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Trends and determinants of energy intensity in China: A study using index decomposition and econometric analysis

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ABSTRACT

The Sustainable Development Goal (SDG) 7 underscores the global imperative to accelerate progress in energy efficiency. This paper investigates the drivers of energy intensity changes in China from 2006 to 2022 using provincial panel data, Fisher's Ideal Index decomposition, and fixed-effects econometric models. Results show that efficiency improvements are the primary contributor to reductions in energy intensity, while structural shifts have a limited impact. GDP per capita exhibits a nonlinear effect: growth increases intensity at lower income levels but reduces it at higher levels through rising environmental awareness and shifts toward low-energy products. Energy prices significantly influence intensity and structural effects, though regulatory distortions limit their effectiveness. Fiscal capacity and population growth increase energy demand, highlighting the need for green fiscal investments and energy-saving policies. Regional analysis reveals stronger efficiency gains in central and eastern provinces, while western provinces face resource and technology constraints. The findings support differentiated, regionally tailored policies to achieve sustained energy reductions and low-carbon development.

1. Introduction

The United Nations Sustainable Development Goals (SDGs) 7 require countries around the world to redouble their efforts to improve energy efficiency (EE). China has experienced remarkable growth since the implementation of economic reforms in 1978, with its GDP reaching an astounding US$14.72 trillion by 2020 (NBSC, 2021; Peng et al., 2024). Nonetheless, this rapid economic growth has been accompanied by a substantial increase in energy consumption and carbon emissions (Figure A1). In 2010, China's primary energy consumption exceeded 3.5 billion tons of coal equivalent, surpassing that of the United States and establishing China as the world's largest energy consumer (BP, 2020). The international community is increasingly pressuring China to take on a more significant role in the mitigation of global climate change, although its per capita carbon dioxide emissions are relatively low (IPCC, 2019; WMO, 2024). China has established ambitious energy and climate targets to promote sustainable development (Karplus and Zhang, 2023). However, the pace of energy intensity reduction has slowed, while overall energy consumption continues to rise. A comprehensive understanding of recent trends in energy consumption and intensity is therefore essential for advancing the country's energy transition and strengthening its energy conservation efforts.

China is the world's largest consumer of fossil fuels and plays a pivotal role in the global response to climate change. The government first introduced energy intensity targets in the 11th Five-Year Plan (FYP, 2006–2010). In the 13th FYP (2015–2020), the Chinese government aimed to decrease energy intensity by 15 % (NDRC, 2016). A variety of administrative procedures were enacted to attain this objective, including the shutdown of heavily polluting power facilities. Furthermore, the national target was allocated to individual provinces, and its

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attainment was incorporated into the performance evaluations of local officials (Jotzo et al., 2018; Kok et al., 2011). Moreover, China is an extensive nation marked by considerable regional inequalities in economic advancement, energy resource availability, and climatic conditions (Li et al., 2023; Zhu et al., 2019). As a result, significant disparities in energy intensity exist among the country's regions. The 14th FYP (2020–2025) has set the energy intensity reduction target at 13.5 % (NDRC, 2022). Since 2006, intensity targets have driven a steady decline in China's overall energy intensity. However, the rate of decline has gradually slowed, mainly because the most easily attainable measures have already been implemented.

The drivers of changes in energy intensity in China are crucial for designing effective policy measures and forecasting future trends. This topic has garnered substantial research attention since the 1990s (Guan et al., 2014; Masnadi et al., 2018). Most studies have employed a decomposition approach to isolate the contributions of efficiency improvements and structural changes (Nie and Kemp, 2013; Tian et al., 2021). In addition, improvements in energy intensity do not fully reflect technological progress in energy use (Gorus and Karagol, 2022). The reason is that energy intensity can be affected by a variety of factors, such as income (Perillo et al., 2022), resource endowments, and price levels (Wu and Ding, 2021). This method distinguishes between micro-level efficiency improvement and macro-level changes in energy use caused by structural economic changes. Additionally, Metcalf (2008) and Ma et al. (2010) highlighted several key factors that may influence changes in energy intensity. For instance, higher energy prices are expected to reduce energy demand, while the substitution of energy with other manufacturing inputs may lead to changes in energy consumption patterns.

The purpose of this paper is to examine the driving forces underlying changes in China's energy intensity and to explore the regional disparities in its evolutionary trajectories, using a provincial panel dataset covering the period from 2006 to 2022. This study makes three key contributions to the existing literature. First, it adopts an analytical framework that integrates decomposition techniques with econometric methods, following the approach of Metcalf (2008). This allows us to identify the fundamental factors influencing changes in China's energy intensity as well as the mechanisms through which they operate. In addition, the paper incorporates a range of variables, including socio-economic factors and natural resource endowments, to assess their respective impacts on energy intensity. Second, this paper investigates the dynamics of the regional distribution of energy intensity and quantifies the factors that influence it. In doing so, it enhances our understanding of the divergent evolutionary trajectories of energy intensity across regions. Such insights are critical for designing energy reduction policies that are tailored to local conditions. Finally, the study updates and evaluates the changes in China's energy intensity in the pandemic period, thereby offering a more comprehensive perspective on the driving forces behind these shifts.

The paper is structured as follows: Section 2 reviews the literature. Section 3 comprehensively describes the methodology, encompassing the model utilized, data sources, and parameterization. Section 4 describes the main results and discussion. Finally, Section 5 offers the main conclusions and policy implications.

2. Literature review

Many scholars employ energy consumption per unit of GDP as a metric for energy intensity, which encapsulates fluctuations in the energy necessary for daily life and production within a given country or region (Kok et al., 2011; Pelletier et al., 2011; Wurlod and Noailly, 2018). From a regional perspective (Table 1), energy intensity in most developed countries is declining, although certain individual countries demonstrate an upward trend (Gorus and Karagol, 2022; Lu et al., 2018). Mendiluce et al. (2010) examined the increasing energy intensity in Spain from 1990 to 2006, identifying the economy's structure as the primary factor driving differences in energy intensity within the EU15.

Similarly, Hajko (2012) analyzed energy consumption in EU countries by decomposing it into economic factors, structural changes, and energy intensity. Okajima (2013) examined the increase in energy intensity in 1990, attributing it primarily to elevated energy consumption in Japan's industrial and commercial sectors. Similarly, Moshiri and Duah (2016) analyzed the factors influencing energy intensity in Canada from 1981 to 2008, concluding that the decline in energy intensity was largely driven by improvements in energy efficiency rather than structural changes.

From a sectoral perspective, research on energy intensity primarily focuses on energy-intensive sectors such as industry manufacturing (Corsini et al., 2016; Fouquet, 2014; Karimu et al., 2017). For instance, Voigt et al. (2014) determined that the energy intensity of 40 major economies decreased by 18 % between 1995 and 2007, with this improvement primarily attributed to technological advancements. Yu et al. (2022) employed a dynamic panel threshold regression model to examine the impact of renewable energy development on energy intensity across 82 countries. Their findings indicate that advancements in renewable energy significantly reduce energy intensity.

