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Energy intensity convergence among Chinese provinces: a Theil index decomposition analysis

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Abstract

China, the world's largest carbon emitter, has one of the most stringent provincial emissions reduction programs, incorporated into its Five-Year National Plan to reduce carbon emissions. However, the widening energy intensity gap between provinces poses a great challenge for carbon reduction. In this study, we analyze the convergence of Energy intensity (EIC), i.e., the time-dependent decrease of differences among regional energy intensity over time focusing on a data set of 30 Chinese provinces from 2000 to 2015. Our goal is to identify the provinces that are responsible for the observed divergence in energy intensity and identify the factors causing that divergence in each individual case. The Theil index is used to capture inter-provincial energy inequality. We use the LMDI decomposition analysis to identify the drivers of energy inequality (energy consumption structure, energy efficiency, and industrial structure). The results suggest that reducing energy intensity in Inner Mongolia, Xinjiang, and Hebei is the key to solving China's increasing energy intensity "gap" dilemma. The factors causing the energy intensity divergence in Inner Mongolia and Xinjiang are related to lagging economic growth and low energy efficiency, which impedes carbon emission reductions significantly. The factors causing the divergence of energy intensity in Hebei are rooted in its heavy industrial structure. Our findings are directly applicable to crafting regional energy policy with more targeted and practical emission reduction programs.

Keywords Energy intensity · σ Convergence · Decomposition analysis

1 Introduction

Reducing energy intensity is an important strategy to ensure sustainable economic development and a key to alleviating the pressure of carbon emissions in China, where energy intensity (*EI*) is the ratio of energy utilization to economic output. China stated that the goals are "carbon peak by 2030 and carbon neutrality by 2060" [1]. China's energy intensity saw an overall decreasing trend during 2000–2020, but the gap among regions is widening. The highest energy intensity of provinces was about 9 times the lowest one in 2000, while this ratio expanded to about 23 times in 2020. The widening energy intensity gaps among provinces pose a new challenge for further reduction of energy intensity in China [2, 3].σ convergence of energy intensity, defined as the difference in energy intensity among provinces over time, is crucial to narrowing these gaps [4]. σ convergence describes the convergence of decreasing differences in *EI* across regions over time, that is *EI* gaps narrowing. And β convergence refers to the fact that regions with higher initial *EI* have lower *EI* growth rates than those with lower initial *EI*. Compared to the beta convergence, the sigma convergence can represent

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the *EI* gaps better. By studying the provincial contributions to the σ convergence of *EI* in China, the key provinces can be identified, providing feasible guidance to specific provinces in solving the problem of *EI* gap widening and *EI* reduction.

Existing studies have mainly documented whether or not there is convergence in energy intensity in China; very few studies have explored the causes of the energy intensity gaps. For example, Zheng and Xinqing [5] explore the σ convergence of China's water intensity from 2003 to 2013 using a Gini coefficient to find that China's industrial and ecological water intensity show a σ convergence, and they proposed that efficiency in water resources utilization should be improved based on the policy of "comprehensive planning, regional balance, and enhanced allocation". Yan et al. [6], on the other hand, use log deviation mean, Gini coefficient and Theil index to explore the convergence of carbon emission intensity of China's provinces from 1995 to 2012. The results show a tendency for the differences between provinces in China's carbon emission intensity to expand, and there is no evidence of σ convergence. In contrast, this paper adds an analysis of the driving forces of σ convergence and examines *EI* in both province and industry dimensions. Liu et al. [7] use the log deviation mean, Gini coefficient, and the Theil index to study the differences in pollutant emission intensity in China and more specifically examine the contribution of inter- and intra-regional variability. Based on industry-level data, Wang Juan and Zhang Ke-Zhong use the σ convergence method to explore the convergence of carbon emissions from 1996 to 2014 in China for agriculture, industry, construction, transportation, retail trade, and others [8]. The results show a convergence trend of carbon emissions in the above-listed industries. The only cross-country study we were able to find is Wang and Zhou [9]. The authors study the sub-provincial contributions to σ convergence of carbon emissions per capita in 14 countries around the world, which found that global emissions inequality derives mainly from China and India. Inequality in global emissions is declining at an accelerating rate, which has been driven by narrowing gaps in per capita consumption levels across countries and impeded by widening gaps in the emissions intensity of the consumption base. In 2018, Bilgili and Ulucak [10] investigated whether there is a convergence of per capita ecological footprints among the G20 countries, and came up with conclusive results on the existence of club convergence. In 2020, Li et al. [11] determined the progress of convergence of global CO_2 emissions in terms of both production and consumption, they draw conclusions on the different convergence effects and factors influencing the production and consumption side of carbon emission. In 2020, Zhu and Lin [12] studied the energy intensity convergence of 193 cities in China and found four convergence clubs, which showed great differences in energy intensity. In 2022, Peng et al. [13] explored whether there is a convergence club for TFEE[1] in BRI[2] countries. It is concluded that the TFEE of BRI countries overall converges to three different convergence clubs, and that China's outward FDI in low-carbon industries in BRI countries is conducive to facilitating the convergence to the energy-efficient and high-efficiency clubs. In 2022, Hübler et al. [14] examined the impact of international trade on structural convergence and carbon emissions and concluded that international trade contributes significantly to structural convergence, which also leads to increased carbon emissions. In 2023, Balado-Naves et al. [15] examined the impact of spatial spillovers on the growth and convergence of energy intensity in 153 countries, concluding that convergence is higher in neighboring countries. Limited studies have explored EI σ convergence in China, and there are no studies focusing on the driving forces from the perspective of the industry dimension, which is crucial for solving the problem of the expanding energy intensity differences in China.

We fill in the research gap on the driving forces analysis of energy intensity σ convergence in China by combining the Theil index method and the Laspeyres factor decomposition method. Then we analyze the sub-provincial contributions to energy intensity σ convergence in 30 provinces in China from 2000 to 2015. The σ convergence is characterized from the perspective of differences between regions. It represents a decrease in differences, not a decrease in energy intensity. We further identify the key provinces that cause the widening divergence of energy intensity and the driving factors behind this divergence, using the logarithmic mean Divisia index. The logarithmic mean Divisia index (LMDI) method belongs to the Index Decomposition Analysis (IDA). The LMDI additive (LMDI I) is able to decompose the overall quantity into multiple factors and quantitatively analyze the degree of contribution of individual factors. Thus, we provide theoretical support for setting energy-saving tasks in key provinces from the perspective of energy intensity convergence and lay out the foundation for formulating coordinated regional energy policies. Our results allow for crafting targeted policy recommendations for reducing the disparity in energy intensity among provinces.

