	1.246	Guangzhou, Shenzhen
Central Plains	2.044	2.094	2.720	2.770	2.916	2.816	2.907	2.445	2.307	2.059	Zhenzhou, Luoyang
Middle Yangtze	1.675	1.578	1.578	1.436	1.442	1.409	1.397	1.103	1.074	1.267	Wuhan, Changsha, Nanchang
Guan-Zhong Plain	12.846	13.167	13.740	14.095	14.370	14.874	15.321	15.550	15.321	15.802	Xi'an
Chengdu-Chongqing	2.474	2.492	2.574	2.764	2.718	2.725	2.809	2.833	2.767	2.778	Chongqing, Chengdu

3. Model Building, Variable Selection, and Data Description

3.1. Model Building and Variable Selection

In theory, energy efficiency is not only affected by spatial structure, but also by other factors such as industrial structure, foreign direct investment, technological level, energy consumption structure, etc. Therefore, it is necessary to observe the real impact of spatial structure on energy efficiency when these factors are held as constant. In addition, the data used in this paper are the panel data on 137 cities from 2008 to 2017. The time span is relatively short, and the number of individuals relatively large. The data constitute a short panel. Hence a general panel-data regression model is adopted. Thus, in order to investigate how the spatial structure of UAs can affect the energy efficiency of cities, this panel model can be built as follows:

$$Eff_{it} = \beta_0 + \beta_1 Spastr_{it} + \sum_{j=1}^m \beta_j X_{jit} + u_i + v_i + \varepsilon_{it} \quad (3)$$

where i, t respectively represent city and year; Eff is energy efficiency; $Spastr$ denotes the index of spatial structure; X is the control variable; m is the number of X ; and the u, v , and ε are all random disturbance terms.

Eff , the ratio of effective output to effective input, is the explained variable in this study. The method used to measure the energy efficiency of the total factors for each city is the super-efficiency slacks-based measure (SBM), which considers both expected and undesired outputs [47,48]. Three input–output indexes are chosen to measure energy efficiency.

First, there is the input index. Energy input, capital investment, and labor input are all included in this input index. Energy input is a function of energy consumption, and based on the characteristics of the industrial structure of each province, the specific accounting methods for energy use vary across provinces. In particular, there are hardly any heavy industries in Jiangsu Province or Zhejiang Province, so energy input is multiplied by the electricity consumption of each city along with a ratio: Namely, the ratio between the total electricity consumption of the province where the city is located and the total national energy consumption. By contrast, in Liaoning Province and Gansu Province, the input index of each city is calculated via the ratio of the consumption of liquefied petroleum gas to total national total energy consumption. For the other cities, the energy input is multiplied by the energy consumption per unit of GDP and the regional GDP. Capital investment can be measured by fixed capital stock, and the estimation method is the perpetual-inventory method: $K_t = K_{t-1}(1 - \delta) + I_t$, where K is the capital stock; I represents the investment of fixed assets; and δ is the depreciation rate. The value of δ is 10.96%, according to the method of Haojie, S. [49]. Taking 2007 as the base period, the fixed-assets inventory in base period can be estimated by the Reinsdorf-Cover formula [50]: $K_0 = I_0(1 + g) / (\delta + g)$, where K_0 represents the fixed-assets stock at the end of 2007; I_0 is the amount of the fixed-assets investment in 2007; and g represents the average growth rate of fixed-assets investment in the past, which can be calculated by the geometric average growth rate of fixed assets investment during the period 2000–2007. Labor input, finally, can be measured by the average of employment.

Second, there are expected output index and unexpected output index in the output index. The expected output index is measured by the regional GDP of each city. For unexpected output index, if we adopt the improved entropy method, industrial wastewater, SO_2 , and solid-smoke (ash or dust) emissions can be consolidated into a comprehensive pollution index to describe this index.

$Spastr$ is the key explanatory variable in this paper. This index has been described in detail in Section 2.

As for X in Equation (3), although there are many causes affecting energy efficiency, four variables are selected as the control variables, in view of the research goals of this paper. These variables include industry structure ($Indstr$), foreign direct investment (FDI), technology ($Tech$), and energy-consumption

structure (*Ecstr*). In other words, the value of m in the Equation (3) is 4. To take each of these four variables in turn:

Industrial structure (*Indstr*). This variable can be calculated as the proportion of the tertiary industry relative to GDP. Although energy dependence varies across industries, in general, the energy consumption of the tertiary industry is relatively low. Thus, the value of the coefficient of industrial structure is expected to be positive.