The research on China's energy issues has primarily been conducted at the regional level (Chen et al., 2023b; Jiang et al., 2017) and within energy-intensive sectors such as industry (Huang et al., 2017a). From a regional perspective, Wu (2012) found that the substantial decline in regional energy intensity in China was primarily driven by improvements in energy efficiency, with structural changes playing a relatively

Table 1
Study of factors influencing energy intensity.

Author (year)	Region (sector)	Methodology	Period	Conclusions
Mulder and de Groot (2012)	Netherlands	IDA	1987–2005	The Netherlands is reducing the intensity of energy, with structural changes playing an important role
Okajima (2013)	Japan	Fischer Ideal Index	1965–2004	Japan's energy intensity declined by 73 % from 1970 to 2003, mainly through efficiency improvements
Mulder and de Groot (2012)	OECD (Services)	Index Decomposition and Econometrics	1980–2005	Structural changes have a significant impact on the energy intensity of services, with limited energy efficiency effects
Karimu et al. (2017)	Sweden (Industry)	Non-parametric analysis	1990–2018	Energy prices are an essential factor in Sweden's energy intensity
Huang et al. (2017b)	China	Spatial panels	2000–2014	Technological advances play a dominant role in total energy intensity
Guang et al. (2019)	China	Shapley and quantile regression	2000–2016	Economic growth is the most prominent factor contributing to differences in energy intensity
Jain and Goswami (2021)	South Asia	Logarithmic Mean Divisia Index	1990–2014	More abundant energy resources lead to energy inefficiency
Gorus and Karagol (2022)	OECD	Decomposition analysis	1980–2018	Energy intensity changes can be attributed to energy efficiency improvements
Wang and Zhou (2023)	China	DEA and spatial econometric	2006–2015	China's energy efficiency shows noticeable regional differences and spatial clustering characteristics

minor role. Pang and Su (2017) analyzed energy intensity using panel data from 1995 to 2014 across 29 provinces in China. Their findings indicate that energy price distortions, largely resulting from excessive government intervention, are more pronounced in the central regions. Similarly, Cheng et al. (2020) used a frontier approach to estimate energy efficiency in 30 Chinese provinces between 1997 and 2016. Their findings revealed significant geographical disparities in energy efficiency, with the eastern region exhibiting the highest efficiency and the western region the lowest.

At the sectoral level, Zhao et al. (2010) used an exponential decomposition technique to analyze industrial energy intensity from 1998 to 2006. Their results show that the fast expansion of energy-intensive sectors was the leading cause of the rising energy intensity. In contrast, energy savings were attributed mainly to improvements in energy efficiency. Similarly, Qi et al. (2020) found that approximately half of the energy in coal-intensive sectors was not fully utilized, based on their study of energy efficiency in 14 major coal-intensive sectors in China from 2006 to 2015. Xie et al. (2018) employed stochastic frontier analysis to evaluate the energy efficiency of the transportation sector in Chinese provinces from 2007 to 2016. Their findings reveal an average energy input efficiency of 0.673, indicating substantial potential for improvement in the industry. Besides assessing energy efficiency, plenty of research has investigated the factors that influence it (Chen et al., 2024; Fisher-Vanden et al., 2004). These studies have highlighted critical characteristics, including per capita income, energy prices, direct investment, and resource endowments, as significant influences on energy efficiency (Casey, 2024; Kok et al., 2011). For example, when market forces are at work, fluctuations in electricity prices can induce a rebound effect on energy intensity (Sardianou, 2007).

At the micro level, a reduction in electricity prices may elevate demand compared to alternative energy sources, even with stable economic activity. Income is a significant factor affecting consumption of energy decisions (Mills and Schleich, 2010). The correlation between income and energy intensity is intrinsically intricate, as income can influence energy consumption through multiple avenues. First, income serves as an indicator of socio-economic development, which is anticipated to reduce energy intensity (Jiang et al., 2014; Ma and Yu, 2017). Elevated income levels correlate with heightened public awareness of environmental sustainability and resource conservation, fostering the adoption of energy-efficient practices and eco-friendly behaviors (Farajzadeh and Nematollahi, 2018). Second, income simultaneously influences access to energy-intensive technologies or infrastructure, as it represents a critical economic barrier for non-adopters (Barnes et al., 2019). Increased income may stimulate demand for energy-consuming goods and services, paradoxically driving higher energy intensity (Abbas et al., 2024). Thus, the net effect of income growth on energy intensity hinges on the relative dominance of these opposing pathways (Song and Zheng, 2012). The interchangeability of energy with other production inputs has been extensively discussed. Numerous studies have produced different estimates of the elasticity of substitution for these production processes.

While past research examined the factors influencing energy efficiency, most have focused on particular areas or energy-intensive sectors such as manufacturing and building. Besides, research exploring the broader drivers behind changes in energy efficiency remains relatively underdeveloped. Moreover, limited research has addressed the potential for energy efficiency improvements and the regional disparities across different areas of China. Furthermore, there has been a notable lack of attempts to analyze the key factors influencing energy efficiency from a spatial perspective.

3. Methodology and data

3.1. Fisher factorial decomposition

Decomposition analysis is a prevalent technique for discovering and assessing the determinants of energy intensity (Ang et al., 2010; Chen et al., 2023a; Li et al., 2016). This method disaggregates energy intensity into several contributing elements, including energy efficiency, structural composition, and energy mix (Ouyang and Lin, 2015). The standard decomposition methods include the Paasche index (Hong et al., 2017), the Laspeyres index (Ang and Xu, 2013), and the Divisia index (Zhang et al., 2016). However, the Paasche and Laspeyres indices often yield residuals during decomposition (Eva et al., 2021). The Fisher index method adheres to the factor reversal test and satisfies the three axioms of weak indicators, thereby overcoming the limitations of the Laspeyres and Paasche index (Lin and Du, 2014). This method provides a more robust analysis by addressing the negative effects of both structural and efficiency factors. The results obtained provide an effective means to visualize and analyze the factors influencing changes in energy intensity across different regions of China (Fisher-Vanden et al., 2016). For example, Mulder and de Groot (2012) used the Fisher Ideal Index method to examine fluctuations in energy intensity across OECD countries. The findings suggest that the most significant factor influencing energy intensity is variations in economic sectors.

In this paper, we address the research of Tajudeen et al. (2018). The Fisher index approach models the properties of several contributing elements by breaking energy intensity into efficiency and structural effects.

$$e_t = \frac{E_t}{Y_t} = \sum_i \frac{E_{it}}{Y_t} = \sum_i \frac{E_{it}}{Y_{it}} \frac{Y_{it}}{Y_t} = \sum_i e_{it} s_{it} \tag{1}$$

Here, e_t represents the energy intensity in year t, while E_t and Y_t denote the total energy consumption and GDP in year t, respectively. E_{it} and Y_{it} indicate the total energy consumption and GDP in year t across different regions i. Additionally, e_{it} and s_{it} represent the efficiency effects and structural effects in different regions, respectively. e_t can be further decomposed into a functional composition of e_{it} and s_{it}.