The rest of the study is structured as follows. Section 2 shows the research methodology; Sect. 3 introduces the Data source and analysis; Sect. 4 discusses the results and Sect. 5 concludes and puts forward policy recommendations.

[1] Total-factor energy efficiency.

[2] Countries along with the Belt and Road Initiative.

Table 1 Meaning of variables in the models

Variables	Meaning
EI	Energy intensity
q	Economic share, i.e. share of output,
ECijk	The consumption of energy k in industry j in Province i
ECij	The total energy consumption in the industry j of Province i
VAij	The value added of industry j in Province i
VAi	The sum of the value added of each industry in Province i
ESijk	The energy consumption structure effect in industry j of Province i
EIij	The energy intensity effect of industry j in Province i
ISij	The industrial structure effect of industry j in Province i

2 Research methodology

2.1 Decomposition of the energy intensity Theil index

In this study, we consider all 30 provinces in China (excluding Tibet, Hong Kong, Taiwan, and Macau due to lack of data). In this paper, we apply the Theil index, which is a measure of income inequality with good decomposability properties. According to Wang and Zhou [9], the general expression of the Theil index is as follows:

$$\mathrm{I(EI)} = \sum_{\mathrm{i}} \mathrm{q_i} \ln \left(\mathrm{EI_u}/\mathrm{EI_i}\right) \tag{1}$$

where *i* represent each province in China. Each province contains three industries $j, j = 1,2,3$, which represent the primary, secondary, and tertiary industries, respectively. The subscript represents the average of national. The Theil index in Province *i* is, its positive value means that the energy intensity of this province is lower than the national average, and vice versa. For example, the theil index in Tianjin in 2000 is -0.00324, which means that Tianjin's *EI* was higher than the national average *EI* in 2000. The lower limit of the index is 0, while the upper limit depends on the sample. Larger values of indicate higher inequity and more significant differences in energy intensity between provinces.

In this study, the logarithmic mean Divisia index (LMDI) is used to decompose the Theil index (Table 1).

2.2 Decomposition of σ-convergence of energy intensity

EI σ convergence describes a convergence where the variation in energy intensity across provinces decreases over time. According to Eq. (2), the absolute change in the value of the Theil index from time 0 to time T can be described as $\mathrm{I(EI)^T} - \mathrm{I(EI)^0}$. If it is less than 0, it indicates that the difference keeps getting smaller with time and presents a σ convergence. And vice versa. The specific expression is as follows.

$$\begin{aligned}\mathrm{I(EI)^T} - \mathrm{I(EI)^0} = &\left(\sum_{\mathrm{i}} \mathrm{q_i^T} \ln \mathrm{D_{ES}^{u,i,T}} + \sum_{\mathrm{i}} \mathrm{q_i^T} \ln \mathrm{D_{EI}^{u,i,T}} + \sum_{\mathrm{i}} \mathrm{q_i^T} \ln \mathrm{D_{IS}^{u,i,T}}\right) \\ &- \left(\sum_{\mathrm{i}} \mathrm{q_i^0} \ln \mathrm{D_{ES}^{u,i,0}} + \sum_{\mathrm{i}} \mathrm{q_i^T} \ln \mathrm{D_{EI}^{u,i,0}} + \sum_{\mathrm{i}} \mathrm{q_i^T} \ln \mathrm{D_{IS}^{u,i,0}}\right) \\ = &\ \Delta I_{\mathrm{qshare}} + \Delta I_{\mathrm{ES}} + \Delta I_{\mathrm{EI}} + \Delta I_{\mathrm{IS}}\end{aligned} \tag{2}$$

where Δ indicates that this decomposition is an additive decomposition and $\Delta \mathrm{I_{qshare}}$, $\Delta \mathrm{I_{ES}}$, $\Delta \mathrm{I_{EI}}$, $\Delta \mathrm{I_{IS}}$ are economic structure effect, energy consumption structure effect, energy efficiency effect, and industrial structure effect, respectively. Among them, the economic structure effect is introduced to characterize the effect on the σ convergence of energy intensity, which is caused by the changing economic share of each Province over time. Equation (2) is the essential time IDA model. Since the decomposition of the logarithmic form is more complicated at the industry level, the Shapley/Sun (S/S) decomposition is chosen in this study based on the Laspeyres method, i.e., the principle of decomposing one factor at a time [16]. The expression of its decomposition is as follows.

$$\Delta I_{\text{qshare}} = \frac{1}{2}\sum_{\text{ijk}}\left(q_i^T - q_i^0\right)\begin{pmatrix} w_{ijk}^0 \mathit{ln}\frac{ES_{ujk}^0}{ES_{ijk}^0} + w_{ijk}^T \mathit{ln}\frac{ES_{ujk}^T}{ES_{ijk}^T} + w_{ijk}^0 \mathit{ln}\frac{EI_{uj}^0}{EI_{ij}^0} \\ + w_{ijk}^T \ln\frac{EI_{uj}^T}{EI_{ij}^T} + w_{ijk}^0 \mathit{ln}\frac{IS_{uj}^0}{IS_{ij}^0} + w_{ijk}^T \mathit{ln}\frac{IS_u^T}{IS_i^T} \end{pmatrix} \tag{3}$$

$$\Delta I_{ES} = \frac{1}{2}\sum_{\text{ijk}}\left(q_i^T + q_i^0\right)\left(w_{ijk}^T \ln\frac{ES_{ujk}^T}{ES_{ijk}^T} - w_{ijk}^0 \ln\frac{ES_{ujk}^0}{ES_{ijk}^0}\right) \tag{4}$$

$$\Delta I_{EI} = \frac{1}{2}\sum_{\text{ijk}}\left(q_i^T + q_i^0\right)\left(w_{ijk}^T \ln\frac{EI_{uj}^T}{EI_{ij}^T} - w_{ijk}^0 \ln\frac{EI_{uj}^0}{EI_{ij}^0}\right) \tag{5}$$

$$\Delta I_{IS} = \frac{1}{2}\sum_{\text{ijk}}\left(q_i^T + q_i^0\right)\left(w_{ijk}^T \ln\frac{IS_{uj}^T}{IS_{ij}^T} - w_{ijk}^0 \ln\frac{IS_{uj}^0}{IS_{ij}^0}\right) \tag{6}$$

Equations (3) to (6) reveal the sources and influencing factors of the σ convergence. If the above indicators' values are positive, i.e. the Theil index increases, there is energy intensity convergence. On the contrary, if these indicators are negative, the Theil index decreases, and then the above differences are reduced meaning a convergence.

