

## Article

# A Study on the Measurement of Regional Energy Consumption Efficiency and Decomposition of Its Influencing Factors in China: New Evidence for Achieving SDGs

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**Abstract:** With the growth of global population and economic development, people are facing the problem of increasing scarcity of renewable energy and unsustainable energy use. To achieve the sustainable development goals (SDGs) proposed by the United Nations, research on energy consumption efficiency has become particularly important. This research evaluates the energy consumption efficiency of 270 cities in China through an improved EBM model and finds a common phenomenon of low energy consumption efficiency in the cities, with the highest efficiency in northeast China and the lowest efficiency in eastern China. In addition, the efficiency of industrial exhaust emissions most significantly positively correlates with the efficiency of employed population and total energy consumption efficiency, while the efficiency of regional GDP does not significantly correlate with the efficiency of the two input variables. Using the LMDI method to decompose the driving factors of energy consumption efficiency in the cities, we find that the most important factor affecting energy consumption efficiency is their own energy endowment. Therefore, to improve the energy consumption efficiency of its cities, the China government should comprehensively consider factors such as regional economic development level, industrial structure, and technological level differences, formulate relevant energy-saving and emission-reduction policies, focus on optimizing the energy consumption structure, encourage technological progress and innovation, and help increase investment in science and technology.

**Keywords:** Chinese cities; energy consumption efficiency; EBM; LMDI



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## 1. Introduction

Energy is necessary for human production and maintenance of life. From a global perspective, the global demand for traditional energy is at its highest historical level. In 2022, the proportion of fossil fuels in global energy consumption was 82%. At the same time, global oil consumption hit 99.53 million barrels per day, accounting for 31.6%, while coal consumption was at 8.3 billion tons, accounting for approximately 26.7%. And total global greenhouse gas emissions related to energy increased by 1.0%, reaching 41.3 billion tons of carbon dioxide equivalent, which is the highest level in history and mainly from energy combustion and industrial processes [1]. With the large amount of industrial exhaust emissions, atmospheric pollutants such as sulfur dioxide, nitrogen oxides, particulate matter, etc. can form haze and acid rain, posing a threat to air quality and human health. The massive emissions of CO<sub>2</sub> can also accelerate global climate change, potentially causing extreme weather and rising sea levels [2]. With ecological environment protection an urgent topic as early as 2015, the United Nations proposed the Sustainable Development Goals (SDGs), aimed at comprehensively addressing development issues spanning 2015 to 2030 in the social, economic, and environmental dimensions by switching the global development model to a sustainable development path.

In 2022, carbon dioxide emissions generated by energy combustion and industrial processes accounted for 89% of total energy-related greenhouse gas emissions [1]. With the increasing consumption of energy by countries around the world, China, as one of the fastest growing economies, is also experiencing rapid advancement in energy production and consumption. In 2022, its total energy consumption reached 5.41 billion tons of standard coal, or an increase of 2.9% compared with the previous year. Its consumption of coal increased by 4.3%, accounting for 56.2% of the total energy consumption, or an increase of 0.3 percentage points from 2021 [1]. Coal is the main energy source in China, and the energy structure dominated by coal will be difficult to change for a considerable period of time in the future.

Coal consumption is the main cause of coal smoke-type air pollution and the main source of greenhouse gas emissions, but the relatively backward coal consumption mode has led to low energy consumption efficiency in China. On the one hand, if the country continues to use energy inefficiently, then it will lead to the depletion of energy resources and bring huge harm to human society. On the other hand, inefficient use of energy can generate excessive waste of gas, wastewater, and other waste, causing serious pollution to the environment [3]. Therefore, studying energy efficiency is clearly important. Improving energy efficiency helps reduce energy consumption and environmental pollution, and protect the ecological environment. In addition, such improvement not only cuts resource consumption, but also lowers production costs and raises economic benefits. By improving energy efficiency, the sustainable development goals proposed by the United Nations can be achieved.

The contribution of this article to the literature is as follows. (1) Unlike previous studies that mainly focused on the energy consumption efficiency of individual countries and different provinces, this study selected 270 prefecture level cities in China as the research objects, making the research results more comprehensive and specific. And for the sake of conciseness, these 270 cities are grouped into four distinct regions, and the division of these regions is discussed. (2) This study adopted the EBM-DEA model, taking into account the differences in radial scale and non-radial relaxation variables, which avoids the computational errors of radial and non-radial DEA models compared with traditional SBM models. (3) Compared with other factor decomposition methods, the LMDI method can decompose the changes into the contribution changes of various factors in different time dimensions, revealing the main trend and typical characteristic of overall indicator. This study can help decision-makers understand the impact of different factors on overall indicator changes and formulate corresponding policy measures. The LMDI method is used to analyze the factors that affect urban energy consumption efficiency in different years, making the research more in-depth and specific.

## 2. Literature Review

### 2.1. *The Influencing Factors of Energy Consumption Efficiency*

In the current situation where energy development is increasingly valued internationally, the academic community is actively conducting related research and discussions on energy efficiency. Improving energy efficiency not only helps to control excessive energy consumption and alleviate environmental problems, but also forces enterprises to engage in healthy competition, thereby controlling energy prices. Therefore, the academic community is gradually focusing on summarizing the influencing factors of energy efficiency from different perspectives. For example, the degree of spatial agglomeration of urban industries plays a crucial role in energy consumption efficiency. Kraft [4] analyzed the relationship between energy consumption and gross national income based on data from the United States from 1947 to 1974 and found that GNP and energy consumption have a one-way causal relationship—that is, economic growth drives energy consumption.

Another viewpoint suggests a mutual influence between economic growth and energy consumption. Asafu-Adjaye [5] conducted an analysis based on cointegration tests and error correction models and noted a causal relationship between energy consumption and

GDP in India and Indonesia, as well as a bidirectional causal relationship between energy consumption and GDP in the Philippines and Thailand. Bellke et al. [6] used panel data to analyze the relationship between economic growth and energy consumption in OECD countries from 1981 to 2007 and showed a bidirectional causal relationship between the two. There are also scholars in China who used other methods to study the relationship between the two. Zhang et al. [7] applied geographic- and time-weighted regression to analyze the influencing factors of energy efficiency in China. The results showed, overall, that the level of economic development has an inhibitory effect on TFEE in the east region of China (negative) and a promoting effect in the central and west regions (positive). However, from a temporal perspective, the negative correlation between the level of economic development in the east region and energy efficiency has gradually shifted to a positive correlation.

The industrial structure usually manifests as the proportion of the three major industries to the national economy. The international classification standards for industries are not entirely the same, but they can be roughly divided into three categories. Generally speaking, different industries consume different amounts of energy during the production process, resulting in varying impacts on energy efficiency. There is no consensus in the academic community regarding the specific impact of industrial structure on energy efficiency. One viewpoint supports that optimizing the industrial structure has a positive impact on improving energy efficiency. Newell [8] suggested that a shift in the focus of a region's national economy from heavy industry to light industry, or a corresponding adjustment in the internal composition of industry, can lead to a significant decrease in energy consumption per unit of GDP in that region.

According to a World Bank report, from 1990 to 2000, China focused on optimizing its industrial structure and made corresponding upgrades by continuously increasing the proportion of the service industry, resulting in a 35–45% decrease in energy consumption per unit of GDP. Even though most academic discussions have confirmed that optimizing the industrial structure can promote better resource allocation patterns and further improve energy efficiency, some scholars still hold objections to this, maintaining a certain degree of caution in their views and believing that the effects of optimizing industrial structure have certain applicable conditions. Ang & Zhang [9] expressed that, during the process of industrial development, industrial structure only has a weak impact on energy consumption per unit of GDP, and it cannot be determined whether this is a positive or negative impact. The empirical results of Wei & Shen [10] indicated that adjusting industrial structure does not absolutely improve energy efficiency, but does, to some extent, promote it.