The two components of the index are derived using the Fisher factor decomposition method. The energy intensity factor $I_t = \frac{e_t}{e_0}$ is calculated according to equation (2). Subsequently, the total energy intensity $e_0 = \sum_i e_{i0} s_{i0}$ for the base year is also determined, and the Laspeyres and Paasche index can be derived from the Fisher Ideal Index.

$$L_t^{act} = \frac{\sum_i^n e_{i0} s_{it}}{\sum_i^n e_{i0} s_{i0}} \quad L_t^{eff} = \frac{\sum_i^n e_{it} s_{i0}}{\sum_i^n e_{i0} s_{i0}} \tag{2}$$

$$P_t^{act} = \frac{\sum_i^n e_{it} s_{it}}{\sum_i^n e_{it} s_{i0}} \quad P_t^{eff} = \frac{\sum_i^n e_{it} s_{it}}{\sum_i^n e_{i0} s_{it}} \tag{3}$$

Following the Laspeyres and Paasche indexes, this paper decomposes the changes in energy intensity into two types of indexes. One reflects changes in economic structure as structural indexes, and the other captures changes in energy efficiency as efficiency indexes. These indexes are calculated as geometric averages of the Laspeyres and Paasche indexes.

$$F_t^{act} = \sqrt{L_t^{act} P_t^{act}} \tag{4}$$

$$F_t^{eff} = \sqrt{L_t^{eff} P_t^{eff}} \tag{5}$$

The total energy intensity index is:

$$\frac{e_t}{e_0} = I_t = F_t^{act} F_t^{eff} \tag{6}$$

When the structural index remains constant, a decrease in the efficiency index signifies a reduction in energy consumption per unit of

GDP. Conversely, a decline in the structural index indicates that, with energy efficiency held constant, the economy is shifting towards less energy-intensive production methods.

3.2. Regression model

In this paper, decomposition analysis is applied to generate panel data on each province's intensity, efficiency, and structure index from 2006 to 2022. From the previous study, it can be learned that there are differences in energy intensity across regions. The reason may be attributed to various factors, such as economic development levels, energy prices, industry investment, and resource endowment. In order to study the influencing factors and mechanisms driving energy intensity across different regions, this paper conducts a regression analysis on various indexes.

$$y_{it} = \beta\chi_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{7}$$

where y_{it} denotes the three previous indices, χ_{it} covers a range of influences, μ_i represents the time-invariant individual fixed effect, which is the provincial fixed effect; γ_t shows the year fixed effect; and ε_{it} is the error term. β is the vector of coefficients for the explanatory variables. This paper incorporates GDP per capita as an explanatory variable, acknowledging its multidimensional influence on energy intensity through distinct mechanisms (Huang et al., 2022). The elevation of GDP levels typically induces two countervailing effects: while economic expansion generally increases energy demand through enhanced living standard aspirations, it simultaneously fosters energy-saving consciousness through cultural capital accumulation (Liu et al., 2021). The latter manifests as a growing societal preference for energy-efficient technologies and sustainable consumption patterns. To capture these complex dynamics, our econometric specification operationalizes this relationship through the inclusion of both GDP per capita and its quadratic term, enabling rigorous examination of potential nonlinearities in the GDP-energy intensity nexus.

Energy prices are a critical factor influencing energy consumption (Lin and Xie, 2015). An increase in energy prices tends to decrease individuals' willingness to use energy, prompting them to seek alternative means of production as substitutes for energy products. Birol and Keppler (2000) apply economic theory to suggest that increasing energy prices through market-based mechanisms represents a primary approach to reducing energy intensity. Similarly, Huang et al. (2017b) argue that higher energy prices contribute to lowering China's energy intensity. While China's energy market is gradually transitioning toward market-oriented reforms, many energy prices remain tightly controlled by the government (Yan, 2015). This study uses a provincial-level Fuel Power Purchasing Price Index (PPIRM) rather than individual crude oil, natural gas, or coal prices. Moreover, the energy index is influenced mainly by overall energy prices (rather than individual prices), and PPIRM is a good indicator to measure and represent it (Zhou et al., 2017). This PPIRM better captures the actual cost of energy as it reflects the purchasing prices of fuel and power at the provincial level.

Investment, recognized as one of the "three pillars" of China's economy, is a significant factor influencing energy intensity (Lin and Xie, 2015). On the one hand, investment provides enterprises with the capital necessary to develop energy-saving technologies, upgrade production equipment, and enhance energy efficiency. On the other hand, as businesses expand, there is often an increased demand for energy products to support production processes (Huang et al., 2017b). The paper uses per capita energy sector investment for this measure due to data limitations.

China is experiencing rapid urbanization, which is expected to drive an increased demand for energy, particularly in transportation and infrastructure development (Bilgili et al., 2017; Shahbaz et al., 2015). However, compact urbanization theory posits that residential and workplace locations become more centralized as urbanization progresses. This centralization can lead to a reduction in overall energy demand and consumption. Increasing reliance on electricity as an energy source during urbanization significantly affects domestic energy consumption. The electricity consumption growth rate is an essential indicator of electrification, urbanization, and energy intensity.

The paper also employs the energy gap, which is the ratio of province energy production per capita to national energy production per capita, as a surrogate for resource endowment over geographical areas (Huang et al., 2017a; Song and Zheng, 2012). Previous literature underscores the prevalence of the resource curse phenomenon within the energy sector (Song et al., 2018; Wu et al., 2018). Namazi and Mohammadi (2018) demonstrated that abundant energy resources shape regional energy dynamics and environmental outcomes by altering industrial structures and stifling technological innovation. Furthermore, energy-rich regions often develop industrial clusters dominated by resource-intensive sectors, which exacerbates local energy consumption and accelerates environmental degradation (Balsalobre-Lorente et al., 2018; Gerelmaa and Kotani, 2016). Concurrently, Adom and Adams (2018) highlighted that resource abundance correlates with artificially suppressed energy prices and inefficient utilization patterns, resulting in technologically obsolete energy inputs. Provinces with more favorable resource endowments are likely to attract more significant investment in energy-intensive industries. In contrast, regions with less favorable endowments may have more substantial incentives to develop technologies that enhance energy utilization efficiency. The paper also employs the energy gap, which is the ratio of provincial energy production per capita to national energy production per capita, as a surrogate for resource endowment over geographical areas (Huang et al., 2017a; Song and Zheng, 2012).

In addition to the core explanatory variables, we control for government budget revenue and the natural population growth rate to mitigate omitted variable bias. Government budget revenue proxies local fiscal capacity, which significantly affects environmental outcomes by influencing investments in energy-saving infrastructure and regulatory enforcement (He, 2015). Regions with stronger fiscal capability tend to allocate more budgetary resources toward environmental protection, thereby affecting energy intensity and structure. At the same time, rapid population growth generates expanding energy demand and public service needs (Morikawa, 2012), while also influencing labor supply and consumption patterns. Given China's context between 2006 and 2022—marked by rapid socio-economic and demographic shifts—incorporating these variables helps isolate the impact of core economic predictors from demographic and fiscal dynamics.