The interpretation of the indicator at the provincial level needs to be judged by the relative position of each province's energy intensity to the national average. The σ convergence of energy intensity only represents a decrease in differences, not a decrease in energy intensity. For example, a negative value of the indicator represents convergence, meaning that the *EI* of a province with higher energy intensity than the national average decreases and gradually approaches the national average; for provinces with low intensity it is manifested as an increase in the *EI*. That is, the energy intensity of high-energy intensity provinces is decreasing, which is shown as promoting convergence. The declining energy intensity of low-energy-intensity provinces is a hindrance to convergence. Thus, promoting convergence is not our goal. The focus of this study is to identify the key provinces with high energy intensity that lead to the widening of energy intensity differences in China through the study of the sources of σ convergence and to explore the difficulties of energy intensity decline in key provinces through factor decomposition analysis.

3 Data source and analysis

We collect data for 30 provinces (autonomous regions and municipalities directly under the central government) in China from 2000 to 2015 (excluding Tibet Autonomous Region, Hong Kong Special Administrative Region, Macau Special Administrative Region, and Taiwan Province due to lack of data). The data for each province is subdivided into three industries. Among them, (1) primary industry, which includes agriculture, forestry, animal husbandry, and fishery; (2) secondary industry, which includes industry and construction; and (3) tertiary industry, which includes transportation, commerce, finance, communication, education, service, and other service sectors. Data on energy consumption from 2000–2015 are obtained from the China Energy Statistical Yearbook11, and the physical quantities of various energy consumption are converted into standard coal quantities according to the energy conversion factors provided in the China Energy Statistical Yearbook11.[3] Among them, this study uses electricity conversion coefficients based on thermal power generation technologies (average amount of fuel consumed per kWh of electricity produced) for different provinces in different years to convert electricity consumption values into standard coal values, as this better reflects the actual amount of primary energy input required for secondary energy consumption. Electricity conversion coefficients for 30 provinces from 2000 to 2015 were obtained from the China Electricity Statistical Yearbook [17]. To reflect the heterogeneity among different industries, we converted the value added of industries into constant prices with 2000 as the

[3] We categorize energy sources into five main categories: total coal, total oil, natural gas, electricity and other energy sources, according to the energy balance sheet provided by the China Energy Statistics Yearbook, which is an authoritative sourcebook for business and government use.

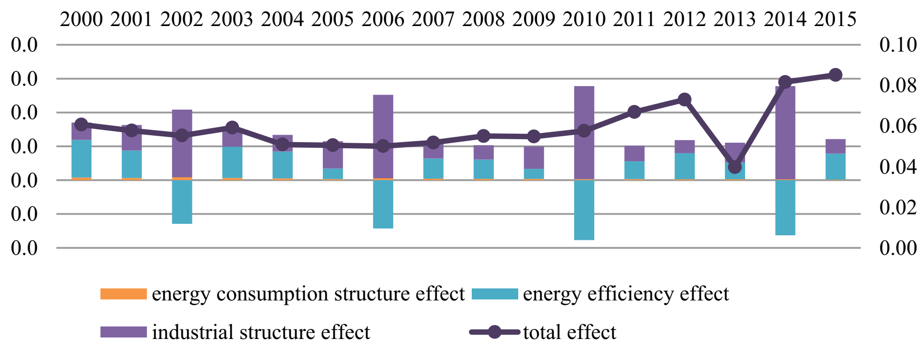

Fig. 1 Trend of China's EI Theil index and decomposition results from 2000–2015

base year using the price indices of three industries in different provinces. According to suggestions by Ma [18], both the value added and the price indices were obtained from the China Statistical Yearbook [19].[4]

4 Results and discussion

4.1 Convergence analysis of China's energy intensity based on Theil index

As can be seen from Fig. 1, the Theil index of energy intensity in China increased from 0.061 in 2000 to 0.085 in 2015. It shows that the difference in energy intensity among the 30 provinces in China increased from 2000 to 2015, i.e., it did not meet the convergence. Specifically, China's Theil index of energy intensity showed a decreasing phase from 2000 to 2006 (0.061 decreased to 0.050), with a slight fluctuation only in 2003. Xi Jinping, who was just elected president in 2013, put forward the concept of "Clear waters and green mountains are as good as mountains of gold and silver." in 2005, and China has been paying more attention to environmental protection ever since. In 2013, there is a small decreasing trend, which is related to the effective implementation of the Action Plan for Prevention and Control of Air Pollution issued by the State Council of China in 2013. However, the overall energy intensity of China's Theil index from 2006 to 2015 is mainly in an increasing phase (Theil index increased from 0.050 in 2006 to 0.085 in 2015). It indicates that the period from the 11th and 12th Five-Year Plan is the main stage of China's widening energy intensity gap.

According to Fig. 1, it is also known that the impact of the structural effect of energy consumption is not significant. The industrial structure effect is always a positive influencing factor, and the energy efficiency effect is a positive contributing factor in the remaining years, except for 2001, 2005, 2009 and 2013, when the energy efficiency effect is an inhibiting factor on the increase of the energy consumption intensity Theil index.

4.2 Sub-provincial contribution to the σ convergence of energy intensity in China

The σ convergence is characterized from the perspective of differences among regions, so the σ convergence of energy intensity only represents a decrease in differences, not a decrease in energy intensity. If the energy intensity of a low energy-intensity province increases, it will reduce the gap with the average level and promote convergence instead. Therefore, the goal of this study is not to promote the σ convergence of energy intensity, but to find the key provinces with high intensity and lower reduction rate than the average, which means "lagging behind" in the reduction of energy intensity. Moreover, this paper also explores the difficulties of energy intensity reduction in the key provinces through factor decomposition and puts forward targeted policy recommendations for these provinces.