Due to the acceleration of China's urbanization process, scholars have gradually incorporated the level of urbanization into the analysis framework of factors affecting energy efficiency. The concentration of urbanization level is reflected in the level of infrastructure, and the construction of infrastructure promotes the sustainable development of urbanization. Some scholars have noted that the higher the level of infrastructure development, the more various industries and economic activities affected by population agglomeration will generate economic effects in space. Improving enterprise production methods through knowledge and technology spillover effects can spur energy efficiency.

Capello et al. [11] proposed the compact city theory, based on the states in which compact urban development can reduce resource and environmental use. Liu & Sweeney [12] found through empirical research that compact city development helps reduce greenhouse gas emissions and energy consumption. However, some scholars hold opposite views. Burgess [13] believed that the improvement of infrastructure level will drive the development of urbanization, and in the process of urbanization, there may be congestion effects, which cannot avoid some environmental pollution problems such as garbage siege, increased water pollution, and serious waste of land resources. This will have a negative impact on the improvement of energy efficiency.

In addition to the aforementioned influencing factors, technological level also has an important impact on resource consumption efficiency. Doms et al. [14] studied the impact of technological progress on energy efficiency from a microscopic perspective. Their results

showed that the overall energy intensity and power energy intensity of enterprises adopting advanced manufacturing technology are lower than those of enterprises not adopting this technology. Other scholars have further demonstrated, from the perspectives of country and industry, that technological level has a positive effect on resource consumption efficiency. Mielnika & Goldenberg [15] used data from 20 developing countries to study the relationship between FDI and energy intensity and found that, with the increase in foreign direct investment, energy intensity significantly decreases. The improvement in foreign direct investment efficiency is the result of the combined effect of advanced management skills and more modern technological factors.

Constructing an environmental DEA model by considering carbon dioxide production in the industrial sector, Wu et al. [16] stated that energy efficiency improvement in China's industrial sector is mainly driven by technological progress. Lin & Barak [17] and Jules-Daniel & Joëlle [18] reported in their research that green technology improves energy efficiency, reduces carbon emissions and ineffective waste in enterprise production, and is an effective measure for energy conservation and consumption reduction. Jonathan & Fridley [19] found that technological progress can improve energy efficiency, and further research is needed on the influencing factors of energy consumption efficiency in the fields of economic growth, industrial structure, economic system reform, environment, and energy conservation policies.

Resource endowment directly affects energy consumption efficiency and also has an indirect impact on it through energy prices. The literature has suggested that energy prices can also impact energy efficiency, based on the theory that energy is a factor of production. Fisher et al. [20] analyzed panel data from approximately 2500 large- and medium-sized industrial enterprises in China from 1997 to 1999 and believed that the rise in energy prices is one of the main factors leading to a decrease in energy efficiency in China. Edelstein & Kilian [21] believed that reasonable regulation and guidance of energy prices are beneficial for improving China's energy efficiency. Filipovic & Golusin [22] found that energy prices suppress energy intensity growth and affect energy consumption efficiency, while per capita energy consumption and economic growth promote energy intensity growth.

## 2.2. Energy Consumption Efficiency Evaluation and DEA Method

Due to the simple processing method of Data Envelopment Analysis (DEA), which does not require understanding the specific form of the production function and is also easy to expand to other forms to handle multi-output situations, it is widely used in the study of energy efficiency. Many scholars have not included environmental pollutants as unexpected outputs in the calculation system when calculating energy efficiency values. In recent years, studying total factor energy efficiency under environmental constraints has become an academic hotspot. With the increasing severity of environmental pollution, governments have increased constraints on the environment, leading many scholars to consider environmental constraint indicators and incorporate them into DEA models. This research method can avoid overestimating energy efficiency values.

Hu & Wang [23] studied regional energy efficiency in China by introducing a non-parametric DEA method. Subsequently, this method and subsequent improved models gradually became the most commonly used for energy efficiency research in China. Fare [24] considered pollutant emissions as a bad output condition and calculated total factor productivity using the DEA method based on the ML index. However, there are issues with non-circularity and non-transferability in the measurement of the ML index in the cross-period direction distance function. Due to the many shortcomings of SM and ML, Oh [25] established an environmentally sensitive production growth index called the Global Malmquist Luenberger (GML) index to solve the existing problems. Chang [26] calculated total factor energy efficiency by taking into account environmental constraints.

Scholars have also proposed their own thoughts through empirical analysis using the DEA model. Zhu et al. [27] analyzed the current situation and trends of China's regional

environment based on the public weight DEA model of choosing public weight priority. That paper proposed suggestions to improve regional energy consumption efficiency.

Based on the DEA method, a large amount of literature has examined and compared the energy efficiency between different economies. Miketa [28] analyzed the impact of sector economic activity, capital formation, and industrial energy prices on energy consumption intensity using data from 10 manufacturing industries in 39 countries from 1971 to 1996. The research results indicated that energy intensity is influenced by capital formation, and this influence increases with the increase in sector output. Sun & Meriso [29] constructed a conceptual framework based on materialization and non-materialization and established a relatively complete decomposition model to measure energy efficiency. A statistical analysis was conducted on the Rasberg Index of OECD countries from 1960 to 1995, resulting in the annual average energy efficiency and skill potential of OECD countries.

Hu & Wang [23] conducted a comparative study on the total factor energy consumption efficiency of various regions in China from 1995 to 2002 using the DEA method. Mulder & Groot [30] analyzed and studied the convergence and differentiation of energy productivity among member countries of the Organization for Economic Cooperation and Development based on industry data. Miketa & Mulder [31] collected relatively similar panel data to study the convergence and differences in energy productivity among 56 countries.

### 2.3. LMDI Method and Driving Effect Analysis

Given the advantages of the logarithmic mean Divisia index (LMDI) method, which is easy to calculate, has no residual values, and can solve zero-value problems, its early applications mostly focused on the factors affecting carbon emissions. Taking the factors influencing carbon emissions in the construction industry as an example, Lu et al. [32] studied the main driving factors of carbon emissions in China's construction industry based on the LMDI model. Xiang et al. [33] developed the PyLMDI tool to simplify the calculation process of the LMDI decomposition analysis method and expand its application scope, allowing users to quickly obtain decomposition results by inputting decomposition models and data. Lu et al. [34] used the LMDI model to decompose the changes in total energy consumption in the construction industry, believing that area, structure, population, value, and energy intensity are key influencing factors. Chontanawat et al. [35] applied the LMDI method to decompose the sources of changes in CO<sub>2</sub> emission levels and intensity in Thailand's manufacturing industry and found that both showed an increasing trend year by year. Reducing energy intensity at the enterprise level is an effective means of achieving carbon reduction.

In addition to applying LMDI to the construction industry, many scholars have also applied it to other aspects. Yasmeen et al. [36] decomposed Pakistan's per capita carbon emissions at the national level based on the LMDI method. The results showed that to curb the increase in carbon emissions, energy efficiency should be improved, while the energy structure should continue to upgrade from traditional energy to renewable energy. Belloumi & Achour [37] identified the influencing factors of transportation energy consumption in Tunisia using the LMDI model and measured their corresponding contributions. Research has shown that, overall, economic output, transportation intensity, population size, and transportation structure have a positive impact on energy consumption, while energy intensity has a negative impact on energy consumption.

Chinese scholars have also used the LMDI decomposition method to study provinces, regions, and other aspects. Chong et al. [38] analyzed the energy consumption growth in Guangdong Province using the LMDI decomposition method and found that per capita GDP and population growth are the dominant factors affecting consumption growth. Chen et al. [39] evaluated the degree of coordination between mineral resource development, economy, and environment in the Yangtze River Economic Belt based on an improved Coupled Coordination Degree Model (CCDM) and estimated its dynamic evolution trend. In addition, many studies have combined the current situation of energy and mineral



development in China and the different characteristics of energy and mineral demand at different stages of socio-economic development to make theoretical evaluations of the efficiency of energy and mineral development. However, currently, no scholars have conducted LMDI decomposition on the energy consumption efficiency of cities in China.