Foreign direct investment (*FDI*). The proportion of foreign direct investment relative to regional GDP is taken as the estimated value of this index. On the one hand, when R&D intensity reaches a certain level, the technology spillover of *FDI* may have a beneficial impact on energy intensity [51]. On the other hand, *FDI* may cause environmental degradation, as is especially evident in the western region of China [52–54], leading to a ‘pollution paradise’. Therefore, the value of the coefficient of *FDI* remains uncertain.

Technological level (*Tech*). This variable is measured by the number of employees working in scientific research and technical-service industries, in increments of 10,000 persons. The higher the technical level, the better the energy efficiency, and, thus, the more energy consumption will decrease. However, as technology improves, the scale of production will expand; this may cause diminishing returns and even lead to the increase of pollution emissions, resulting in a technical ‘rebound effect’ [55,56]. This ‘rebound effect’ involves changes induced by improvements in technological efficiency that reduce the impact of these same improvements on energy intensity [57]. Therefore, the coefficient of this variable is unknown.

Energy consumption structure (*Ecstr*). The value of this variable corresponds to the proportion of total electricity consumption relative to total energy consumption. Energy-consumption structure is a vital factor affecting energy efficiency. Electricity is a relatively clean energy, so the coefficient is expected to be positive.

3.2. Data Description

We substitute the data for the three input–output indexes into the super-efficiency SBM model to calculate the energy efficiency of each city. However, due to space limitations, this paper shows only the average of the energy-efficiency ratings for UAs in even years. We sort those ratings from high to low, in hopes of comparing and analyzing the energy efficiency of the ten UAs in a more macroscopic way. The results are given in Table 4.

What can be concluded from Table 4 is that the energy efficiency of the eastern UAs is higher than that of the central and western UAs. Further conclusions can be drawn from a more specific analysis of the situation of the eastern UAs. The energy efficiency of the Pearl River Delta UA remains in the top two, the value far exceeding those for other UAs prior to 2010, with a maximum value of 0.7526. The ranking of the Yangtze River Delta UA rises significantly and remains in the top three after 2012, with the value rising from 0.2591 to 0.6370. By contrast, the energy efficiency of the Beijing-Tianjin-Hebei UA is relatively low, with an average value of 0.4088. The reason is that, although the energy efficiency of the central cities, Beijing and Tianjin, is high, the energy efficiency of the prefecture-level cities in Hebei Province is low, causing the lower average value for the Beijing-Tianjin-Hebei UA as a whole. The ranking of the Central and Southern Liaoning UA is at the top three from 2008 to 2014, and reached the first place in 2014, with a value of 0.6881, but in 2016 the ranking deeply decreases because GDP fell sharply and pollution emissions increased. As for the central and western UAs, the energy efficiency varies from 0.20233 to 0.4809, resulting in low-ranking UAs, although the gap separating them from the eastern UAs reveals a shrinking trend.

Table 4. Average energy efficiency and ranking of the ten UAs.

UAs	2008	Ranking	2010	Ranking	2012	Ranking	2014	Ranking	2016	Ranking
Central and Southern Liaoning	0.3688	3	0.3743	3	0.6221	2	0.6881	1	0.4942	6
Beijing-Tianjin-Hebei	0.2804	5	0.3193	5	0.4003	7	0.5283	5	0.5158	4
Shandong Peninsula	0.3549	4	0.3366	4	0.4378	5	0.5890	4	0.5333	3
Yangtze River Delta	0.2591	6	0.2714	7	0.5696	3	0.6148	3	0.6370	2
West Coast Strait	0.3813	2	0.3982	2	0.4737	4	0.5079	6	0.5040	5
Pearl River Delta	0.7009	1	0.7526	1	0.7453	1	0.6620	2	0.6512	1
Central Plains	0.2174	9	0.2023	10	0.3914	9	0.4142	9	0.4066	9
Middle Yangtze	0.2259	8	0.2320	9	0.3932	8	0.4809	7	0.4617	7
Guan-Zhong Plain	0.2308	7	0.2548	8	0.3441	10	0.3525	10	0.3323	10
Chengdu-Chongqing	0.2126	10	0.2823	6	0.4220	6	0.4794	8	0.4309	8

Note: Data are taken from the China City Statistical Yearbook, the China Energy Statistical Yearbook, and Statistical Yearbooks compiled by provinces for the years 2001 and 2008–2018. The municipal district is used as the statistical caliber.