3.3. Data

This paper utilizes energy consumption and GDP data from 30 provinces in China from 2006 to 2022 (Table 2). According to Li et al. (2013) and Lin and Xie (2015), energy intensity is calculated by dividing the total amount of energy consumed by the GDP of the region.

Economic and energy data are primarily sourced from the China Statistical Yearbook, the China Energy Statistical Yearbook, and the Provincial Statistical Yearbooks. Economic data are deflated at constant 2010 prices, and logarithmic transformations are applied to the data before econometric analysis to address heteroscedasticity. In accordance with the methodology of Li et al. (2013), the nation is divided into three regions: the east, central, and west regions (Table A1).

4. Results and discussion

4.1. Energy intensity trends

This paper constructs energy intensity, structure, and pure intensity indexes for each province from 2006 to 2022 and presents their averages in Fig. 1. The results indicate that energy intensity in China exhibited a decreasing trend during this period, with a 42.1 % reduction in 2022

Table 2
Statistical analysis of different variables.

Variables	Definition	Mean	St. Dev	Min	Max
ln(GDP)	Log GDP per capita (2006 comparable prices)	0.56	0.25	−0.13	1.16
$(\ln GDP)^2$	Squared log GDP per capita	0.37	0.28	0.01	1.34
Price	Fuel power purchasing price index (2006 = 1)	1.35	0.23	0.68	2.44
Gap	The ratio of province energy production per capita to national energy production per capita	1.38	2.5	0	14.09
Investment	The investment amount in the energy industry per capita (2006 comparable prices)	0.26	0.24	0.03	1.6
Electricity	Growth rate of electricity consumption	0.08	0.06	−0.09	0.38
Gov_income	Log government budget revenue (2006 comparable prices)	7.39	0.97	4.04	9.55
Pop_rate	Natural population growth rate	4.35	3.19	−5.75	11.78

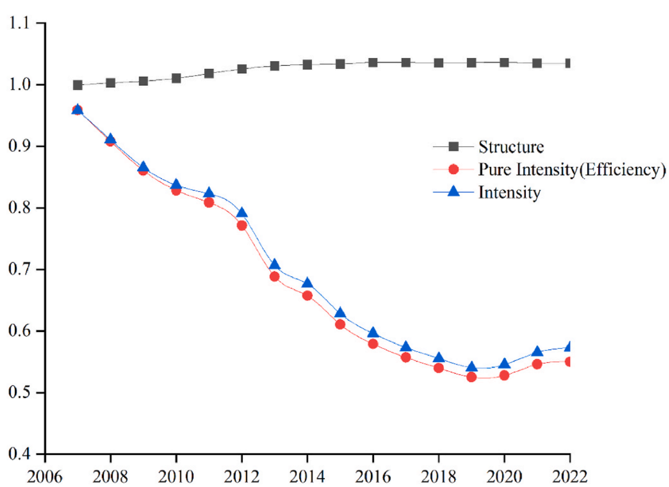

Fig. 1. Changes in energy intensity and decomposition factor indicators (2006–2022).

compared to 2006. Advancements in technology have been the primary factor in reducing energy intensity, while structural effects have played a negligible role.

Moreover, the research indicated that the reduction in energy intensity was more significant between 2011 and 2014. This trend can be attributed to the Chinese government's implementation of several significant energy policy initiatives during this period, including the Long-term Development Plan for Renewable Energy. The phenomenon is noteworthy in that the COVID-19 pandemic and associated embargo measures have influenced changes in China's energy intensity, leading to a partial rebound. This rebound poses additional challenges to the achievement of China's energy targets. This phenomenon is consistent with the findings of previous studies. For instance, Liao et al. (2007) demonstrated that pure intensity factors significantly contributed to the reduction in energy intensity from 1997 to 2006, while the impact of structural adjustments was relatively minor.

Fig. 2 demonstrates a declining trend in energy intensity across the three regions, with notable disparities among them. The most significant reduction in energy intensity is observed in the western regions. For instance, energy intensity in the Beijing and Tianjin provinces decreased from 9.4 tons of standard coal per thousand yuan in 2006 to 4.1 tons per thousand yuan in 2022, representing a decline of more than 50 % (NBSC, 2021). The energy intensity values of Shanxi and Gansu are higher than the national average (Figure A2).

Despite the declining trend in energy intensity within the western region, the average value remains higher compared to the central region. This reflects that economic growth in the western region is still heavily reliant on energy consumption, with a relatively weak decoupling between energy use and economic expansion. The principal reason for this is the substantial share of coal in the energy consumption framework of the western provinces. For instance, energy consumption in Shaanxi Province totaled 135 million tonnes of standard coal in 2019, with coal comprising 0.98 billion tonnes, or roughly 70 % of the overall consumption (NBSC, 2021). As a traditional energy source, coal is characterized by high carbon emissions and environmental pollution, which complicates efforts to conserve energy and hinders the transformation of Shaanxi Province's energy structure. Nevertheless, the Western region is still facing significant challenges in energy utilization. The government should expand its energy-saving and emissions-reduction initiatives to promote the green transformation of the economy.

The energy intensity in the central region was 8.3 tonnes of standard coal per thousand yuan in 2010, which decreased to 4.7 tonnes per thousand yuan by 2022, indicating a 43 % reduction. Most of the provinces in the central region are resource-intensive. For example, coal consumption in Shanxi Province increased from 285 million tons to 392 million tons from 2015 to 2022 reflecting a 37 % rise. This indicates that economic development and coal consumption in Shanxi Province remain tightly coupled (NBSC, 2021). Shanxi Province must expedite the enhancement of its energy framework and diminish the excessive utilization of coal to attain a sustainable economic transformation. The western and central areas possess considerable potential for enhancing pure intensity and mitigating emissions in the future. These regions should collaborate closely to improve pure intensity through strengthened cooperation. Energy intensity rose slightly during the epidemic in the eastern regions, which are the most economically developed and energy-intensive areas of China.

4.2. Determinants of energy intensity

The paper conducts a Hausman test for energy intensity, efficiency, and structure (Table 3). The results indicate that the p-values for the three models are below 0.01, resulting in the rejection of the null hypothesis and suggesting that a fixed effects model is appropriate. According to these Hausman test results, the fixed effects model is deemed more suitable for this analysis.

We conducted cross-sectional dependence tests and found that, although the results are not uniformly significant across methods, there is evidence of cross-sectional dependence. To address this potential issue, we adopt the Driscoll–Kraay robust standard error approach, which corrects for cross-sectional dependence and provides more reliable inference (Hoechle, 2007). The detailed test results are reported in Appendix Table A2.

This paper employs a fixed effects model, with the results of the three regressions presented in Table 4. GDP per capita and its squared term are statistically significant, indicating a clear nonlinear relationship. This reveals that GDP per capita exerts a multifaceted effect on energy intensity. As GDP per capita rises, the energy consumption of the population increases, leading to higher energy intensity. However, as populations become more environmentally conscious, they may begin to prioritize low-energy consumption products, which can subsequently reduce energy intensity. In the regression equations for intensity and efficiency, GDP per capita generally has a negative impact on the equation, while it exerts a predominantly positive effect on the structure equation.