LMDI analysis has been widely used to explain changes in CO<sub>2</sub> emissions related to electricity. Chong et al. [40] introduced an LMDI decomposition method based on energy allocation analysis. They pointed out that population, per capita GDP, and energy intensity are still the main factors affecting changes in energy-related CO<sub>2</sub> emissions in Malaysia, indicating that the impact of technology driven factors is increasingly significant. Oliveira & Jesus [41] used LMDI to study the impact of power generation capacity factors and their evolution on carbon emission intensity in Latin America and the Caribbean.

### 3. Methods

#### 3.1. EBM–DEA Model

This research uses an improved EBM model to measure the energy consumption efficiency of cities in China. The improved EBM model is an extension of the original EBM model to include unexpected outputs as follows:

$$\sigma^* = \min \frac{\phi - \nu_x \sum_{i=1}^m \frac{\omega_i^- s_i^-}{x_{i0}}}{\zeta + \nu_y \sum_{r=1}^s \frac{\omega_r^+ s_r^+}{y_{r0}} + \nu_b \sum_{p=1}^m \frac{\omega_p^{b-} s_p^{b-}}{x_{i0}}} \quad (1)$$

$$s.t. \begin{cases} \sum_{j=1}^n x_{ij} \lambda_j + s_i^- - \phi x_{i0} = 0, & i = 1, \dots, m, \\ \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ - \zeta y_{r0} = 0, & r = 1, \dots, s, \\ \sum_{j=1}^n b_{pj} \lambda_j + s_p^{b-} - \zeta b_{p0} = 0, & i = 1, \dots, m, \\ (\lambda_j \geq 0, \quad s_i^- \geq 0, \quad s_r^+ \geq 0, \quad s_p^{b-} \geq 0) \end{cases} \quad (2)$$

In the above formula,  $\sigma^*$  reflects the optimal efficiency value formed by the EBM model in measuring DEA. In formula calculations, the efficiency value  $\phi$  is formed in a radial environment;  $s_i^-$  means the relaxation amount corresponding to the  $i$ th relevant input factor in a non-radial environment;  $(x_{i0}, y_{r0})$  means the input-output vector value corresponding to the 0th DMU;  $\omega_r^+$  and  $\omega_p^{b-}$  respectively represent  $r$  expected output and  $p$  unexpected output;  $\omega_i^-$  means the weight corresponding to the  $i$ th relevant input element, which can indicate the importance of  $i$  and conforms to  $\sum_{i=1}^m \omega_i^-$ ;  $\nu_x$  refers to the relevant core parameters that simultaneously satisfy the radial variation ratio and non-radial relaxation vector, with a numerical range of not less than 0 and not greater than 1; and  $b_{p0}$  means the  $p$ th unexpected output corresponding to the 0th province in the model.

#### 3.2. LMDI

The logarithmic mean Divisia index (LMDI) method is a factor decomposition approach developed based on the Exponential Decomposition Method (IDA). The LMDI method is based on Kaya's expansion and uses the logarithmic mean method to analyze the influencing factors. Compared with other exponential decomposition methods, the LMDI decomposition method has advantages such as fully decomposable factors and no residual terms. Therefore, the LMDI method is chosen to analyze the driving effect of energy consumption efficiency in cities of China.

As shown in Table 1, relying on existing raw data indicators, the Kaya identity is used to decompose the green total factor energy efficiency into:

$$ML = \frac{S}{Ec} \times \frac{C}{S} \times \frac{ML \times En}{C} \times \frac{Ins \times Ec}{En} \times \frac{Ec}{Ins \times Ec} = k \times j \times n \times r \times c \quad (3)$$

**Table 1.** Constructing the Kaya identity index for energy consumption efficiency in the cities.

Factor	Representation	Abbreviation
Spatial clustering effect	$S/Ec$	$k$
Infrastructure effect	$C/S$	$j$
Energy endowment effect	$(ML \times En)/C$	$n$
Technology level effect	$(Ins \times Ec)/En$	$r$
Industrial structure effect	$Ec/(Ins \times Ec)$	$c$

Note:  $ML$  is the efficiency of urban energy consumption in China,  $S$  is urban land area,  $Ec$  is gross urban product,  $C$  is urban fixed asset investment,  $En$  is total urban energy consumption, and  $Ins$  is the ratio of the added value of the secondary industry to the gross urban product.

According to the LMDI decomposition method, the change in energy consumption efficiency of the cities from the base period to year  $t$  is called  $\Delta ML$ , which is composed of five parts: spatial agglomeration effect ( $k_{eff}$ ), infrastructure effect ( $j_{eff}$ ), energy endowment effect ( $n_{eff}$ ), technology level effect ( $r_{eff}$ ), and industrial structure effect ( $c_{eff}$ ).

$$\Delta ML = ML_t - ML_0 = k_{eff} + j_{eff} + n_{eff} + r_{eff} + c_{eff} \quad (4)$$

$$k_{eff} = \sum \frac{ML_t - ML_0}{\ln ML_t - \ln ML_0} \times \ln \frac{S_t/Ec_t}{S_0/Ec_0} \quad (5)$$

$$j_{eff} = \sum \frac{ML_t - ML_0}{\ln ML_t - \ln ML_0} \times \ln \frac{C_t/S_t}{C_0/S_0} \quad (6)$$

$$n_{eff} = \sum \frac{ML_t - ML_0}{\ln ML_t - \ln ML_0} \times \ln \frac{(ML_t \times En_t)/C_t}{(ML_0 \times En_0)/C_0} \quad (7)$$

$$r_{eff} = \sum \frac{ML_t - ML_0}{\ln ML_t - \ln ML_0} \times \ln \frac{(Ins_t \times Ec_t)/En_t}{(Ins_0 \times Ec_0)/En_0} \quad (8)$$

$$c_{eff} = \sum \frac{ML_t - ML_0}{\ln ML_t - \ln ML_0} \times \ln \frac{Ec_t/(Ins_t \times Ec_t)}{Ec_0/(Ins_0 \times Ec_0)} \quad (9)$$

In the formula, the lower corners of the variable  $t$  and 0 represent the  $t$ -year and base period, respectively.