4. Empirical Analysis

4.1. The Impact of Spatial Structure on Energy Efficiency

The data for all ten UAs were subjected to a regression analysis, to test whether spatial structure has a significant impact on the energy efficiency of UAs. According to the F-test, the LR-test, and the Hausman-test, the fixed-effect model proved to be the best model for this analysis. In order to ensure more stable results for this regression and enhance the reliability of the analysis, the estimation process of regression Equation (3) is divided into several steps. First of all, the mono index is regarded as the key explanatory variable, and all the four control variables are included, resulting in Model 1. Then, the most important spatial-structure index is used as the explanatory variable to estimate Equation (3), and the estimated regression equation shown in Model 2 is obtained. Finally, the four control variables, *Indstr*, *FDI*, *Tech*, and *Ecstr*, are joined with Model 2, one by one, for purposes of regression, yielding, respectively, Model 3, Model 4, Model 5, and Model 6. This method is adopted to test the robustness of the regression results, and thereby ensure the reliability of the analysis. The regression estimation results are shown in Table 5.

Table 5. Regression Estimation Results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	−0.0243 ** (0.0104)	−0.0125 *** (0.0039)	−0.0267 ** (0.0123)	−0.0262 ** (0.0120)	−0.0256 ** (0.0120)	−0.0246 ** (0.0120)
<i>Indstr</i>	0.5925 *** (0.0438)		0.5780 *** (0.0446)	0.5741 *** (0.0436)	0.5801 *** (0.0434)	0.5981 *** (0.0439)
<i>FDI</i>	−0.0014 *** (0.0001)			−0.0015 *** (0.0002)	−0.0014 *** (0.0002)	−0.0014 *** (0.0002)
<i>Tech</i>	0.0060 *** (0.0017)				0.0059 *** (0.0017)	0.0060 *** (0.0017)
<i>Ecstr</i>	0.0267 *** (0.0101)					0.0264 *** (0.0101)
Constant	0.1949 *** (0.0271)	0.04671 *** (0.0181)	0.2291 *** (0.0391)	0.2888 *** (0.0390)	0.2715 *** (0.0392)	0.2395 *** (0.0409)
σ_u	0.1697	0.1629	0.1845	0.1897	0.1769	0.1684
σ_e	0.1464	0.1609	0.1510	0.1475	0.1468	0.1465
ρ	0.5734	0.5062	0.5989	0.6232	0.5920	0.5693
N	1370	1370	1370	1370	1370	1370
Relevant test	F-test: F=11.95[0.0000]; LM-test: 1139.19[0.0000]; Hausman-test: 17.85[0.0031]					

Note: Due to limited space, this paper can only list the F-test, LR-test, and Hausman-test of Model 6. ***, ** respectively indicate that the coefficients are significant at a 1% and 5% level. The values in parentheses are standard variances, and the values in brackets are *P* values.

What can be seen from Table 5 is that, from Model 1 to Model 6, the regression coefficients of each variable may float slightly, but the sign of each coefficient remains the same, indicating that the results are robust. In addition, the estimates of the core explanatory variable, *Spastr*, are −0.0243, −0.0125, −0.0267, −0.0262, −0.0256, and −0.0246, respectively, and at a 5% level of significance, all the coefficients are significantly negative, in a manner that is consistent with the previous expectation. Thus, the Hypothesis H1 cannot be rejected, indicating that spatial structure of UA does significantly impact energy efficiency.

However, because of space limitations, this paper only analyses the results of Model 1 and Model 6. In Model 1 and Model 6, the values of the estimated coefficient of *Spastr* are −0.0243 and −0.0246, showing that as the value of spatial-structure index adopted in Model 6 increases, comparing the increase for mono index, energy efficiency decreases more. This is because the spatial-structure index is larger than the mono index, which was discussed in the Section 2.3. In other words, the higher the concentration degree of factors contributing to UAs, the lower the energy efficiency. This is because the majority of ten UAs used for this analysis are relatively mature, and the construction of the central

cities is nearly complete. In such circumstances, if the UAs blindly gather their required elements into central cities, the central cities may become overcrowded, leading to the relative surplus of labor and the slow development of secondary cities due to a lack of resources. This chain of events can obstruct needed industrial upgrading and ultimately reduce the energy efficiency of UAs. Yet a reasonable distribution of the elements necessary for UAs across each city can bring many benefits: Effectively regulating levels of population, capital, and industry; reducing the congestion costs for central cities; facilitating the specialization of production and thus promoting the rational division of labor. These benefits would, in turn, allow energy efficiency to be improved.