Energy price is significant in the regression results for intensity and structure across the three regressions, but not for efficiency. The relationship between price and energy intensity indicates that a negative coefficient suggests that higher energy prices can significantly reduce

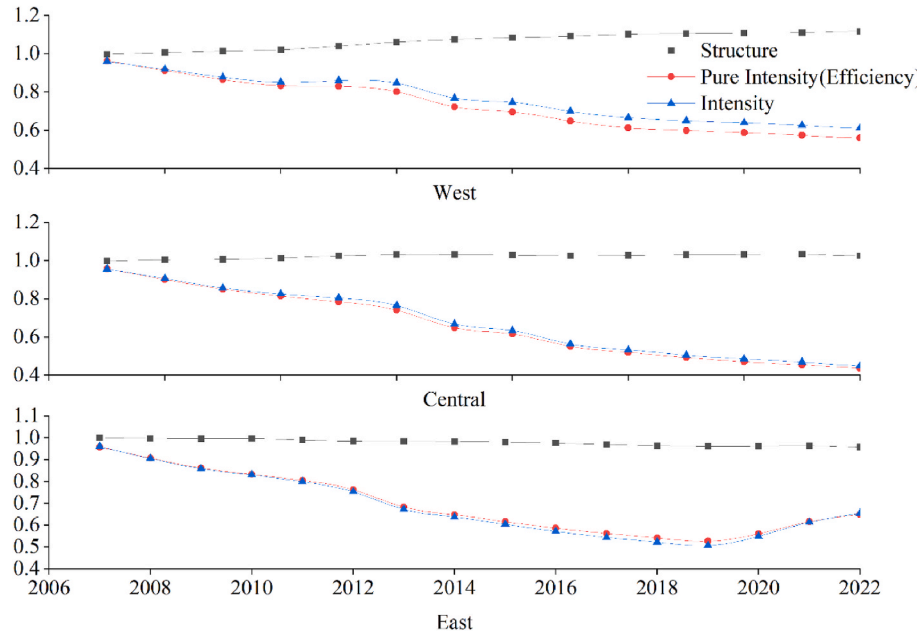

Fig. 2. Subregional indicators of energy intensity and decomposition factors (2006–2022).

Table 3
Hausmann test results.

Variables	Hausmann test (p-value)
Intensity	139.40***(0.000)
Structure	40.82***(0.000)
Efficiency	142.72*** (0.000)

Note: *, **, *** denote significant at 10 %, 5 % and 1 % statistical levels.

Table 4
Analysis of basic regression results.

	Intensity	Structure	Efficiency
ln(GDP)	−0.80***	0.65***	−1.44***
	(0.000)	(0.000)	(0.000)
$(\ln GDP)^2$	−0.80***	−0.36***	−0.45***
	(0.000)	(0.000)	(0.000)
Price	−0.16**	−0.12***	−0.05
	(0.030)	(0.000)	(0.475)
Gap	0.06***	0.01*	0.05***
	(0.000)	(0.079)	(0.001)
Investment	0.24***	−0.01	0.26***
	(0.000)	(0.502)	(0.000)
Electricity	−0.11	−0.00	−0.11
	(0.435)	(0.926)	(0.373)
Gov_income	0.16***	0.07***	0.09**
	(0.001)	(0.000)	(0.044)
Pop_rate	0.01*	0.02***	−0.01
	(0.075)	(0.008)	(0.229)
Constant	−0.70***	−0.54***	−0.16
	(0.004)	(0.000)	(0.446)
R^2	0.879	0.372	0.907
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: *, **, *** denote significant at 10 %, 5 %, and 1 % statistical levels. Driscoll-Kraay standard errors are shown in parentheses. Same below.

energy intensity. This negative correlation has also been confirmed by the empirical estimates (Huang et al., 2017b). In general, increasing energy prices serves as an effective policy instrument for enhancing energy use efficiency. On the other hand, China's energy pricing mechanism is transitioning from a planned economy toward partial marketization, resulting in the coexistence of market-determined and government-regulated prices. The long-term distortions in energy prices may make it difficult to determine the impact of price increases on energy intensity. For instance, electricity prices are strictly regulated by the government, while oil and natural gas prices are adjusted within defined limits in response to international market fluctuations. Although coal prices are comparatively more market-oriented, coal is primarily consumed in power generation. Therefore, China must develop a comprehensive understanding of the relationship between energy prices and energy intensity. Such insights not only enable policymakers to evaluate the effectiveness of existing pricing policies but also guide the formulation of future energy pricing strategies.

Energy intensity is low in regions with limited resource endowments. This can be attributed to China's energy-scarce provinces, such as Shanghai and Zhejiang, which are among the more economically developed regions. These regions possess more excellent technological capabilities and skilled talent, enabling them to implement energy-saving and emission-reduction initiatives effectively. As a result, their efforts to conserve energy and reduce emissions have been among the most prominent in the country. For example, Zhejiang Province utilized 217 million tonnes of standard coal in 2018, with an energy intensity that was lower than the national average.

The provinces with abundant energy endowments, such as Shaanxi and Xinjiang, are generally less economically developed regions. These regions demonstrate inadequacies in their ability to conserve energy and reduce emissions. For instance, Shaanxi Province utilized 0.98 billion tonnes of standard coal, representing over 70 % of its annual energy consumption in 2019. The proportion of coal is more significant than the national average, and energy conservation and emission reduction are under tremendous pressure. Therefore, the government should account for regional differences when formulating energy policies. These policies should be tailored to reflect each region's unique resource endowments and economic characteristics. In regions with scarce resources, the government should enhance guidance and support for energy-saving and emission-reduction policies to promote optimizing the energy structure. For resource-rich regions, technology transfer and talent introduction should be increased. Companies may help foster long-term economic growth by cutting emissions and increasing energy efficiency.

Investment has a positive effect on energy intensity and efficiency. The main reason for this is possible that investments can help the energy sector get better technology and make the process of making energy more efficient. Nevertheless, investment can also facilitate the growth of the energy sector, thereby multiplying the size of energy-intensive industries. Consequently, the government should increase its investment in renewable energy sources, including solar and wind. Additionally, the north-western and central regions must decrease their reliance on traditional energy sources to lower their intensity. The advancement of electrification contributes to reduced energy intensity. People's lives are increasingly using secondary energy, and energy utilization efficiency is constantly improving. Consequently, enterprises should strengthen the research development and application of energy technology to promote the development and popularization of efficient technology. Concurrently, society raises financial support for research initiatives to enable the conversion of scientific and technical successes into practical output.