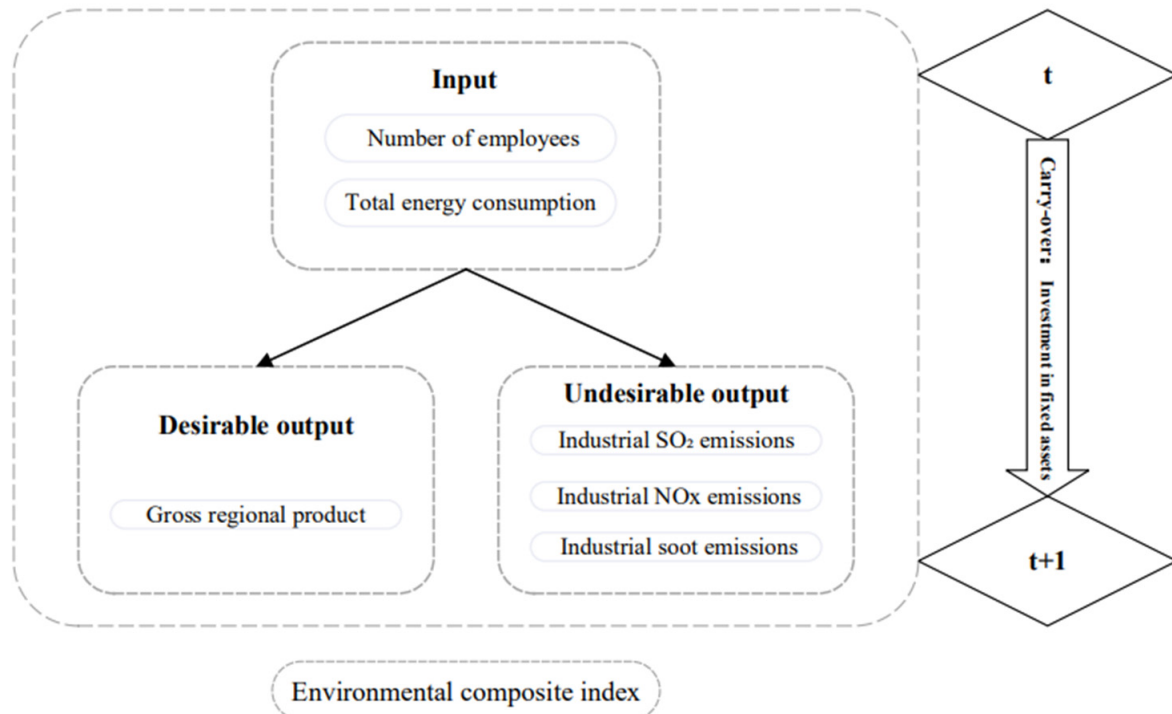
## 4. Results

### 4.1. Data Description

This study selects data from 270 prefecture-level cities in China from 2010 to 2020. Among them, 33 cities in the northeast are mainly concentrated in the Heilongjiang, Jilin, and Liaoning provinces. The industrial structure of the northeast region is dominated by major industrial projects such as steel, energy, chemicals, and heavy machinery. The eastern region has 82 cities, accounting for the highest proportion of 30.4%. The eastern region of China is the most economically developed region, with a large population density, mainly concentrated in high-tech industries, service industries, import and export industries, and other advantageous industries. The western region has 79 cities, most of which are economically underdeveloped and need to be further developed. Of these cities, 76 are located in the central region, connecting the east with the west and the south with the north, making it a key region for new-type urbanization. Appendix A summarizes the specific names and locations of the study sample cities. Figure 1 shows the research framework and related indicators based on the EBM-DEA model.

The main design ideas of the EBM-DEA model in this article are as follows. It takes the total number of employed people and total energy consumption for each year as inputs, urban GDP as expected output, and industrial SO<sub>2</sub> emissions, industrial NO<sub>x</sub> emissions, and industrial smoke emissions caused by energy consumption as unexpected outputs. The  $t$  and  $t + 1$  stages are connected by carrying forward the variable capital stock. Through the entropy weight-TOPSIS method, the five variables of government expenditure, the proportion of urban secondary industry, population density, per capita GDP, and urban

education expenditure are summarized to obtain the urban environmental comprehensive index as an exogenous variable and to examine the impact of the application of exogenous variables on urban energy consumption efficiency. Table 2 lists the specific explanations of each indicator.



**Figure 1.** Research framework and related indicators based on the EBM-DEA model.

**Table 2.** Meanings of input and output variables.

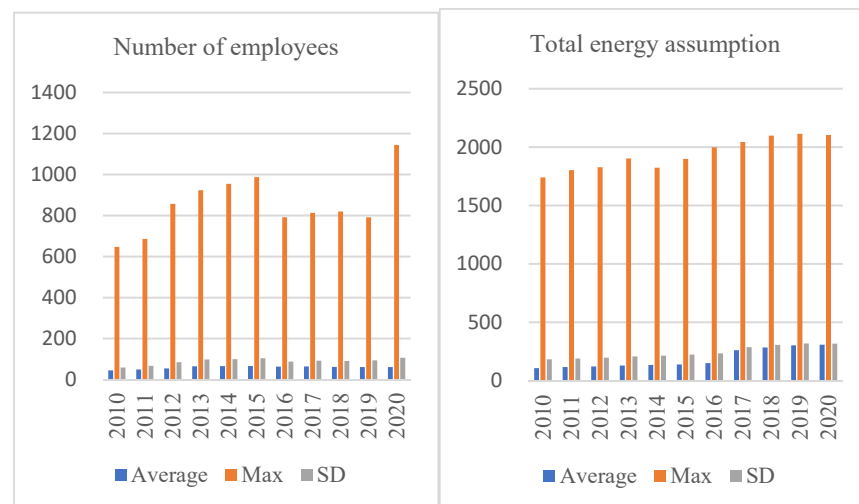
Variable	Meaning	Indicator Attribute	Unit
Number of employees	Number of employees in urban enterprises	Input	10,000 people
Total energy consumption	Comprehensive consumption of various energy sources by national and non-material production sectors during a certain period of time	Input	10,000 tons
Regional GDP	Final results of production activities of all resident units in the local area during a certain period of time	Desirable output	CNY 100 million
Industrial SO <sub>2</sub> emissions	Amount of SO <sub>2</sub> emitted by enterprises in the production process	Undesirable output	10,000 tons
Industrial NOx emissions	Amount of NOx emitted by enterprises in the production process	Undesirable output	10,000 tons
Industrial smoke emissions	Weight of particulate matter emitted by enterprises during the production process	Undesirable output	10,000 tons

Note: The data are sourced from the China Statistical Yearbook 2011–2021.

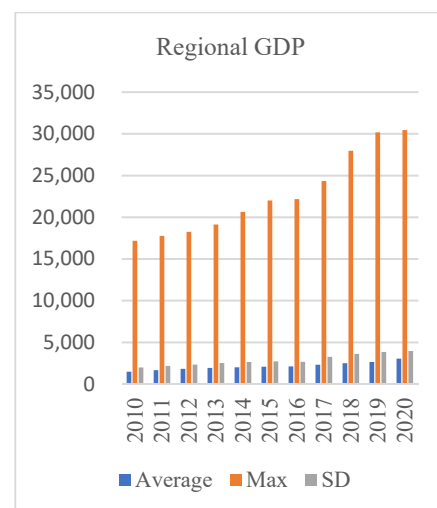
#### 4.2. Descriptive Statistics

This study calculates the average, maximum, and standard deviation of input (number of employees, total energy consumption) and output (regional GDP, industrial SO<sub>2</sub> emissions, industrial NOx emissions, and industrial smoke emissions) and analyzes the trend of data changes. Please refer to Figures 2–4 for details. The data are sourced from the China Statistical Yearbook 2011–2021.