As for the four control variables in Model 1 and Model 6, the estimated coefficient of *Indstr* are 0.5925 and 0.5981, and at a 5% level of significance, both of these coefficients are significantly positive. This is in line with the expected results: The higher the proportion of the tertiary industry relative to GDP, the higher the energy efficiency. The estimated coefficients of *FDI* are both -0.0014 , and at a 5% level of significance, these coefficients are significantly negative, showing that the increase of foreign investment is not conducive to improving energy efficiency. A possible reason is that the developed technologies of foreign companies are not introduced along with the investment; instead, the huge energy consumption of the manufacturing industries puts added pressure on the environment. What's more, air and water pollution in one city can spread to other, nearby cities, further expanding the area of the damage [58]. Thus, the 'pollution paradise' hypothesis may be confirmed [59,60]. The estimated coefficients of *Tech* are 0.0060 in both two models, which are significantly positive at a 5% level of significance; therefore, the improvement of technology can indeed promote energy efficiency, and energy efficiency is not affected by a technical 'rebound effect'. Meanwhile, the estimated coefficients of *Ecstr* are 0.0267 and 0.0264, and are significantly positive at a 5% level of significance. Thus, the higher the proportion of electricity consumption, the more the consumption of clean energy, and the higher the energy efficiency.

4.2. Regional Heterogeneity in the Impact of Spatial Structure on Energy Efficiency

In addition to the regression analysis covering all samples of the impact of spatial structure on energy efficiency, this paper also carried out a regression analysis of the eastern, central, and western UAs, to examine whether there is regional heterogeneity in the impact of spatial structure on energy efficiency. Both the mono index and the spatial-structure index are included in this analysis. Model 1 is calculated via the mono index, while Model 6 selects the spatial-structure index as the core explanatory variable. The regression results of Equation (3) are listed in Table 6.

Table 6. Regression estimation results by regions.

Variables	Eastern UAs		Central UAs		Western UAs	
	Model 1	Model 6	Model 1	Model 6	Model 1	Model 6
<i>Spastr</i>	−0.3903 ** (0.0806)	−0.2183 *** (0.0387)	−0.2508 *** (0.0655)	−0.0769 *** (0.0265)	0.4227 *** (0.0933)	0.0274 *** (0.0103)
<i>Indstr</i>	0.6402 *** (0.0705)	0.6279 *** (0.0702)	0.3706 *** (0.0766)	0.3851 *** (0.0771)	0.6019 *** (0.0707)	0.7114 *** (0.0669)
<i>FDI</i>	−0.0009 *** (0.0002)	−0.0008 *** (0.0002)	−0.0009 ** (0.0004)	−0.0010 ** (0.0004)	−0.0011 *** (0.0004)	−0.0012 *** (0.0004)
<i>Tech</i>	0.0254 (0.0044)	0.0226 *** (0.0045)	0.0361 *** (0.0103)	0.0381 *** (0.0103)	−0.0011 (0.0013)	−0.0009 (0.0013)
<i>Ecstr</i>	0.0714 ** (0.0130)	0.0727 *** (0.0129)	−0.1011 *** (0.0186)	−0.1015 *** (0.0187)	0.0662 ** (0.0278)	0.0585 *** (0.0285)
Constant	0.3884 *** (0.0742)	0.4456 *** (0.0757)	0.4315 *** (0.0661)	0.3764 *** (0.0640)	−0.5384 *** (0.1253)	−0.2022 ** (0.0860)
σ_u	0.1868	0.2382	0.1052	0.1101	0.1217	0.2305
σ_e	0.1537	0.1527	0.1294	0.1305	0.0983	0.1010
ρ	0.5962	0.7088	0.3978	0.4160	0.6052	0.8390
N	690	690	410	410	270	270

Note: Due to limited space, this paper can only list the regression results of model 1 and model 6. ***, ** respectively indicate that the coefficients are significant at a 1% and 5% level. The values in parentheses are standard variances.

As Table 6 shows, the estimated coefficients of the *Spastr* in Model 1 and Model 6 in each region are significant at a 5% level. All the absolute values of the estimated coefficients of *Spastr* in Model 1 are larger than those values are in Model 6. This pattern suggests that neglecting to consider the concentration degree of cities will lead to an overestimation of the impact on energy efficiency of the concentration degree of factors contributing to UAs. What's more, the estimated coefficients of *Spastr* for the eastern, central, and western regions in Model 1 are −0.3903, −0.2508, and 0.4227, respectively, while the values in Model 6 are −0.2183, −0.0769, and 0.0274, respectively. Therefore, the Hypothesis H2 cannot be rejected, indicating that there is heterogeneity in the influence of spatial structure on energy efficiency. A more detailed analysis of the results of Model 6 will help clarify this conclusion.