To further explore the source of the σ convergence of energy intensity, the σ convergence process of energy intensity is decomposed into 30 provinces. According to the contribution of each province to the convergence, 30 provinces in China are divided into four categories: high-energy-intensity provinces that promote convergence, low-energy-intensity provinces that promote convergence, high-energy-intensity provinces that hinder convergence, and low-energy-intensity provinces that hinder convergence. Table 2 shows the contribution of the four categories.

[4] In order to improve accuracy, we calculate the real GDP specific to the provincial sectors based on the GDP indices of the different provincial sectors for the 2000-based period.

Table 2 Provincial contribution to energy intensity convergence in China

Provinces promoting σ convergence (contribution, %)	
High energy intensity	Shanxi (8%) Guizhou (3%) Gansu (7%)
Low energy intensity	Shandong (−76%) Fujian (−47%) Jiangsu (−46%) Jiangxi (−33%) Henan (−29%) Sichuan (−23%) Shaanxi (−17%) Yunnan (−15%) Zhejiang (−10%) Hainan (−9%) Guangxi (−0.5%)
Provinces hindering σ convergence (contribution, %)	
High energy intensity	Inner Mongolia (−39%) Xinjiang (−30%) Hebei (−24%) Qinghai (−4%) Ningxia (−0.04%)
Low energy intensity	Beijing (138%) Shanghai (98%) Liaoning (53%) Heilongjiang (45%) Hubei (40%) Chongqing (32%) Jilin (30%) Tianjin (19%) Anhui (18%) Hunan (10%) Guangdong (1%)

During 2000–2015, the contribution to the convergence of China's energy intensity mainly comes from the low-energy-intensity regions: Shandong Province (−76%), Fujian Province (−47%), Jiangsu Province (−46%) and Jiangxi Province (−33%). The regions that hinder the convergence of energy intensity in China originate from the low energy intensity regions of Beijing (138%), Shanghai (98%), Liaoning (53%), Heilongjiang (45%), Hubei (40%), and the high energy intensity regions of Inner Mongolia (−39%), Xinjiang (−30%), and Hebei (−24%). This result indicates that the dispersion of energy intensity in China is mainly due to the widening differences in energy intensity between low-energy-intensity regions (Beijing, Shanghai, and Liaoning Provinces) and high-energy-intensity regions (Inner Mongolia, Xinjiang, and Hebei Provinces). Inner Mongolia, Xinjiang, and Hebei Provinces are the key provinces for energy intensity reduction in China. In addition, the energy intensity of the high-energy intensity provinces that hinder convergence (such as Qinghai and Ningxia Provinces) gradually widened the gap with the national level, indicating that its energy intensity is declining slowly. Despite its relatively small share, it is still the object of concern for the reduction of energy intensity in China.

According to convergence theory, the rate of energy intensity reduction in high-energy-intensity provinces gradually exceeds that in low-energy-intensity provinces, so the energy-saving and emission reduction potential of low-energy-intensity provinces will gradually decrease. In addition, since low-energy-intensity provinces have already reduced their energy intensity significantly, further reduction of energy intensity will increase their energy-saving costs. In the future, China's energy conservation tasks should be gradually transferred from low-energy-intensity provinces to high-energy-intensity provinces, which will help optimize China's energy conservation costs and coordinate regional emission reduction tasks. Therefore, based on the convergence contribution results of the above four categories of provinces, this study suggests reducing the energy conservation tasks of the low-energy-intensity regions that hinder convergence (e.g., Beijing, Shanghai, etc..) moderately, and increasing the energy conservation tasks of the high-energy-intensity provinces that hinder and promote convergence (e.g., Qinghai, Ningxia, Inner Mongolia, Xinjiang, and Hebei Provinces). In addition, since the energy intensity of low energy intensity regions that promote convergence (e.g., Shandong, Jiangsu.) has been relatively slow to decline, it is recommended that the current energy conservation tasks be maintained to accelerate the decline in their energy intensity.

Combined with Table 3, we further explore the factors influencing the σ convergence of energy intensity in key provinces to identify the difficulty of decreasing energy intensity in key provinces (Inner Mongolia, Xinjiang, and Hebei Provinces). The economic structure, energy structure, energy efficiency, and industrial structure effects of Inner Mongolia are −0.0020, −0.0002, −0.0201, and 0.0128, respectively, and the more backward economic level accompanied by low energy efficiency is the main factor that hinders the reduction of energy intensity in Inner Mongolia. The economic structure, energy structure, energy efficiency, and industrial structure effects of Xinjiang are −0.0005, −0.0001, −0.0092, and 0.0024, respectively. Xinjiang also faces the problem of the level of economic development, and energy efficiency needs to be further improved. For such a province, setting energy efficiency targets needs to be combined with economic development goals, with economic development driving the development of advanced technologies, especially the development of advanced energy efficiency and emission reduction technologies, and accelerating the decoupling of economic development from energy consumption. Scientific research investment should be combined with their characteristics, focusing on investment to more economic growth effect and energy saving and emission reduction technology areas, then gradually eliminate backward production capacity technology. For example, Xinjiang can eliminate backward production capacity technologies such as small power generating units, build a modern energy industry chemical base, and support the development of advanced intelligent manufacturing and electronic information industries. In addition, as Xinjiang has the geographical advantage of proximity to the border and unique agricultural products, it can establish a modern organic agricultural products processing industry and create a well-known brand of

Table 3 Decomposition results of energy intensity convergence in China, 2000–2015