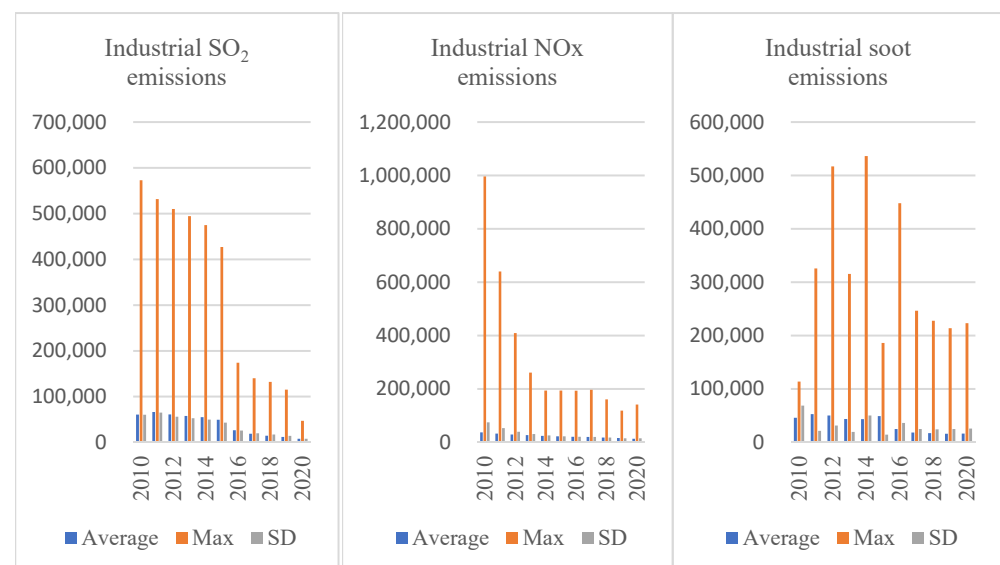




**Figure 2.** Changes in investment indicators from 2010 to 2020.



**Figure 3.** Changes in expected output indicators from 2010 to 2020.



**Figure 4.** Changes in unexpected output indicators from 2010 to 2020.

For the input indicators, Figure 2 shows that the overall change in employment is not significant from 2010 to 2020. The maximum value increases year by year from 2010 to 2015, sharply decreases in 2016, and remains stable at around 800 until 2019. In 2020, it skyrockets to a historical high. The total energy consumption remains relatively stable from 2010 to 2016, but increases in 2017, and remains relatively stable in the following years.

As shown in Figure 3, the trend of changes in regional GDP between 2010 and 2020 is not significant, but it is worth noting that its maximum value gradually rises and reaches its peak in 2020. On the one hand, investment promotes enterprise production and innovation, increases employment opportunities, and helps economic growth. The confidence and decision-making of investors also affect the development of the economy. Therefore, the government should formulate various policies to promote investment, such as reducing taxes, increasing infrastructure construction, attracting foreign investment, etc., in order to draw forth even more investment. On the other hand, consumer purchasing power has a significant impact on economic development. If consumers have strong confidence, then they will purchase more products and services, thereby promoting the production and sales of enterprises. Therefore, the government should take measures to increase consumer purchasing power, such as increasing wages and reducing inflation rates.

Figure 4 shows industrial SO<sub>2</sub> emissions with a decreasing trend year by year, and the maximum value achieving a sharp decline in 2016. The industrial NO<sub>x</sub> emissions are also decreasing year by year, but compared to industrial SO<sub>2</sub>, their decline rate is relatively stable. As China continues to increase its efforts in controlling industrial pollution, the effectiveness of domestic industrial pollution control is very significant. The emissions of industrial smoke and dust do not change significantly between 2010 and 2015, but suddenly decrease in 2016, and the subsequent trend remains relatively stable. The deep control of industrial exhaust gas pollution is one of six key targets of the Blue-Sky Project launched by the China government in 2016. Enterprises in various key industries fulfill their main responsibilities for pollution control, study the Air Pollution Prevention and Control Law and industry emission standards seriously, and conduct timely self-inspections. As a result, the amount of industrial smoke and dust emissions has been continuously decreasing since then.

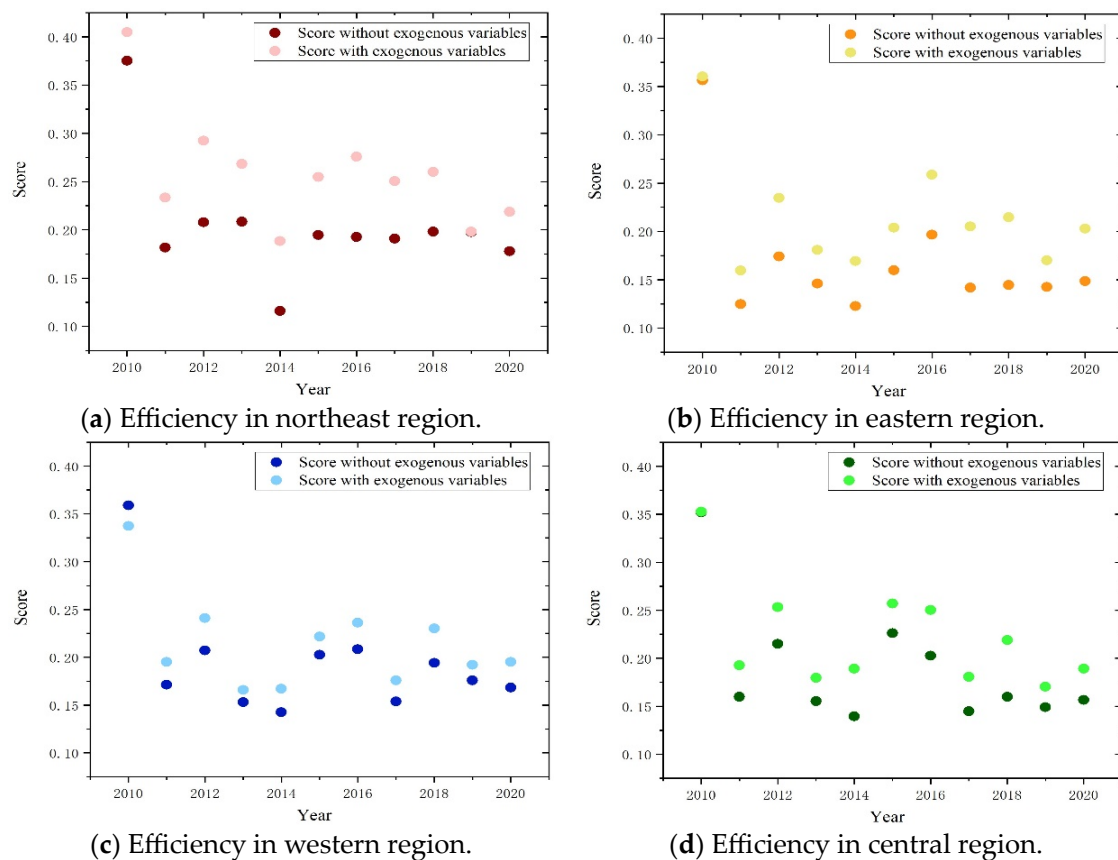
#### 4.3. Analysis of Energy Consumption Efficiency in Cities of China

##### 4.3.1. Total Efficiency Analysis

Between 2010 and 2020, without considering exogenous variables (environmental comprehensive index), the average total efficiency value of these 270 sample cities is 0.1885. After considering exogenous variables, the average total efficiency value increases to 0.2272. In 2018, the General Office of the State Council issued relevant documents, specifying by 2020 that the average annual concentration of PM<sub>2.5</sub> in Beijing, Tianjin, Hebei, and surrounding areas must decrease by more than 15% compared with 2015, and the PM<sub>2.5</sub> concentration in the Yangtze River Delta region must decrease by 18%. Under the guidance of this plan, cities in the east region have taken a series of measures to reduce pollution emissions and continuously improve energy consumption efficiency based on their strong economic strength, resulting in an overall average efficiency value showing an upward trend.

As shown in Figure 5, from the trend of efficiency values in the northeast, east, west, and central regions, the presence or absence of exogenous variables did not have a significant impact on the degree of change in efficiency values from 2010 to 2020. However, after considering exogenous variables, the overall efficiency value level shows a certain upward trend. As for the northeast region, its efficiency value decreases by nearly 0.2 in 2011, from 0.3751 in 2010 to 0.1816 in 2011. It then slightly rebounds in 2015 and remains stable at around 0.2 until 2020. As for the east region, regardless of whether exogenous variables are considered or not, its efficiency value in 2010 is the highest in recent years, at around 0.36, with some fluctuations between 2011 and 2017. However, between 2017

and 2020, when exogenous variables are not considered, the efficiency value changes relatively steadily.