At a 1% level of significance, the estimated coefficients of *Spastr* for the eastern and central UAs are, respectively, −0.2183 and −0.0769, whereas for the western UAs, the value is 0.0274. This is because the eastern and central UAs are more advanced than the western UAs. For the eastern and central areas, reasonably distributing some of the factors from the central cities to other cities will help alleviate the low energy efficiency caused by the cost of congestion. At the same time, it is beneficial for secondary cities to undertake industrial transfers from central cities, thereby introducing relatively advanced management experience and production technology. By contrast, western UAs are relatively backward, and the concentration degree of factors is too low, causing production factors to be quite widely dispersed. Therefore, gathering the elements into the central cities is beneficial, so that the enterprises in the central cities can share infrastructure and exchange production technology in order to achieve scale effects and an agglomeration economy. Reciprocally, the development of the central cities can enhance their own radiation capacity and drive the production level of the secondary cities, improving the energy efficiency of the UAs. In short, the reason why the impact of spatial structure on energy efficiency differs across the eastern, central, and western UAs is that the development stages of the three areas are different. At the early stage of UAs, a higher concentration degree of factors is beneficial for improving energy efficiency due to the siphon effect. However, as UAs mature, an over-aggregation of factors will reduce the energy efficiency of cities, and the solution is taking full advantage of radiation effect. This pattern is consistent with the previous theoretical analysis.

The two models also enable some further analysis of the four control variables. At a 5% level of significance, the impact of *Indstr* on energy efficiency is significantly positive, while the impact of *FDI* is significantly negative. This finding is consistent with the regression results for the full sample. At a significance level of 1%, the estimated coefficients of *Tech* for the eastern and central UAs are positive;

for western UAs, however, this result is not significant, though the values are negative. This finding shows that the technical level is significantly positively correlated with energy efficiency. Finally, at a 5% level of significance, the estimated coefficients of $Ecstr$ for the eastern and western UAs are significantly positive, this finding again being consistent with the regression results for the full sample. However, the estimated coefficients for the central UAs are significantly negative, probably because the central UAs use large amounts of thermal power generation with low power-generation efficiency, thus reducing the energy efficiency of this region.

5. Conclusions and Policy Implications

The energy efficiency of UAs is always a vital focus in the regional research, and the factor distribution of UAs is affected by the inter-connected development between cities. Therefore, based on the data of China's ten representative UAs, this paper investigated the influence of spatial structure of UAs on energy efficiency. In order to scientifically measure the spatial structure of UAs, the mono index used to describe the index of spatial structure was modified, and the spatial-structure index was redefined as the ratio of the mono index to the concentration degree of cities. Meanwhile, considering the different development degree of UAs, the influence of spatial structure on energy efficiency was further studied from the eastern, central, and western regions. The main conclusions are as follows:

(1) The spatial structure, namely the concentration degree of factors, can significantly affect energy efficiency, and for full sample data, the higher the concentration degree is, the lower the energy efficiency will be.

(2) There is the heterogeneity for the impact spatial structure of UAs on energy efficiency: For eastern and central UAs, with the accumulation of factors, the energy efficiency will be reduced; as for western UAs, the higher the concentration degree is, the higher the energy efficiency will be.

In light of the results of this study, there are some policy implications. First, the mature UAs, which are mostly distributed in the eastern and central regions, should disperse the resources of the central cities to the surrounding cities, mitigating the crowding effect of central cities and upgrading the technology and industrial structure of surrounding cities. Thus, the UAs can realize the coordinated development. Second, western UAs should guide the factors (such as labor, capital, etc.) contributing to central cities to get the benefits of scale effects and agglomeration economy.