	Economic effect	Energy structure effect	Efficiency effect	Industrial structure effect	Total effect
Beijing	0.0010	0.0030	0.0119	0.0179	0.0338
Tianjin	−0.0001	0.0001	−0.0030	0.0076	0.0047
Hebei	0.0007	−0.0001	−0.0008	−0.0057	−0.0060
Shanxi	0.0013	0.0001	−0.0026	0.0030	0.0019
Inner Mongolia	−0.0020	−0.0002	−0.0201	0.0128	−0.0095
Liaoning	0.0010	0.0000	0.0226	−0.0107	0.0129
Jilin	0.0000	0.0001	0.0042	0.0030	0.0073
Heilongjiang	0.0000	0.0002	0.0304	−0.0196	0.0109
Shanghai	0.0002	0.0005	0.0095	0.0138	0.0240
Jiangsu	0.0000	0.0005	0.0053	−0.0171	−0.0113
Zhejiang	0.0009	0.0002	0.0076	−0.0111	−0.0024
Anhui	0.0000	0.0001	0.0051	−0.0009	0.0044
Fujian	−0.0006	0.0001	−0.0201	0.0092	−0.0114
Jiangxi	0.0000	−0.0003	−0.0109	0.0032	−0.0080
Shandong	0.0001	−0.0002	−0.0062	−0.0124	−0.0187
Henan	0.0000	−0.0001	0.0057	−0.0127	−0.0071
Hubei	0.0000	−0.0001	0.0221	−0.0122	0.0098
Hunan	0.0011	−0.0001	0.0000	0.0015	0.0025
Guangdong	−0.0014	−0.0004	−0.0123	0.0142	0.0002
Guangxi	0.0000	0.0000	0.0003	−0.0005	−0.0001
Hainan	0.0003	−0.0003	−0.0059	0.0037	−0.0023
Chongqing	−0.0003	0.0002	0.0026	0.0052	0.0077
Sichuan	−0.0001	−0.0002	−0.0056	0.0002	−0.0056
Guizhou	−0.0008	0.0000	0.0009	0.0007	0.0008
Yunnan	0.0000	−0.0001	−0.0035	0.0000	−0.0036
Shaanxi	−0.0002	0.0000	−0.0069	0.0030	−0.0041
Gansu	−0.0001	0.0000	−0.0006	0.0024	0.0018
Qinghai	0.0001	0.0000	−0.0019	0.0009	−0.0009
Ningxia	0.0004	0.0000	−0.0009	0.0004	0.0000
Xinjiang	−0.0005	−0.0001	−0.0092	0.0024	−0.0074
National	0.0010	0.0031	0.0182	0.0021	0.0244

regional agricultural products. Inner Mongolia can vigorously develop new functional materials industries, and reasonably use its scarce metals and natural resources, such as Graphene.

The effects of economic structure, energy structure, energy efficiency, and industrial structure in Hebei are 0.0007, −0.0001, 0.0008, and −0.0057, respectively. The industrial structure is the key factor that hinders its energy intensity reduction. The industrial structure effect in Hebei may be due to its own heavy industry structure and burden with some heavy industries from Tianjin and Beijing. This result suggests that the transfer of heavy industries from developed to less developed regions will further increase the energy intensity gap in China. This study suggests that the energy-saving task in Hebei should focus on upgrading and optimizing the industrial structure. Hebei should take over the industries of other provinces and adhere to the concept of environmental protection. With the development of the "Xiong'an New Area Plan", Hebei should pay more attention to the development of intelligent manufacturing, such as big data, automobile manufacturing, and innovative industries, and undertake the industries of Beijing and Tianjin by "complementing the chain" to improve the industrial chain of each region.

The effects of economic structure, energy structure, energy efficiency, and industrial structure in Qinghai are 0.0001, 0.0000, −0.0019, and 0.0009, respectively, while the effects of economic structure, energy structure, energy efficiency, and industrial structure in Ningxia are 0.0004, 0.0000, −0.0009, and 0.0004, respectively. The main problem of decreasing energy intensity is lower energy efficiency, and the task of energy conservation should be to improve energy efficiency as the primary goal. In addition, Qinghai and Ningxia are important strategic resource continuity areas in China, and energy efficiency improvement should also focus on resource-carrying capacity. Qinghai is rich in mineral resources, and its economic development is supported mainly by salt lake chemical and non-ferrous metal mining industries. Therefore, Qinghai should pay attention to the development of resources and enhance energy efficiency through deep processing and process upgrading of salt lake resources and non-ferrous metals. Ningxia is rich in coal resources, so its heavy industry has developed rapidly. Therefore, it should improve energy processing and conversion efficiency, eliminate backward production capacity such as small power generating units, and build a modern energy industry chemical industry to reduce energy intensity.

Among the low-energy-intensity provinces, this study also analyzes the factor decomposition of the provinces that contribute more and have a smaller decrease in energy intensity, including four provinces such as Shandong, Fujian, Jiangsu, and Jiangxi. From the decomposition results, it can be seen that the economic, energy structure, energy efficiency, and industrial structure effects of Shandong are 0.0001, −0.0002, −0.0062, and −0.0124, respectively, which shows that the higher energy intensity growth rate of Shandong is mainly resulted by the energy-intensive industrial structure and lower energy efficiency. Hu et al. [20] pointed out that Shandong Province has maintained the second-highest GDP in China in recent years, accompanied by a large amount of energy consumption and a heavily industrialized industrial structure. Since the 14th Five-Year Plan, China has put forward the total energy requirement. Shandong is unable to drive economic growth through energy-intensive industries. Shandong's energy-saving tasks are to adjust the industrial structure and increase the proportion of tertiary and high-tech industries while also paying attention to improving the energy efficiency of manufacturing industries.

The primary sources of energy intensity convergence in Fujian are the economic structure effect, efficiency effect, and industrial structure effect, which are −0.0006, −0.0201, and 0.0092, respectively, the energy efficiency effect mainly hinders the energy intensity reduction. In contrast, the industrial structure plays a facilitating role. Similar to Fujian, Jiangxi also has the problem of low energy efficiency. All the above provinces need to focus on developing and applying energy-saving technologies, especially in energy-intensive industries. The energy structure effect, efficiency effect, and industrial structure effect in Jiangsu are 0.0005, 0.0053, and −0.0171, respectively, which shows that the heavy industrialized industrial structure hinders the decrease of its energy intensity. Similar findings were obtained by Wang et al. [21]. The authors concluded that the industrial structure adjustment after 2002 hindered the energy saving and emission reduction in Jiangsu due to the lag in investment in energy-intensive industries and the initial overdraft of energy inputs. Jiangsu should pay attention to the development of high-tech industries, change the economic growth driven by heavy industry, and constantly coordinate the contradiction between economic development and energy consumption.