**Figure 5.** Changes in energy consumption efficiency by region from 2010 to 2020.

After considering exogenous variables, the efficiency value fluctuates slightly, but the overall efficiency value has been increasing over the past four years. This may be due to the relatively developed economy in northeast China, followed by a slowdown in economic growth. Much energy equipment is not fully utilized and cannot achieve optimal efficiency, which has had a certain impact on energy consumption efficiency. However, due to varying degrees of slowdown between regions, the overall efficiency value still only increases and does not decrease.

The efficiency value of the west region fluctuates between 2011 and 2020, but remains at around 0.2. Although the west region has abundant energy resources, due to its long-term shortcomings in funding and technology, natural resources are difficult to develop and utilize reasonably, and energy utilization efficiency is not high, resulting in overall low efficiency values. For the east region, regardless of whether exogenous variables are considered or not, the overall efficiency value change is not significant. However, it is worth noting that, compared to not considering exogenous variables, the efficiency value in the central region remains relatively stable after considering exogenous variables between 2015 and 2016. This is because although there are regional differences, considering exogenous variables, the energy endowment and economic development level of the central regions are relatively balanced, and so the efficiency value is relatively stable.

From the perspective of different regions, the overall efficiency value of the northeast region is the highest among the four regions. The northeast region has abundant wind, solar, and hydropower resources, and these new energy sources have advantages such as green environmental protection and renewable energy, which are of great significance for solving the energy industry and environmental problems in the northeast region. Moreover,



a certain degree of correlation, there is a strong positive correlation between employment, total energy consumption, and SO<sub>2</sub> emissions. However, the correlation between regional GDP and total energy consumption is not high, and it is in a leading position compared with the efficiency values of other indicators. This may be because the growth in employment mainly relies on traditional industries with huge energy consumption and high pollution emissions, and the role of traditional industries in promoting regional GDP is very limited.

As shown in Figure 6b, although the mean efficiency of sub-indicators considering exogenous variables is lower than that without considering exogenous variables, the lowest efficiency value of sub-indicators considering exogenous variables is higher than its efficiency value without considering exogenous variables. This may be because, without considering exogenous variables, the energy consumption process of a city only relates to a few factors directly related to it, while its own endowment is ignored, which naturally leads to low energy consumption efficiency. After considering exogenous variables, the correlation between total energy consumption and SO<sub>2</sub> emissions becomes stronger, which may be because the current harmful gas emissions in the cities of China almost all come from urban energy consumption.

#### 4.4. Analysis of the Driving Effect of Energy Consumption Efficiency in Cities of China

From Figure 7, the main influencing factor of energy consumption efficiency changes from 2011 to 2020 is the energy endowment of cities themselves. The change in energy endowment dominates the trend of energy consumption efficiency changes in various cities. Although other factors have fluctuated slightly over the past decade, they still cannot affect the overall trend of urban energy consumption efficiency. This may be because cities with richer energy endowments have more efficient energy consumption processes, and the overall energy utilization process experience of cities is richer than other cities lacking energy endowments. However, from 2016 to 2017, the energy consumption technology level in the cities experienced a cliff-like decline, ultimately leading to a significant decline in the energy consumption efficiency of the cities during the current period.

From the comparison between Figure 7a,b, we see that the trend of changes in various factors considering exogenous variables is almost the same as that of factors not considering exogenous variables. However, after considering exogenous variables, the change in energy consumption efficiency increases, leading to a larger range of changes in the overall trend.

#### 4.5. Multiple Paired Sample Friedman Test for Energy Consumption Efficiency by Region

According to Table 3, the significance  $p$ -value is 0.002 \*\*\*, indicating significant statistical results. This indicates that, without considering exogenous variables, there is a significant difference between Efficiency in northeast China, Efficiency in east China, Efficiency in west China, and Efficiency in central China; the Cohen's  $f$  value is 0.214, indicating a slight difference.

**Table 3.** Friedman test for energy consumption efficiency without exogenous variables.

Efficiency without Exogenous Variables	Sample Size	Median	Standard Deviation	Statistic	$p$	Cohen's $f$
Efficiency in northeast China	11	0.195	0.062	14.673	0.002 ***	0.214
Efficiency in east China	11	0.146	0.066			
Efficiency in west China	11	0.176	0.059			
Efficiency in central China	11	0.16	0.062			

Note: \*\*\* represents significance levels of 1%.

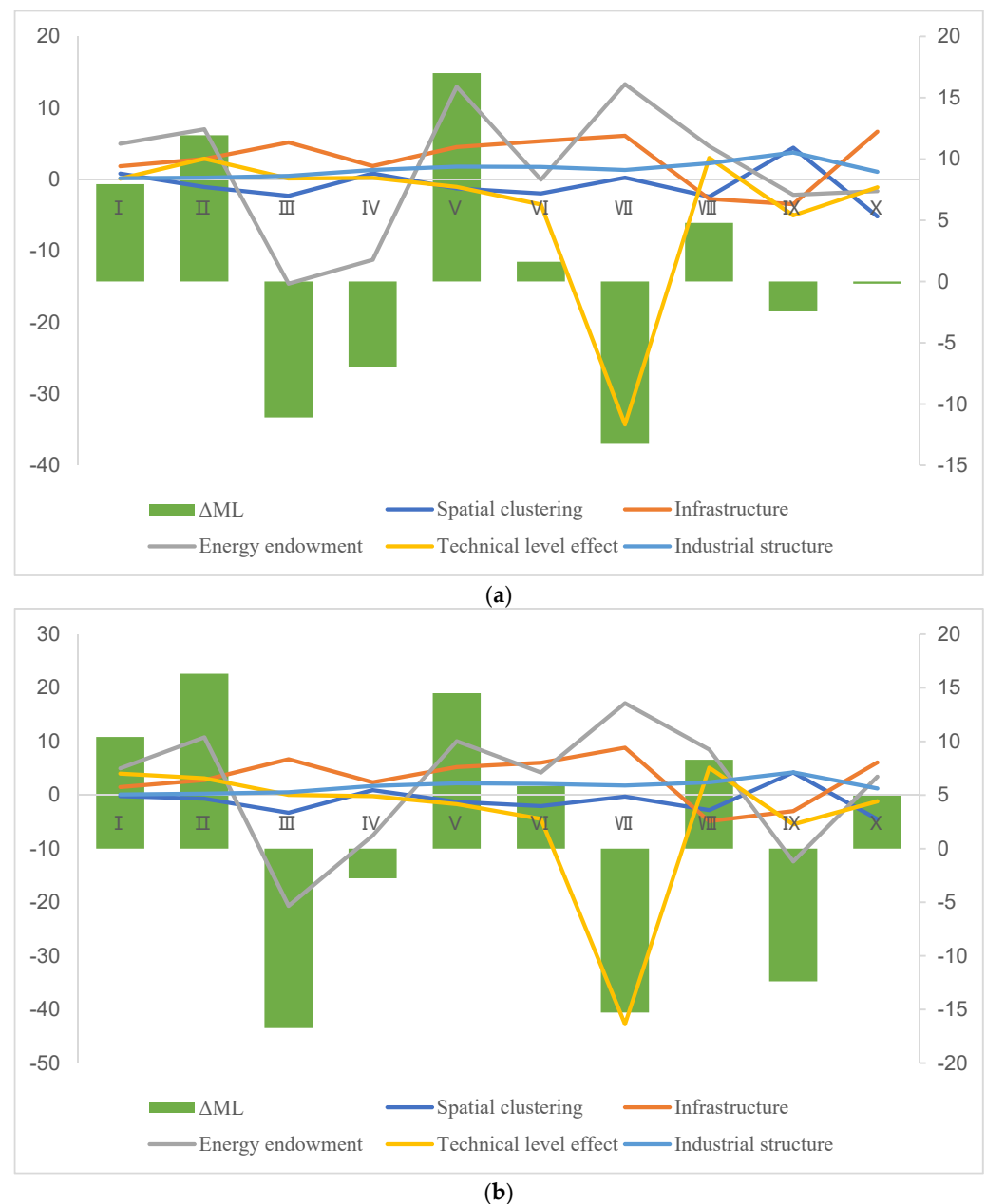
According to Table 4, the significance  $p$ -value is 0.001 \*\*\*, indicating significant statistical results. This indicates that, considering exogenous variables, there is a significant difference between Efficiency in northeast China, Efficiency in east China, Efficiency in west China, and Efficiency in central China; the Cohen's  $f$  value of the difference is 0.353, indicating a moderate degree of difference.