The regression results also indicate that government budget revenue exerts a significantly positive effect on energy intensity, structure, and efficiency. This suggests that while higher fiscal capacity enables governments to invest more in economic development and infrastructure, such investments may simultaneously expand energy demand and strengthen the dominance of energy-intensive industries. Similarly, the natural population growth rate is positively associated with both energy intensity and structure, reflecting that population expansion stimulates energy consumption and infrastructure construction, thereby raising energy demand. However, its effect on efficiency is not significant, implying that population growth does not directly alter energy utilization efficiency. Considering the study period of 2006–2022, when China was undergoing rapid economic development, these results are consistent with the broader context: fiscal expansion and demographic growth often coincided with surging industrialization and energy demand. This highlights the importance of guiding fiscal expenditure toward green investments and implementing energy-saving measures in the context of both economic growth and demographic change.

4.3. Regional heterogeneity analysis

China has significant heterogeneity in terms of economic, demographic, and resource endowments (Duan et al., 2025). Following the approach of Li et al. (2013), the nation is divided into three regions: east, central, and West for heterogeneity analysis (Table 5). While the regional results are broadly consistent with the overall findings, notable differences remain. GDP per capita is generally significant across regions, but its effect is more pronounced in the central and eastern areas. This can be attributed to the fact that the eastern region is more economically developed and relies on a diversified energy mix. As inefficient coal consumption declines, other, more efficient energy sources are adopted on a larger scale, leading to a reduction in energy intensity. By contrast, the effect is less pronounced in the western region, where shortages of skilled labor, capital, and mature technologies constrain the transition toward higher energy efficiency.

The energy gap is insignificant in the western region but exhibits significant effects in the other two regions. The western region is the most resource-abundant area in China, with Inner Mongolia, Xinjiang, and Shaanxi together accounting for more than 33 % of the country's total energy production in 2022. Moreover, coal remains the dominant primary energy source in these regions, and investment in coal-related industries continues to play a critical role in supporting local economic development. By contrast, the eastern region is a major energy consumer, with Shanghai, Zhejiang, Guangdong, Shandong, and Jiangsu alone accounting for 50 % of national energy consumption in 2022. China's ongoing economic transformation is accelerating the growing role of electricity within the national energy consumption structure, a trend that is particularly pronounced in the eastern region. Furthermore, there is an overall demographic direction in China that is moving from the west to the center and east. Rising labor costs and resource constraints in the east are likely to incentivize industries to relocate inland.

Therefore, the government should adopt targeted policy measures to enhance energy efficiency. First, interregional cooperation and coordination need to be strengthened to facilitate resource sharing and technological exchange. Second, energy policies should be diversified to create enabling environments tailored to the specific development needs of each region. In addition, greater emphasis should be placed on fostering innovation in energy technologies to accelerate the adoption of clean energy solutions.

4.4. Robustness testing

First, we analyze the data by conducting robustness checks using both the LSDV and bootstrap methods. The findings reveal that the results from these different models are consistent with the benchmark (Table 6). It indicates that the conclusions are stable.

To further assess the robustness of our findings, we winsorize the key dependent variables at the 1 % and 5 % tails to mitigate the influence of outliers. The results, reported in Table 7, are consistent in sign and statistical significance with the baseline estimates.

Table 5
Analysis of regional heterogeneity results.

	I	S	E	I	S	E	I	S	E
	West			Central			East		
LnGDP	−0.08	0.18**	−0.25	2.73***	1.56***	1.17**	1.83***	0.37*	1.45***
	(0.735)	(0.033)	(0.203)	(0.006)	(0.001)	(0.045)	(0.000)	(0.083)	(0.000)
$(\text{LnGDP})^2$	−0.33***	0.23*	−0.56***	−3.54***	−1.11**	−2.44***	−1.35***	−0.12	−1.22***
	(0.005)	(0.067)	(0.000)	(0.000)	(0.030)	(0.000)	(0.000)	(0.144)	(0.000)
Price	−0.50***	0.03	−0.54***	−0.25***	−0.29***	0.04	−0.33***	0.03	−0.36***
	(0.000)	(0.400)	(0.000)	(0.001)	(0.000)	(0.517)	(0.003)	(0.450)	(0.000)
Gap	0.00	0.00	−0.00	−0.01**	−0.02***	0.01	0.13***	0.10***	0.03
	(0.795)	(0.467)	(0.824)	(0.033)	(0.000)	(0.143)	(0.000)	(0.000)	(0.181)
Investment	0.48***	−0.16***	0.64***	−0.08	0.09*	−0.17	−0.17	0.19	−0.36***
	(0.001)	(0.000)	(0.000)	(0.591)	(0.073)	(0.175)	(0.302)	(0.110)	(0.007)
Electricity	0.10	−0.05	0.15	0.78*	0.38*	0.40	1.22**	0.34**	0.87**
	(0.440)	(0.656)	(0.455)	(0.072)	(0.075)	(0.126)	(0.014)	(0.050)	(0.015)
Gov_income	0.07***	−0.00	0.07***	−0.11**	0.04*	−0.16**	−0.10***	−0.04**	−0.06***
	(0.001)	(0.858)	(0.001)	(0.024)	(0.073)	(0.011)	(0.000)	(0.020)	(0.000)
Pop_rate	0.02*	0.00	0.02	0.02*	0.02***	−0.00	0.01*	0.01*	0.00*
	(0.062)	(0.944)	(0.156)	(0.073)	(0.000)	(0.993)	(0.060)	(0.081)	(0.088)
Constant	−0.10	−0.05	−0.05	0.38***	−0.32**	0.71***	0.16	−0.04	0.21
	(0.469)	(0.666)	(0.760)	(0.001)	(0.049)	(0.002)	(0.405)	(0.570)	(0.204)
R^2	0.794	0.564	0.806	0.949	0.766	0.951	0.856	0.496	0.933
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: I: Intensity; S: Structure; E: Efficiency.

Table 6
Robustness analysis of results.

	Intensity	Structure	Efficiency	Intensity	Structure	Efficiency
	LSDV			Bootstrap		
ln(GDP)	−0.80***	0.65***	−1.44***	−0.80***	0.65***	−1.44***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(lnGDP)^2	−0.80***	−0.36***	−0.45***	−0.80***	−0.36***	−0.45***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price	−0.16***	−0.12***	−0.05	−0.16**	−0.12***	−0.05
	(0.001)	(0.000)	(0.294)	(0.024)	(0.000)	(0.493)
Gap	0.06***	0.01***	0.05***	0.06***	0.01**	0.05***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.011)	(0.000)
Investment	0.24***	−0.01	0.26***	0.24***	−0.01	0.26***
	(0.000)	(0.445)	(0.000)	(0.000)	(0.519)	(0.000)
Electricity	−0.11	−0.00	−0.11	−0.11	−0.00	−0.11
	(0.285)	(0.950)	(0.247)	(0.368)	(0.945)	(0.327)
Gov_income	0.16***	0.07***	0.09***	0.16***	0.07***	0.09**
	(0.000)	(0.000)	(0.004)	(0.001)	(0.006)	(0.018)
Pop_rate	0.01*	0.02***	−0.01**	0.01	0.02***	−0.01
	(0.063)	(0.000)	(0.048)	(0.174)	(0.000)	(0.145)
Constant	−0.19	−0.80***	0.62***	−0.19	−0.80***	0.62***
	(0.372)	(0.000)	(0.001)	(0.469)	(0.000)	(0.004)
R^2	0.908	0.839	0.926	0.897	0.820	0.918
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Robustness analysis of results using Winsorization.