Unlike the above low-energy intensity provinces, Beijing, Shanghai, Liaoning, Heilongjiang, and Hubei have all hindered σ convergence by significantly reducing their energy intensity. The successful experiences of the above provinces are worthy of reference for other cities. The factor decomposition results show that developed regions such as Beijing and Shanghai have reduced their energy intensity mainly by improving energy efficiency and industrial structure, which should be learned by Shandong. Since developed regions such as Beijing and Shanghai have high energy-saving technology, the energy-saving task should optimize production and logistics management strategies. Liaoning, Heilongjiang, and Hubei Provinces have reduced energy intensity mainly by improving energy efficiency. However, the effects of the economic and industrial structures in the above provinces are not conducive to reducing energy intensity. Their successful experience of efficiency improvement is worthy of reference for high-energy-intensity provinces such as Qinghai and Ningxia. Energy efficiency tasks in Liaoning, Heilongjiang, and Hubei need to be combined with industrial planning and economic development goals to optimize and upgrade industrial structures.

4.3 Sub-sector decomposition analysis based on Theil index

As shown in Fig. 2, during the study period, the overall energy intensity Tel index has shown an upward trend, and the industrial sector has been the largest contributor to the energy intensity Teil index, transforming from the largest negative contribution to the largest positive contribution; the wholesale and retail trade and accommodation and catering sectors have contributed the second largest amount of positive contribution to the overall change in the energy intensity Tel index in the period of 2000–2015, but it has shown an upward trend followed by a downward trend, and its positive contribution was surpassed by the other sectors during the 12th Five-Year Plan period; the agricultural sector, the transportation sector, and the other sectors have been on an upward trend in the value of the contributions, and the value of the contributions from the transportation sector has always been positive.

The industrial sector should be the key target for improvement, reducing energy consumption intensity and improving energy utilization efficiency through technological innovation, industrial upgrading and energy management

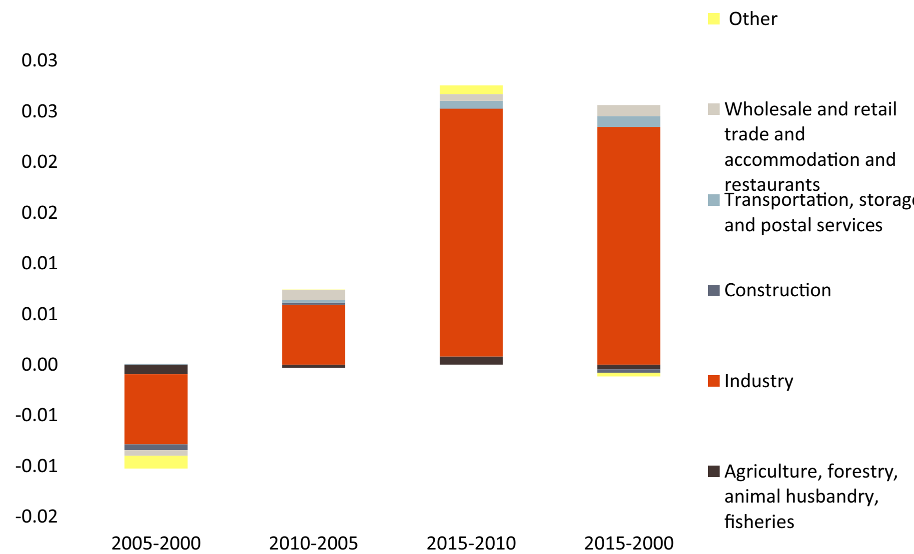

Fig. 2 Results of the decomposition of the EI Theil indicator by sector in China

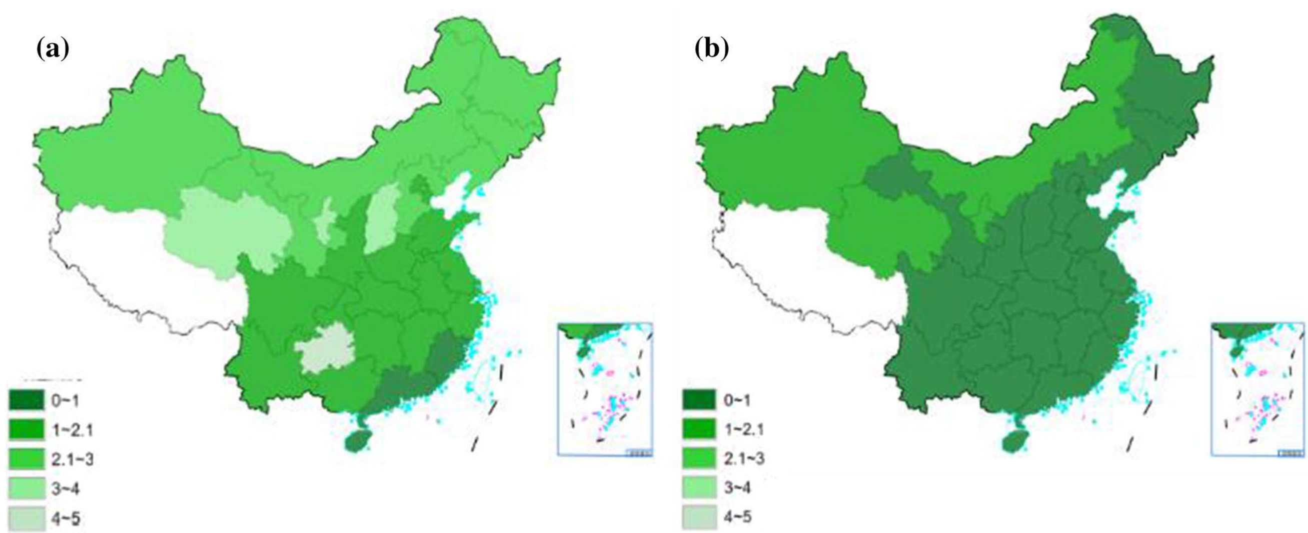

Fig. 3 Spatial distribution of **a** EI in 2000 and **b** EI in 2022

improvement. The transportation sector should promote new energy vehicles and public transportation, optimize transportation network planning and management, and reduce traffic congestion and ineffective driving, thereby reducing energy consumption intensity. The wholesale and retail trade and accommodation and catering sectors should continue to strengthen energy management, optimize the energy consumption structure and reduce unnecessary energy waste. The agriculture sector can reduce energy consumption during agricultural production by promoting modern agricultural technology, improving farming methods and other measures. In addition, the government should formulate and implement relevant policies and measures, such as energy taxes, energy-saving subsidies, and energy-efficiency standards, in order to encourage and support various sectors to improve energy-use efficiency and reduce energy-consumption intensity. At the same time, the Government also needs to strengthen energy statistics and monitoring to master the energy consumption situation of various sectors in a timely manner, so as to provide a scientific basis for the formulation and adjustment of relevant policies.