**Table 4.** Friedman test for energy consumption efficiency with exogenous variables.

Efficiency with Exogenous Variables	Sample Size	Median	Standard Deviation	Statistic	<i>p</i>	Cohen's <i>f</i>
Efficiency in northeast China	11	0.255	0.058	16.309	0.001 ***	0.353
Efficiency in east China	11	0.204	0.057			
Efficiency in west China	11	0.195	0.049			
Efficiency in central China	11	0.193	0.054			

Note: \*\*\* represents significance levels of 1%.



**Figure 7.** Decomposition effect of energy consumption efficiency changes. (a) Decomposition effect of energy consumption efficiency changes without exogenous variables. Note: Time periods I, II, III, IV, V, VI, VII, VIII, IX, and X respectively represent the years 2010–2011, 2011–2012, 2012–2013, 2013–2014, 2014–2015, 2015–2016, 2016–2017, 2017–2018, 2018–2019, and 2019–2020. (b) Decomposition effect of energy consumption efficiency changes with exogenous variables. Note: Time periods I, II, III, IV, V, VI, VII, VIII, IX, and X respectively represent the years 2010–2011, 2011–2012, 2012–2013, 2013–2014, 2014–2015, 2015–2016, 2016–2017, 2017–2018, 2018–2019, and 2019–2020.

## 5. Conclusions and Suggestions

### 5.1. Conclusions

In terms of overall efficiency, the energy consumption efficiency of cities in China is generally low, within a non-good range of 0.4. Moreover, because energy supply is uniformly distributed by the China government according to demand, it has never been able to form a more efficient energy consumption mode, resulting in severe pollution and waste of energy consumption in its cities. This verifies that the relatively backward energy consumption pattern is the main reason for the low energy efficiency in China, which is the argumentation of the achievement of the research objectives.

From the perspective of different regions, the overall efficiency value of the northeast region is the highest among the four regions, and that of the east region is the lowest. This may be because the northeast region, as a long-standing industrial base in China, not only has a relatively rich energy endowment, but also, overall, leads other regions in terms of infrastructure level. Although the east region has to some extent compensated for its insufficient investment in energy consumption infrastructure through rapid economic development in recent years, its energy consumption process overly relies on its own economic growth. Once the urban economic growth slows down, inefficient phenomena such as energy waste become prominent.

Exogenous variables have an improving effect on the overall energy consumption efficiency of cities. This indicates that, after considering other factors of a city's own development environment, the energy consumption process of the city will become more efficient. This may be because when only evaluating the efficiency of the entire energy consumption process, some basic conditions and development directions of the city itself are ignored, and the true energy consumption efficiency is not fully evaluated from the actual situation of different cities.

In terms of sub-indicator efficiency, the emission efficiency of industrial waste gas shows the most significant positive correlation with the efficiency of employment population and total energy consumption, while the efficiency of regional GDP does not show a significant correlation with the efficiency of the two input variables. This indicates that the current growth in employment in the cities mainly relies on traditional industries with high industrial exhaust emissions and high energy consumption. Such employment growth cannot have a significantly positive impact on regional GDP, but instead exacerbates the negative environmental effects brought about by energy consumption.

According to the decomposition of LMDI's impact factors on energy consumption efficiency in cities of China, the main factor affecting energy consumption efficiency in the cities is their own energy endowment. This indicates that the current energy consumption process in the cities still relies on their own energy conditions, and other non-resource background factors have not become the key factors affecting their energy consumption efficiency.

At the same time, the issue of energy efficiency and the decomposition of influencing factors is also important for other developing countries. For one thing, the countries with developing economies need to carefully examine the local economy and ecological environment, issue energy consumption policies tailored to local conditions, and prevent the occurrence of low energy consumption efficiency events such as energy waste from the perspective of energy allocation that the government can control. On the other hand, industrial transformation is an important challenge faced by emerging economies in the process of improving energy efficiency. In addition to China, some countries in Southeast Asia, such as Vietnam and India, also need to gradually transform some polluting industries in urban economic development into clean and environmental protection industries. This study also provides valuable data information and policy basis for energy use in other developing countries.

However, this study also has certain limitations. Although this study conducted empirical analysis on 270 Chinese cities, it still classified and summarized these cities through the commonly used economic regional division method by the Chinese govern-

ment. However, this classification method inevitably has biases in the dimensions of other influencing factors of urban energy consumption. And the factor decomposition made through the LMDI method can only obtain comparable values in essence, about which the decomposition conditions are quite strict. Therefore, it is necessary to further refine the decomposition conditions in the follow-up study.

## 5.2. Suggestions

### 5.2.1. Tailoring Policies to Local Conditions and Improving Overall Energy Consumption Efficiency in Various Regions of China

Attention must be paid to the overall improvement in energy consumption efficiency in various regions of China, and factors such as differences in economic development level, industrial structure, and technological level can be comprehensively considered in each region to formulate relevant energy-saving and emission-reduction policies. Targets should be given to steadily improve the energy utilization efficiency of economically developed areas, make economically underdeveloped areas a key focus for improving energy efficiency, and formulate policies that conform to the development laws of each region based on their unique geographical advantages and current development status to improve energy efficiency. The energy intensity and consumption situation vary greatly among different regions, and so energy policies related to each region must be combined with the actual development situation of each region. The government should develop reasonable policies to improve energy efficiency in each region and conduct strict supervision. For example, the northwest region should be identified as a key area for improving energy efficiency. Economically developed regions should transfer and spread technology to economically underdeveloped areas, while economically underdeveloped areas should introduce and absorb management experience, advanced technology, and development concepts from economically developed areas. China should increase investment in economically underdeveloped areas to help them break free from extensive development.

### 5.2.2. Adjusting Energy Consumption Structure and Reducing Energy Intensity

China is a major energy consumer mainly, relying on coal. Therefore, when crude oil prices rise, the cost of coal replacing crude oil is relatively low. However, lower heat generation and combustion efficiency can lead to a decrease in energy utilization efficiency. In the process of regional economic development, attention should be paid to optimizing the energy consumption structure, reducing dependence on fossil fuels such as coal, oil, and natural gas, reasonably controlling carbon emissions, constructing a new energy consumption structure system dominated by green and low-carbon energies, and promoting the achievement of carbon peak and carbon neutrality goals. In the industrial sector, China should accelerate the implementation of energy substitution, improve the level of industrial energy-saving technology, or replace facilities and technologies mainly based on coal with ones based on natural gas or electricity.

In terms of traditional energy, it is necessary to implement price control, establish a more sound energy market price system, reduce macroeconomic regulation and subsidies on primary energy prices by the state, and make energy prices reflect the real energy supply and demand situation in the market. In terms of clean energy, certain price-preferential policies can be implemented to promote the consumption of clean energy in various industries. In terms of policies, a threshold should be set to restrict the entry of high-energy-consuming industries, reduce the proportion of the secondary industry, and provide policy incentives and assistance to emerging industries such as the service industry. By improving the intermediary effect between industrial structure, price mechanism, and energy consumption structure, China can help promote the optimization of the overall energy consumption structure.