	Intensity	Structure	Efficiency	Intensity	Structure	Efficiency
	Winsorized at 1 %			Winsorized at 5 %		
ln(GDP)	−0.75***	0.64***	−1.41***	−0.68***	0.60***	−1.24***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(lnGDP)^2	−0.80***	−0.35***	−0.45***	−0.75***	−0.34***	−0.46***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price	−0.17**	−0.11***	−0.06	−0.19***	−0.11***	−0.09
	(0.016)	(0.000)	(0.353)	(0.006)	(0.001)	(0.120)
Gap	0.06***	0.01*	0.05***	0.06***	0.02**	0.05***
	(0.000)	(0.076)	(0.001)	(0.000)	(0.018)	(0.002)
Investment	0.24***	−0.02	0.25***	0.25***	−0.01	0.25***
	(0.000)	(0.448)	(0.001)	(0.001)	(0.784)	(0.001)
Electricity	−0.13	−0.01	−0.15	−0.16	−0.01	−0.16
	(0.348)	(0.843)	(0.238)	(0.247)	(0.817)	(0.207)
Gov_income	0.15***	0.07***	0.09*	0.13**	0.06***	0.06
	(0.002)	(0.000)	(0.064)	(0.011)	(0.001)	(0.250)
Pop_rate	0.01*	0.02***	−0.01	0.01*	0.02***	−0.01
	(0.070)	(0.007)	(0.198)	(0.081)	(0.007)	(0.120)
Constant	−0.64**	−0.54***	−0.11	−0.53**	−0.51***	0.06
	(0.011)	(0.000)	(0.604)	(0.049)	(0.000)	(0.815)
R^2	0.881	0.377	0.908	0.885	0.410	0.911
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Driscoll–Kraay standard errors in parentheses. For columns (1) to (3), all dependent variables are winsorized at 1 %. For columns (4) to (6), all dependent variables are winsorized at 5 %.

To further verify the robustness of the baseline regression results, we employ two high-dimensional statistical inference methods based on Lasso. First, the Double-selection method (Belloni et al., 2014) is applied, which performs variable selection separately for both the dependent variable and the main explanatory variable, and then takes the union of selected variables into the final regression, ensuring

Table 8
Robustness analysis of results using machine learning.

	Intensity	Structure	Efficiency	Intensity	Structure	Efficiency
	DS			PO		
ln(GDP)	−0.797***	0.646***	−1.441***	−0.790***	0.639***	−1.427***
	(0.218)	(0.101)	(0.173)	(0.204)	(0.096)	(0.161)
(lnGDP)^2	−0.803***	−0.359***	−0.446***	−0.805***	−0.356***	−0.450***
	(0.112)	(0.058)	(0.08)	(0.105)	(0.055)	(0.076)
N	480	480	480	480	480	480
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: DS = Double-selection Lasso; PO = Partialling-out Lasso. Both methods use Lasso-based variable selection to address potential omitted variable bias.

consistent causal inference in the presence of high-dimensional controls. Second, the Partialling-out method (Chernozhukov et al., 2018) is used, which removes the influence of control variables through residualization before estimating the coefficient of the main explanatory variable, thereby reducing selection bias. The results from both methods remain consistent with the baseline regression, indicating that the results are highly robust (Table 8).

5. Conclusions and policy implications

This paper investigates the determinants of changes in energy intensity using decomposition analysis and fixed-effects models, drawing on provincial panel data from China between 2006 and 2022. By employing Fisher's Ideal Index, energy intensity was decomposed into efficiency and structural effects. The results demonstrate that improvements in energy efficiency remain the dominant driver of reductions in energy intensity, while structural effects exert only a limited influence. These findings highlight the importance of sustaining technological innovation as a central pathway for reducing energy intensity.

The econometric analysis further incorporates the concept of the energy gap—defined as the ratio of a province's per capita energy production to the national average—as a proxy for regional resource endowments. The results reveal that GDP per capita exerts a significant and nonlinear effect on energy intensity: at lower income levels, economic growth stimulates higher energy demand and intensity, whereas at higher income levels, increasing environmental awareness and consumer preferences for low-energy products contribute to reductions in energy intensity. Importantly, energy prices are found to be significant for both intensity and structural effects, although not for efficiency. The negative coefficient suggests that higher energy prices can effectively reduce energy intensity, a finding consistent with prior studies (Hong et al., 2017). Nonetheless, distortions in China's partially marketized energy pricing system—characterized by government regulation of electricity, limited flexibility in oil and gas pricing, and the coal-dominant power sector—complicate the estimation of price impacts. These results underscore the need to deepen market-oriented reforms and to strengthen the policy framework linking energy pricing and efficiency outcomes.

In addition, government budget revenue is shown to have a positive effect on intensity, structure, and efficiency, reflecting that fiscal expansion, while enabling infrastructure development, also stimulates energy demand and entrenches energy-intensive industries. Likewise, the natural population growth rate is positively associated with energy intensity and structure, indicating that demographic expansion increases consumption and infrastructure requirements. However, its insignificant effect on efficiency implies that population growth alone does not directly alter energy utilization efficiency. These results are consistent with China's rapid industrialization during the study period and suggest that guiding fiscal expenditure toward green investments and incorporating energy-saving measures into demographic and infrastructure planning are essential for future policy.

Regional heterogeneity analysis reveals further insights. GDP per capita exerts a stronger influence in the central and eastern regions, where diversified energy mixes and reductions in inefficient coal consumption facilitate efficiency improvements. By contrast, the western region faces persistent constraints due to limited capital, technological capabilities, and skilled labor, which hinder its energy transition. The energy gap is insignificant in the west, reflecting its abundant resource base: Inner Mongolia, Xinjiang, and Shaanxi collectively accounted for more than 33 % of national energy production in 2022. The transformation of China's economy is also accelerating the rising share of electricity in final energy use, a trend most evident in the east.

Taken together, these findings underscore the need for differentiated policy responses. First, interregional cooperation and coordination should be strengthened to promote resource sharing, technology transfer, and industrial upgrading. Second, energy policies should be tailored to the specific development conditions of each region, balancing efficiency gains with structural transformation. Third, fiscal resources should be directed toward green investments and the promotion of clean energy technologies. Finally, innovation and diffusion of advanced energy technologies should be prioritized to accelerate electrification, phase out outdated industrial capacity, and foster a low-carbon transition. By adopting such targeted and regionally sensitive policies, China can achieve sustained reductions in energy intensity while advancing economic modernization and environmental sustainability.

This paper also has some research limitations. The study relies on provincial energy data, limiting the ability to compare differences across specific regional sectors. Besides, the analysis does not account in detail for the major energy and environmental policies implemented in China during this period. These factors may impact the results, and further research should consider them in greater detail.