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References

1. Zhao, P.; Zhang, M. The impact of urbanisation on energy consumption: A 30-year review in China. *Urban Clim.* **2018**, *24*, 940–953. [[CrossRef](#)]
2. Amigues, J.P.; Moreaux, M. Competing land uses and fossil fuel, and optimal energy conversion rates during the transition toward a green economy under a pollution stock constraint. *J. Environ. Econ. Manag.* **2019**, *97*, 92–115. [[CrossRef](#)]
3. Gasparatos, A.; Doll, C.N.; Esteban, M.; Ahmed, A.; Olang, T.A. Renewable energy and biodiversity: Implications for transitioning to a Green Economy. *Renew. Sustain. Energy Rev.* **2017**, *70*, 161–184. [[CrossRef](#)]
4. Ouyang, X.; Wei, X.; Sun, C.; Du, G. Impact of factor price distortions on energy efficiency: Evidence from provincial-level panel data in China. *Energy Policy* **2018**, *118*, 573–583. [[CrossRef](#)]

5. Guan, J.; Kirikkaleli, D.; Bibi, A.; Zhang, W. Natural Resources Rents Nexus with Financial Development in the Presence of Globalization: Is the “Resource Curse” Exist or Myth? *Resour. Policy* **2020**, *66*, 101641. [\[CrossRef\]](#)
6. Li, K.; Lin, B. How to promote energy efficiency through technological progress in China? *Energy* **2018**, *143*, 812–821. [\[CrossRef\]](#)
7. Rajbhandari, A.; Zhang, F. Does energy efficiency promote economic growth? Evidence from a multicountry and multisectoral panel dataset. *Energy Econ.* **2018**, *69*, 128–139. [\[CrossRef\]](#)
8. Cantore, N.; Calì, M.; Te Velde, D.W. Does energy efficiency improve technological change and economic growth in developing countries? *Energy Policy* **2016**, *92*, 279–285. [\[CrossRef\]](#)
9. Bekun, F.V.; Emir, F.; Sarkodie, S.A. Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa. *Sci. Total Environ.* **2019**, *655*, 759–765. [\[CrossRef\]](#)
10. Oyedepo, S.O. Energy and sustainable development in Nigeria: The way forward. *Energy Sustain. Soc.* **2012**, *2*, 15. [\[CrossRef\]](#)
11. Popkova, E.G.; Inshakov, O.V.; Bogoviz, A.V. *Regulatory Mechanisms of Energy Conservation in Sustainable Economic Development*; Energy Sector: A Systemic Analysis of Economy, Foreign Trade and Legal Regulations; Springer: Cham, Germany, 2019; pp. 107–118.
12. Ayres, R.U.; Turton, H.; Casten, T. Energy efficiency, sustainability and economic growth. *Energy* **2007**, *32*, 634–648. [\[CrossRef\]](#)
13. Fernando, Y.; Hor, W.L. Impacts of energy management practices on energy efficiency and carbon emissions reduction: A survey of Malaysian manufacturing firms. *Resour. Conserv. Recycl.* **2017**, *126*, 62–73. [\[CrossRef\]](#)
14. Li, H.; Shi, J.F. Energy efficiency analysis on Chinese industrial sectors: An improved Super-SBM model with undesirable outputs. *J. Clean. Prod.* **2014**, *65*, 97–107. [\[CrossRef\]](#)
15. Makridou, G.; Andriosopoulos, K.; Doumpos, M.; Zopounidis, C. Measuring the efficiency of energy-intensive industries across European countries. *Energy Policy* **2016**, *88*, 573–583. [\[CrossRef\]](#)
16. Fang, C.; Yu, D. Urban agglomeration: An evolving concept of an emerging phenomenon. *Landsc. Urban Plan.* **2017**, *162*, 126–136. [\[CrossRef\]](#)
17. Adams, J.S.; VanDrasek, B.J.; Phillips, E.G. Metropolitan area definition in the United States. *Urban Geogr.* **1999**, *20*, 695–726. [\[CrossRef\]](#)
18. Ramos, R.A.R.; da Silva, A.N.R. A spatial analysis approach for the definition of metropolitan regions—The case of Portugal. *Environ. Plan. B Plan. Des.* **2007**, *34*, 171–185. [\[CrossRef\]](#)
19. Kipnis, B.A. Dynamics and potentials of Israel’s megalopolitan processes. *Urban Stud.* **1997**, *34*, 489–501. [\[CrossRef\]](#)
20. Dadashpoor, H.; Azizi, P.; Moghadasi, M. Land use change, urbanization, and change in landscape pattern in a metropolitan area. *Sci. Total Environ.* **2019**, *655*, 707–719. [\[CrossRef\]](#)
21. Sanesi, G.; Colangelo, G.; Laforzezza, R.; Calvo, E.; Davies, C. Urban green infrastructure and urban forests: A case study of the Metropolitan Area of Milan. *Landsc. Res.* **2017**, *42*, 164–175. [\[CrossRef\]](#)
22. Song, M.; Hu, C. A coupling relationship between the eco-environment carrying capacity and new-type urbanization: A case study of the wuhan metropolitan area in China. *Sustainability* **2018**, *10*, 4671. [\[CrossRef\]](#)
23. Lan, S.L.; Zhong, R.Y. Coordinated development between metropolitan economy and logistics for sustainability. *Resour. Conserv. Recycl.* **2018**, *128*, 345–354. [\[CrossRef\]](#)
24. Yang, C.; Lan, S.; Tseng, M.L. Coordinated development path of metropolitan logistics and economy in Belt and Road using DEMATEL–Bayesian analysis. *Int. J. Logist. Res. Appl.* **2019**, *22*, 1–24. [\[CrossRef\]](#)
25. Li, N.; Wang, K.F. Evaluation of coordinated development of regional resources and economy around Shandong Peninsula urban agglomerations. *J. Groundw. Sci. Eng. Vol.* **2016**, *4*, 220–228.
26. Cottineau, C.; Finance, O.; Hatna, E.; Arcaute, E.; Batty, M. Defining urban clusters to detect agglomeration economies. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 1611–1626. [\[CrossRef\]](#)
27. Kanemoto, Y. Second-best cost–benefit analysis in monopolistic competition models of urban agglomeration. *J. Urban Econ.* **2013**, *76*, 83–92. [\[CrossRef\]](#)
28. Hewings, G.J.; Okuyama, Y.; Sonis, M. Economic interdependence within the Chicago metropolitan area: A Miyazawa analysis. *J. Reg. Sci.* **2001**, *41*, 195–217. [\[CrossRef\]](#)
29. Melo, P.C.; Graham, D.J.; Levinson, D.; Aarabi, S. Agglomeration, accessibility and productivity: Evidence for large metropolitan areas in the US. *Urban Stud.* **2017**, *54*, 179–195. [\[CrossRef\]](#)