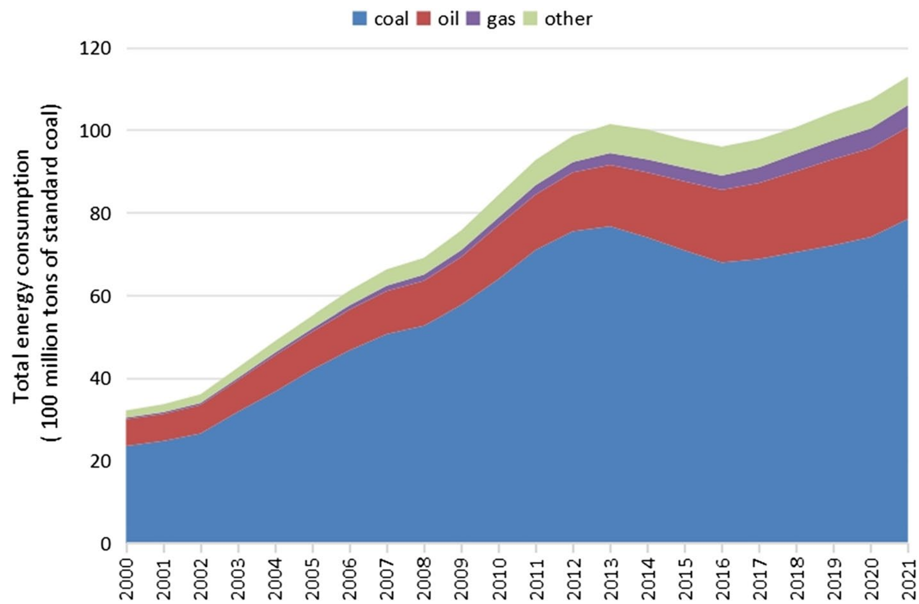

Fig. 4 Energy consumption structure in China, 2000–2021

5 Conclusions

As shown in Fig. 3, China's overall EI shows a downward trend, in order to further realize the "carbon peak by 2030 and carbon neutrality by 2060",[5] the key provinces hindering convergence need to be supported by relevant policies, so as to realize the overall reduction of energy consumption intensity.

The figure shows the structural changes in China's energy consumption from 2000 to 2021, mainly including the changes in the consumption of coal, crude oil and natural gas and their share. It can be seen that China's consumption of coal, crude oil and natural gas in 2000–2021 shows an overall upward trend, except for a brief downward trend during 2013–2016, and that coal maintains its dominant position in the structure of China's energy consumption for a long time. The consumption of coal has increased from 2.35 billion tons in 2000 to 7.85 billion tons in 2021, and the proportion of coal in total energy consumption has always been above 68%, which is determined by China's resource endowment and energy production structure. The proportion of natural gas and other clean energy sources continues to increase, with the proportion of natural gas increasing from 0.01% in 2000 to 0.05% in 2021, but its share in the energy structure is still relatively small (Fig. 4). Although China's energy consumption structure is changing from a coal-dominated structure to a diversified one, coal-dominated status still needs to be changed in order to reduce environmental pollution and realize China's "carbon peak by 2030 and carbon neutrality by 2060"1.

Based on the previous sectoral decomposition, we conclude that in order to reduce the intensity of energy consumption and improve the efficiency of energy utilization, different measures need to be taken for different industries. The industrial sector should be the focus of improvements to reduce energy consumption through technological innovation, industrial upgrading and improved energy management. The transportation sector should promote new energy vehicles and public transportation while optimizing transportation network planning and management. The agricultural sector should utilize modern agricultural technology and improve farming practices to reduce energy consumption.

In this study, the convergence process of energy intensity of 30 provinces in China from 2000 to 2015 was explored, using the σ convergence and its decomposition method based on the Theil index. Firstly, the Theil index of energy intensity in China increased from 0.061 in 2000 to 0.085 in 2015, indicating that the difference in energy intensity among the 30 provinces in China tended to increase during this period, which means it did not satisfy the σ convergence.

The σ convergence was decomposed by the factor decomposition method. The key provinces that led to the widening of the energy intensity difference were identified: during 2000–2015, the primary sources that hindered the convergence were Beijing, Shanghai, Liaoning, Heilongjiang, and Hubei Provinces, which had lower energy intensity; and Inner Mongolia, Xinjiang, and Hebei provinces, which have higher energy intensity. The above results indicate that the

[5] Figure is based on EI data calculated from nominal GDP and the provincial composite GDP index.

increasing differences between low and high-energy-intensity provinces mainly cause the energy intensity dispersion in China. Therefore, the higher energy intensity and lower decline rates in Inner Mongolia, Xinjiang, and Hebei are the keys to solving the dilemma of "dispersion." This study provides policy recommendations based on the difficulties of energy intensity reduction in these provinces.

The difficulty in reducing energy intensity in Inner Mongolia and Xinjiang is due to the backward economy and lower energy efficiency. Therefore, setting their energy-saving targets needs to consider the economic development goals, promote the improvement of energy-saving technology and economic development, and realize the decoupling of economic development and energy consumption. The R&D investment in technology development should be combined with its characteristics, focusing on investing in technology with more economic growth effects, energy saving and emission reduction, and gradually eliminating backward capacity technologies. For example, Xinjiang can eliminate backward production capacities such as small power generating units, build a modern energy industry chemical park, and develop advanced intelligent manufacturing and electronic information industries in a complementary manner. In addition, as Xinjiang has the geographical advantage of being a border province and unique regional agricultural products, it can establish modern organic agricultural products and create famous brands of agricultural products. Inner Mongolia can vigorously develop new functional materials industries, and reasonably use its scarce metals and natural resources, such as Graphene.