### 5.2.3. Increase Investment in Science and Technology and Promote Technological Progress and Innovation

Technological innovation capability is the primary productive force for the development of the oil and gas industry and is also a key factor affecting the quality of low-carbon economic growth in the oil and gas industry. Technological innovation can improve energy efficiency to a certain extent, thereby achieving emission reduction and low-carbon effects. Developed countries are continuously increasing investment in industrial energy-saving technologies, and energy-saving products and equipment are also emerging, steadily improving energy efficiency. The government needs to establish an effective institutional environment, protect technological innovation, and quickly establish communication platforms to promote technology promotion. Considering the differences in economy, technology, resources, and other aspects among different regions, corresponding policies should also be differentiated. For example, the energy-saving potential in the western inland areas is significant, and advanced energy-saving technologies from developed regions should be actively introduced and learned from, so as to narrow the technological gap. Due to the significant mediating effect between local economic level and technological progress, increasing fiscal investment in energy-saving technologies can enhance the mediating effect between the two, thereby exerting the inhibitory effect of technological progress on energy intensity.

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## Appendix A

**Table 1.** 270 Prefecture-level cities in China and their respective locations.

DMU	District	DMU	District	DMU	District	DMU	District	DMU	District	DMU	District	DMU	District	DMU	District
Ankang	Western	Datong	Central	Heihe	Northeast	Jiuquan	Western	Nanjing	Eastern	Shaoyang	Central	Urumchi	Western	Yingtian	Central
Anqing	Central	Dantong	Northeast	Hengshui	Eastern	Kaifeng	Central	Nanning	Western	Shaoxing	Eastern	Wuxi	Eastern	Yingkou	Northeast
Anshun	Western	Deyang	Western	Hengyang	Central	Kelamayi	Western	Nanping	Eastern	Shenzhen	Eastern	Wuhu	Central	Yongzhou	Central
Anyang	Central	Dezhou	Eastern	Huhehaote	Western	Kunming	Western	Nantong	Eastern	Shenyang	Northeast	Wuzhong	Western	Yulin	Western
Anshan	Northeast	Dingxi	Western	Hulunbeier	Western	Laibin	Western	Nanyang	Central	Shiyan	Central	Wuzhou	Western	Yulin	Western
Bazhong	Western	Dongguan	Eastern	Huludao	Northeast	Lanzhou	Western	Neijiang	Western	Shijiazhuang	Eastern	Wuhan	Central	Yuxi	Western
Baicheng	Northeast	Dongying	Eastern	Huzhou	Eastern	Langfang	Eastern	Ningbo	Eastern	Shizuishan	Western	Wuwei	Western	Yueyang	Central
Baishan	Northeast	Eerduosi	Western	Huaihua	Central	Leshan	Western	Ningde	Eastern	Shuangyashan	Northeast	Xian	Western	Yunfu	Eastern
Baiyin	Western	Ezhou	Central	Huaian	Eastern	Lijiang	Western	Panzhihua	Western	Shuozhou	Central	Xining	Western	Yuncheng	Central
Baise	Western	Fangchenggar	Western	Huabei	Central	Lishui	Eastern	Panjin	Northeast	Siping	Northeast	Xianning	Central	Zaozhuang	Eastern
Bengbu	Central	Foshan	Eastern	Huainan	Central	Lianyungang	Eastern	Pingdingshan	Central	Songyuan	Northeast	Xianyang	Western	Zhanjiang	Eastern
Baotou	Western	Fuzhou	Eastern	Huanggang	Central	Liaoyang	Northeast	Pingliang	Western	Suzhou	Eastern	Xiangtan	Central	Zhangjiajie	Central
Baoji	Western	Fushun	Northeast	Huangshan	Central	Liaoyuan	Northeast	Pingxiang	Central	Suqian	Eastern	Xiaogan	Central	Zhangjiakou	Eastern
Baoding	Eastern	Fuzhou	Central	Huangshi	Central	Liaocheng	Eastern	Putian	Eastern	Suzhou	Central	Xinzhou	Central	Zhangye	Western
Baoshan	Western	Fuxin	Northeast	Huizhou	Eastern	Lincang	Western	Puyang	Central	Suizhou	Central	Xinxiang	Central	Zhangzhou	Eastern
Beihai	Western	Fuyang	Central	Jixi	Northeast	Linfen	Central	Qitaihe	Northeast	Suining	Western	Xinyu	Central	Changchun	Northeast
Beijing	Eastern	Ganzhou	Central	Jian	Central	Linyi	Eastern	Qiqihaer	Northeast	Taizhou	Eastern	Xinyang	Central	Changsha	Central
Benxi	Northeast	Guyuan	Western	Jilin	Northeast	Liuzhou	Western	Qinhuangdao	Eastern	Taiyuan	Central	Xingtai	Eastern	Changzhi	Central
Binzhou	Eastern	Guangan	Western	Jinan	Eastern	Liuan	Central	Qingdao	Eastern	Taian	Eastern	Xuzhou	Eastern	Zhaotong	Western
Bozhou	Central	Guangyuan	Western	Jining	Eastern	Liupanshui	Western	Qingyuan	Eastern	Taizhou	Eastern	Xuchang	Central	Zhaoqing	Eastern
Cangzhou	Eastern	Guangzhou	Eastern	Jiamusi	Northeast	Longyan	Eastern	Qingyang	Western	Tangshan	Eastern	Xuancheng	Central	Zhenjiang	Eastern
Changzhou	Eastern	Guigang	Western	Jiaxing	Eastern	Longnan	Western	Qujing	Western	Tianjin	Eastern	Yaan	Western	Zhengzhou	Central
Chaoyang	Northeast	Guiyang	Western	Jiayuguan	Western	Loudi	Central	Quanzhou	Eastern	Tianshui	Western	Yantai	Eastern	Zhongshan	Eastern
Chaozhou	Eastern	Guilin	Western	Jiangmen	Eastern	Luzhou	Western	Rizhou	Eastern	Tieling	Northeast	Yanan	Western	Chongqing	Western
Chenzhou	Central	Haerbin	Northeast	Jiaozuo	Central	Luoyang	Central	Sanmenxia	Central	Tonghua	Northeast	Yancheng	Eastern	Zhoushan	Eastern
Chengdu	Western	Handan	Eastern	Jieyang	Eastern	Luohe	Central	Sanming	Eastern	Tongliao	Western	Yangzhou	Eastern	Zhoukou	Central
Chengde	Eastern	Hanzhong	Western	Jinchang	Western	Maanshan	Central	Xiamen	Eastern	Tongchuan	Western	Yangjiang	Eastern	Zhuhai	Eastern
Chizhou	Central	Changzhou	Eastern	Jinhua	Eastern	Maoming	Eastern	Shantou	Eastern	Tongling	Central	Yangquan	Central	Zhuzhou	Central
Chifeng	Western	Hefei	Central	Jinzhou	Northeast	Meishan	Western	Shanwei	Eastern	Weihai	Eastern	Yichun	Northeast	Zhumadian	Central
Chongzuo	Western	Hechi	Western	Jincheng	Central	Meizhou	Eastern	Shangluo	Western	Weifang	Eastern	Yibin	Western	Ziyang	Western
Chuzhou	Central	Heyuan	Eastern	Jinzhong	Central	Mianyang	Western	Shangqiu	Central	Weinan	Western	Yichang	Central	Zibo	Eastern
Dazhou	Western	Hezhou	Western	Jingmen	Central	Mudanjiang	Northeast	Shanghai	Eastern	Wenzhou	Eastern	Yichun	Central	Zigong	Western
Dalian	Northeast	Hebi	Central	Jingzhou	Central	Nanchang	Central	Shangrao	Central	Wuhai	Western	Yiyang	Central	Haikou	Eastern
Daqing	Northeast	Hegang	Northeast	Jiujiang	Central	Nanchong	Western	Shaoguan	Eastern	Wulanchabu	Western	Yinchuan	Western	Sanya	Eastern



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