30. Gu, Q.; Wang, H.; Zheng, Y.; Zhu, J.; Li, X. Ecological footprint analysis for urban agglomeration sustainability in the middle stream of the Yangtze River. *Ecol. Model.* **2015**, *318*, 86–99. [\[CrossRef\]](#)
31. García-López, M.À.; Muñoz, I. Urban spatial structure, agglomeration economies, and economic growth in Barcelona: An intra-metropolitan perspective. *Pap. Reg. Sci.* **2013**, *92*, 515–534. [\[CrossRef\]](#)
32. Lee, B. “Edge” or “edgeless” cities? Urban spatial structure in US metropolitan areas, 1980 to 2000. *J. Reg. Sci.* **2007**, *47*, 479–515. [\[CrossRef\]](#)
33. Lan, F.; Da, H.; Wen, H.; Wang, Y. Spatial Structure Evolution of Urban Agglomerations and Its Driving Factors in Mainland China: From the Monocentric to the Polycentric Dimension. *Sustainability* **2019**, *11*, 610. [\[CrossRef\]](#)
34. Huang, X.; Yang, J.; Güneralp, B.; Burris, M. US metropolitan spatial structure evolution: Investigating spatial patterns of employment growth from 2000 to 2010. *Urban Sci.* **2017**, *1*, 28. [\[CrossRef\]](#)
35. Fang, C.; Song, J.; Song, D. Stability of spatial structure of urban agglomeration in China based on central place theory. *Chin. Geogr. Sci.* **2007**, *17*, 193–202. [\[CrossRef\]](#)
36. Tan, R.; Zhou, K.; He, Q.; Xu, H. Analyzing the effects of spatial interaction among city clusters on urban growth—Case of Wuhan urban agglomeration. *Sustainability* **2016**, *8*, 759. [\[CrossRef\]](#)
37. Zheng, Z.; Bohong, Z. Study on spatial structure of Yangtze River Delta urban agglomeration and its effects on urban and rural regions. *J. Urban Plan. Dev.* **2012**, *138*, 78–89. [\[CrossRef\]](#)
38. Jia, P.; Li, K.; Shao, S. Choice of technological change for China’s low-carbon development: Evidence from three urban agglomerations. *J. Environ. Manag.* **2018**, *206*, 1308–1319. [\[CrossRef\]](#)
39. Meijers, E.J.; Burger, M.J. Spatial structure and productivity in US metropolitan areas. *Environ. Plan. A* **2010**, *42*, 1383–1402. [\[CrossRef\]](#)
40. Lee, B.; Gordon, P. Urban spatial structure and economic growth in US metropolitan areas. In Proceedings of the 46th annual meetings of the western regional science association, Newport Beach, CA, USA, January 2007.
41. Liu, C.; Wang, T.; Guo, Q. Factors Aggregating Ability and the Regional Differences among China’s Urban Agglomerations. *Sustainability* **2018**, *10*, 4179. [\[CrossRef\]](#)
42. Fang, C.; Guan, X.; Lu, S.; Zhou, M.; Deng, Y. Input–output efficiency of urban agglomerations in China: An application of data envelopment analysis (DEA). *Urban Stud.* **2013**, *50*, 2766–2790. [\[CrossRef\]](#)
43. Han, F.; Xie, R.; Fang, J. Urban agglomeration economies and industrial energy efficiency. *Energy* **2018**, *162*, 45–59. [\[CrossRef\]](#)
44. Liu, B.; Tian, C.; Li, Y.; Song, H.; Ma, Z. Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. *J. Clean. Prod.* **2018**, *197*, 1374–1381. [\[CrossRef\]](#)
45. Ouyang, X.; Mao, X.; Sun, C.; Du, K. Industrial energy efficiency and driving forces behind efficiency improvement: Evidence from the Pearl River Delta urban agglomeration in China. *J. Clean. Prod.* **2019**, *220*, 899–909. [\[CrossRef\]](#)
46. Rongdi, G.; Lixin, T.; Wenchao, L. Analysis of Influencing Factors on Energy Efficiency of Yangtze River Delta Urban Agglomeration Based on Spatial Heterogeneity. *Energy Procedia* **2019**, *158*, 3234–3239. [\[CrossRef\]](#)
47. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [\[CrossRef\]](#)
48. Tone, K. Dealing with undesirable outputs in DEA: A Slacks-based Measure (SBM) Approach. *Present. Napw III Tor.* **2003**, *8*, 44–45.
49. Haojie, S. Re-estimation of China’s Capital Stock K: 1952–2006 Years. *Quant. Econ. Tech. Econ. Res.* **2008**, *25*, 17–31. (In Chinese)
50. Reinsdorf, M.; Cover, M. *Measurement of Capital Stocks, Consumption of Fixed Capital, and Capital Services*; Report on a presentation to the Central American Ad Hoc Group on National Accounts: Santo Domingo, Dominican Republic, 2005.
51. Madariaga, N.; Poncet, S. FDI in Chinese cities: Spillovers and impact on growth. *World Econ.* **2007**, *30*, 837–862. [\[CrossRef\]](#)
52. Zomorodi, A.; Zhou, X. Impact of FDI on environmental quality of China. *Int. J. Bus. Econ. Manag.* **2017**, *4*, 1–15. [\[CrossRef\]](#)
53. Du, J.; Zeng, M.; Xie, Z.; Wang, S. Power of agricultural credit in farmland abandonment: Evidence from rural China. *Land* **2019**, *8*, 184. [\[CrossRef\]](#)