CRediT authorship contribution statement

Weiwei Huang: Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Yang Miao:** Writing – review & editing, Funding acquisition, Data curation. **Huiying Ye:** Writing – review & editing, Data curation. **Weilong Li:** Writing – review & editing, Validation, Supervision, Project administration, Methodology.

Data statement

All data used in this study are obtained from publicly available sources. Detailed information regarding data sources and acquisition methods has been explicitly documented in the relevant sections of the paper.

Declaration of competing interest

The authors declare that there are no conflicts of interest related to this manuscript.

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Appendix

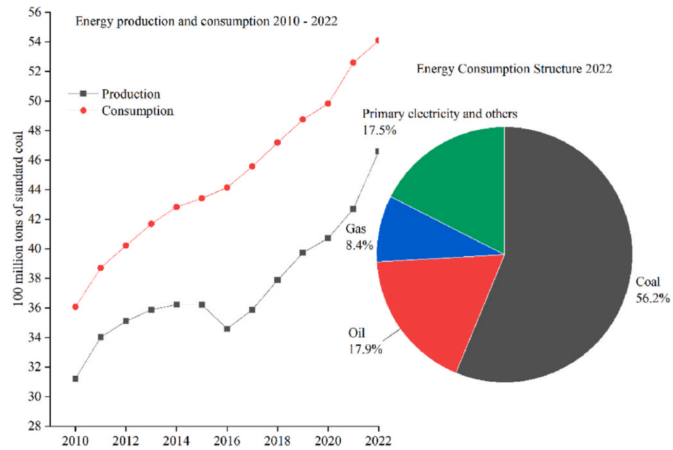

Fig. A1. Energy Production and Consumption in China (2010–2022)
Source: National Bureau of Statistics.

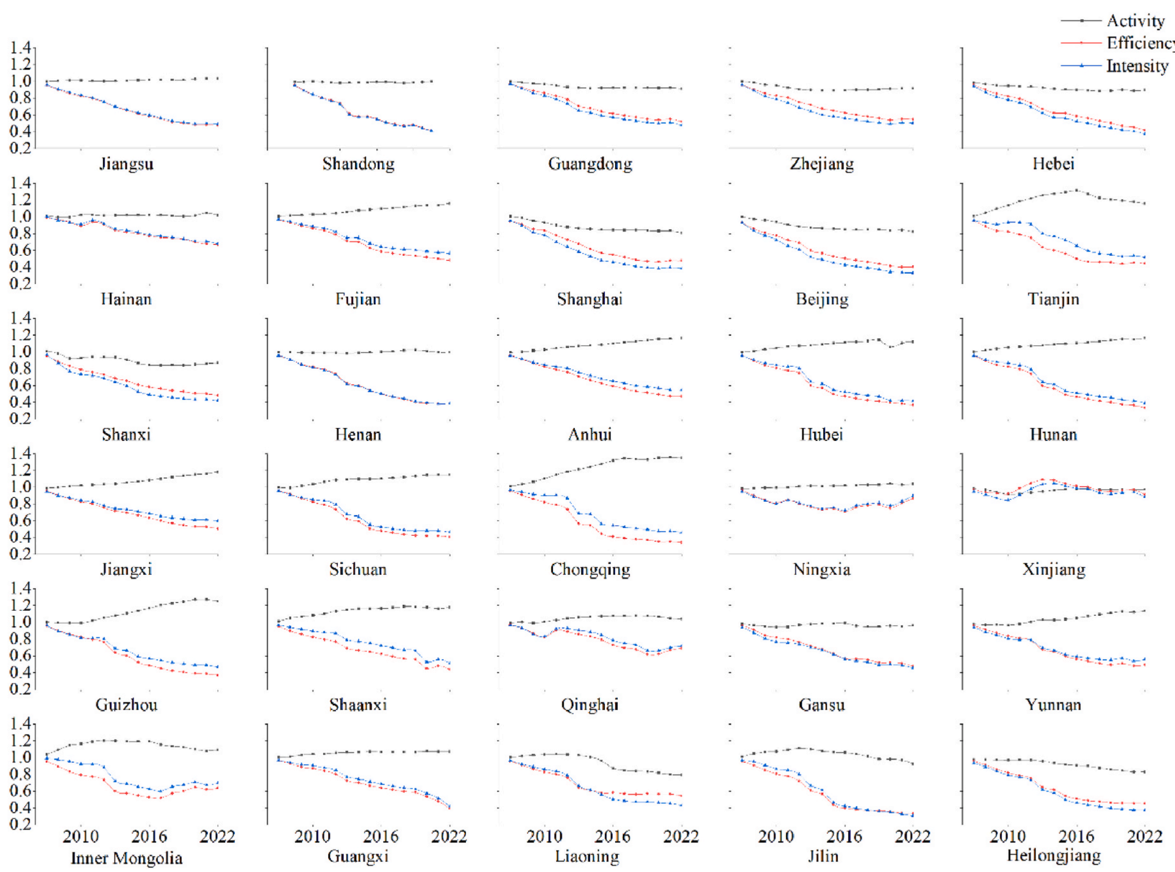

Fig. A2. Changes in energy intensity and decomposition factor indicators by province (2006–2022).

Table A1
Three economic geographic regions of China.

Regions	Provinces
East	Hebei, Beijing, Shanghai, Tianjin, Liaoning, Guangdong, Zhejiang, Jiangsu, Fujian, Shandong, and Hainan
Central	Hubei, Shanxi, Jilin, Henan, Heilongjiang, Jiangxi, Anhui and Hunan
West	Chongqing, Inner Mongolia, Yunnan, Shaanxi, Qinghai, Guangxi, Sichuan, Ningxia, Guizhou, Gansu, and Xinjiang

Table A2
Cross-sectional dependence tests

Dependent variable	Test method	Test statistic	p-value	α = 0.10 CV	α = 0.05 CV	α = 0.01 CV	Avg. abs. corr.	Conclusion
Intensity	Pesaran CD	2.755	0.0059	–	–	–	0.519	Reject H0 (1 %)
	Friedman	24.035	0.7272	–	–	–	0.519	Fail to reject
	Frees	7.621	–	0.1612	0.2116	0.3125	0.519	Reject H0 (1 %)
Structure	Pesaran CD	0.802	0.4228	–	–	–	0.487	Fail to reject
	Friedman	16.265	0.9724	–	–	–	0.487	Fail to reject
	Frees	6.897	–	0.1612	0.2116	0.3125	0.487	Reject H0 (1 %)
Efficiency	Pesaran CD	−0.112	0.9111	–	–	–	0.522	Fail to reject
	Friedman	15.121	0.9841	–	–	–	0.522	Fail to reject
	Frees	6.998	–	0.1612	0.2116	0.3125	0.522	Reject H0 (1 %)

Notes: Tests are conducted on residuals from the fixed-effects model. The Frees test compares the statistic with critical values from the Q distribution. "Avg. abs. corr." is the mean absolute off-diagonal correlation. Rejection indicates the presence of cross-sectional dependence across provinces.

Data availability

Data will be made available on request.

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