The difficulty of decreasing energy intensity in Hebei is due to its heavy industrial structure. The effect of the industrial structure in Hebei may be due to its heavy industrial structure, combined with the acceptance of some heavy industries from Tianjin and Beijing. This study suggests that the energy-saving task in Hebei should focus on upgrading and optimizing the industrial structure. Hebei should implement the concept of green development and take over the industries of Beijing and Tianjin by "complementing the chain". It should also take advantage of the development of the "Xiong'an New Area Plan" to accelerate the development of innovative and environmentally friendly industries, then gradually adjust the structure of energy-intensive industries.

The results recommended that possible opportunities for cooperation among provinces of the same club to curb energy intensity should be considered. It is important to emphasize that energy-saving strategies can only be achieved among provinces of the same club, as there is no complete panel convergence. Second, as South-East Asia (especially China) has considerable potential for renewable energy development, we recommend targeted policy measures to develop and utilize more renewable energy sources in the energy consumption structure to reduce the increase in energy intensity caused by the overconsumption of fossil fuels.

Besides, the decomposition results show that the energy structure effect, energy efficiency effect, and industry structure effect are important influences that contribute to the heterogeneity of the convergence of the energy intensity club. Therefore, According to the analysis, for the provinces with rapid urbanization and "dirty" fuel consumption, it is important to scale up their share of renewable energy sources, especially in their infrastructure and construction sectors, and mandatory fossil fuels reduction measures could be adopted in cement production as a result of increasing demand for cement given the rapid urbanization and industrialization. Improving the energy efficiency in the production process for energy-intensive sectors, such as chemical, energy and metallurgical sectors, are crucial for provinces with heavy industry. For provinces with rapid economic development, policies need to be tailored to diversify economic production activities and trade towards more environmentally friendly sources.

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Data availability The data set is available from the authors upon request.

Declarations

Competing interests The authors declare no competing interests.

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Appendix

In this study, the logarithmic mean Divisia index (LMDI) is used to decompose the Theil index.

The energy intensity of the Province i can be expressed as:

$$EI_i = \sum_{jk} \frac{EC_{ijk}}{EC_{ij}} \frac{EC_{ij}}{VA_{ij}} \frac{VA_{ij}}{VA_i} = \sum_{jk} ES_{ijk} EI_{ij} IS_{ij} \tag{7}$$

Then, the difference between the Province i and the national average can be obtained by Eq. (8) with the following expression.

$$\frac{EI_u}{EI_i} = \frac{\sum_{kj} ES_{ujk} EI_{uj} IS_{uj}}{\sum_{kj} ES_{ijk} EI_{ij} IS_{ij}} = D_{ES}^{u,i} D_{EI}^{u,i} D_{IS}^{u,i} \tag{8}$$

where $D_{ES}^{u,i}$ is the difference between the energy consumption structure of Province i and the national average, $D_{EI}^{u,i}$ is the difference between the energy intensity of Province i and the national average, $D_{IS}^{u,i}$ is the difference between the industrial structure of Province i and the national average.

Equation (8) is the fundamental spatial IDA model. Due to the perfect decomposition of the LMDI I at the level of the whole industries and sub-sectors, in this study, LMDI I is used to perform the decomposition of the above equation, which is given as follows.

$$D_{ES}^{u,i} = \exp\left(\sum_{jk} w_{ijk} \ln \frac{ES_{ujk}}{ES_{ijk}}\right) \tag{9}$$

$$D_{EI}^{u,i} = \exp\left(\sum_{jk} w_{ijk} \ln \frac{EI_{uj}}{EI_{ij}}\right) \tag{10}$$

$$D_{IS}^{u,i} = \exp\left(\sum_{jk} w_{ijk} \ln \frac{IS_{uj}}{IS_{ij}}\right) \tag{11}$$

where $w_{ijk} = L(EC_{ujk}/VA_u, EC_{ijk}/VA_i)/L(EI_u, EI_i)$ is the weighting coefficient. The function $L(a, b)$ is a logarithmic average as follows.

$$L(a,b) = \begin{cases} \frac{a-b}{\ln a - \ln b}, & \textit{if } a \neq b \\ a, & \textit{if } a = b \end{cases} \tag{12}$$

Using Eqs. (8)–(11) instead of Eq. (1):

$$\begin{aligned} I(EI) &= \sum_i q_i \ln D_{ES}^{u,i} + \sum_i q_i \ln D_{EI}^{u,i} + \sum_i q_i \ln D_{IS}^{u,i} \\ &= \sum_{ijk} q_i w_{ijk} \ln \frac{ES_{ujk}}{ES_{ijk}} + \sum_{ijk} q_i w_{ijk} \ln \frac{EI_{uj}}{EI_{ij}} + \sum_{ijk} q_i w_{ijk} \ln \frac{IS_{uj}}{IS_{ij}} \\ &= I_{ES} + I_{EI} + I_{IS} \end{aligned} \tag{13}$$

Equation (13) shows that the influencing factors of energy consumption structure, energy efficiency, and industrial structure can explain the variability of energy intensity in each Province. In addition, this study can also obtain the theil index for each Province or industry by using Eq. (13). For instance, *EI* gap caused by structural heterogeneity of energy consumption in industry *j* can be represented by $\sum_{ijk} q_i w_{ijk} \ln \frac{ES_{ujk}}{ES_{ijk}}$, its positive value indicates that structural differences in energy consumption lead to increased variation in energy intensity, while negative values represent differences in ES resulting in a decreased gap in *EI*. Similarly, the effect of energy efficiency and industrial structure on *EI* can be explained. And the diversity caused by the difference of industry *j* as a whole is $\sum_{ik} q_i w_{ijk} \ln \frac{ES_{ujk}}{ES_{ijk}} + \sum_{ijk} q_i w_{ijk} \ln \frac{EI_{uj}}{EI_{ij}} + \sum_{ijk} q_i w_{ijk} \ln \frac{IS_{uj}}{IS_{ij}}$. Similarly, the energy intensity difference caused by Province *i* can be obtained by $\sum_{jk} q_i w_{ijk} \ln \frac{ES_{ujk}}{ES_{ijk}} + \sum_{ijk} q_i w_{ijk} \ln \frac{EI_{uj}}{EI_{ij}} + \sum_{ijk} q_i w_{ijk} \ln \frac{IS_{uj}}{IS_{ij}}$. The provincial sources, the industrial sources, and the influencing factors sources of EI differences can all be obtained from Eq. (13).

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