54. Liu, X.; Xu, Y.; Ge, Y.; Zhang, W.; Herrera, F. A Group Decision Making Approach Considering Self-Confidence Behaviors and its Application in Environmental Pollution Emergency Management. *Int. J. Environ. Res. Public Health* **2019**, *16*, 385. [[CrossRef](#)] [[PubMed](#)]
55. Binswanger, M. Technological progress and sustainable development: What about the rebound effect? *Ecol. Econ.* **2001**, *36*, 119–132. [[CrossRef](#)]
56. Zhang, W.; Du, J.; Tian, X. Finding a Promising Venture Capital Project with TODIM under Probabilistic Hesitant Fuzzy Circumstance. *Technol. Econ. Dev. Econ.* **2018**, *24*, 2026. [[CrossRef](#)]
57. Lin, B.; Liu, X. Dilemma between economic development and energy conservation: Energy rebound effect in China. *Energy* **2012**, *45*, 867–873. [[CrossRef](#)]
58. Zeng, M.; Du, J.; Zhang, W.K. Spatial-Temporal Effects of PM_{2.5} on Health Burden: Evidence from China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4695. [[CrossRef](#)]
59. Sun, C.; Zhang, F.; Xu, M. Investigation of pollution haven hypothesis for China: An ARDL approach with breakpoint unit root tests. *J. Clean. Prod.* **2017**, *161*, 153–164. [[CrossRef](#)]
60. Sarkodie, S.A.; Strezov, V. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. *Sci. Total Environ.* **2019**, *646*, 862–871. [[CrossRef](#)]



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