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Analysis of the non-linear impact of digital economy development on energy intensity: Empirical research based on the PSTR model

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ABSTRACT

With the rapid development of digital technologies, digital economy (DE) gradually plays a crucial role in changing the pattern of economic and social development. However, the relationship between the DE and energy intensity is still unclear. To fill this gap, this investigation firstly evaluates the development level of the DE of 30 provincial regions in China from 2013 to 2021. Then the non-linear relationship between the DE development and energy intensity is investigated based on the panel smooth transition (PSTR) model taking real GDP, urbanization rate, the proportion of the secondary industry in GDP, R&D funds for industrial enterprises above designated size, and foreign direct investment as transformation variables. The empirical analysis testifies that the DE development can promote the energy intensity and the relationship between the DE development and energy intensity tends to be an invert U shape under the influence of five transformation variables. Values of conversion variables in most provincial regions have not cross thresholds. Especially, the influence coefficients of the DE development on energy intensity have great space to decline under the impact of urbanization rate and the proportion of the secondary industry in GDP. Therefore, the industrial structure should be continuously optimizing and the process of green urbanization should be accelerating. Moreover, it is necessary to stimulate the integration of digitalization technologies and energy system so as to improve energy allocation efficiency and realize energy conservation and emissions reduction.

1. Introduction

The emergence of digital economy (DE) opens a new era theme in the later stage of industrialization and urbanization process. It is a new economic form taking digital resources as the main production factors and information network as a crucial supporter to sufficiently utilize multiple production resources in the society through modern information communication and internet technologies [1,2]. Through the development of DE, the latest information technologies, such as cloud computing, artificial intelligence (AI), and big data, have provided technical assistance for the scale expanding of new-type economies and industries. Hence, the transformation of production mode, social governance, and lifestyle can be promoted and greater economic benefits can be obtained [3,4]. Thus, DE will gradually become the crucial drivers of economic growth and the booster to enhance the national strength in the future. In 2022 and 2023, Chinese government work report highlighted the necessity of DE developing, and pointed out to building digital China and specific goals. According to the China Digital Economy Development Report released by the China Academy of Information and Communications Technology (CAICT) in 2022, the scale of China's DE has reached 45.5 trillion-yuan, accounting for 39.8% of GDP. It indicates that the position of the DE in the national economy is more stable and its supporting role is more obvious. Therefore, to stimulate the growth of the DE, it is of great practical and theoretical value to investigate the DE from China's perspective.

Most of current literature on the DE argued on the correlation between DE and carbon emissions. Some researches hold the view that the DE greatly contributes to carbon emissions reduction [5–7]. And some literature reported that the DE and carbon emissions existed non-linear correlation (Zhang et al., 2022; [8]. Moreover, some studies highlighted the role of the DE in economic growth [9,10]. Some literature pointed out that the DE can promote the development of green economy [11,12] and manufacturing industry [13]. Recently, literature researched on the relationship between the DE and energy has emerged. Some literature indicated that the DE will increase energy consumption, as the growth of the DE needs infrastructure support [14,15]. Some literature put

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forward that the DE can decrease energy consuming, optimize energy allocation, and reverse the traditional energy consuming concept [16, 17]; Noussan et al., 2020).

Through summarizing the existing literature, three primary limitations can be discovered. Firstly, the existing researches primarily focused on investigating the influence of the DE on economic growth, carbon emissions, and other issues. It is difficult to find an investigation on the relationship between the DE and energy consumption. From the perspective of historical development, the economic growth greatly relied on energy consumption. Since the DE becomes the new engine of economic development, the growth of DE depends on information technology infrastructure which requires a huge amount of energy, hence, the relationship between the DE and energy consumption should be investigated. Secondly, the previous literature mainly conducted linear relationship analysis based on panel data model. However, the relationship between the DE and energy consumption exists disputes. The unclear part is whether the DE will lead to a net increase in energy demand as the rebound effect might exist. Hence, researching on the nonlinear relationship between energy consumption and the DE is of crucial significance to achieve the goal of carbon neutrality and mitigate global warming, especially for China which is still in the process of industrialization and urbanization. Thirdly, the influence mechanism of the DE on energy consumption is poorly discussed. Thus, it will be of significant benefit for policy makers to deeply understand the influencing mechanism.

To solve these limitations, this investigation aims at researching on the relationship between the DE and energy intensity and deeply analyzing the mechanism of the DE influencing energy intensity. The data of 30 provincial level regions in China (including 22 provinces, 4 autonomous areas (Inner Mongolia autonomous area, Xinjiang Uygur autonomous area, Guangxi Zhuang autonomous area, and Ningxia Hui autonomous area), and 4 provincial level megacities (including Beijing, Shanghai, Tianjin, and Chongqing). Tibet, Taiwan, Hongkong, and Macau are excluded owing to the shortage of related statistical data.) from 2013 to 2021 are collected for empirical analysis. An index system is established to evaluate the DE development level of 30 provincial regions. And the panel smooth transition model (PSTR) is employed to explore the nonlinear relationship between the DE and energy intensity. And the influencing mechanism is investigated from five aspects: economic scale and structure, society structure, technological innovation, and opening degree. Since economic activities are always deemed as the primary factor increasing energy consumption, and it has been proved that a strong positive correlation exists between economic growth and energy consumption [18], thus, the influencing mechanism will be investigated from economic scale and economic structure perspectives. Moreover, it is verified that the urbanization level and energy consumption have a causal nexus [19]. Hence, the influencing mechanism will be explored from urbanization level aspect. Additionally, technological innovation is commonly regarded as a main factor to restrain the increase of energy consumption, hence, the influencing mechanism will be studied from technological innovation perspective [20]. Under the background of economic globalization, the opening degree is deemed as one of the primary factors influencing energy consumption, thus it is necessary to research the influencing mechanism from opening degree [21].

This paper contributes greatly in the following aspects. First, the nonlinear relationship between the DE and energy intensity is analyzed and an inverted "U" shape relationship under the influence of different transformation variables is discovered. Since it is difficult to finding literature researching on the relationship between the DE and energy intensity, this research empirically discusses the impact mechanism of the DE on energy intensity. Secondly, this research provides some important analysis on the impact mechanism of the DE on energy intensity from provincial level. Most of existing studies suffered from data shortage, hence the empirical analysis is conducted from macro level. While our study calculates the DE development level from provincial perspective and deeply investigates the nonlinear relationship and impact mechanism between the DE and energy intensity in 30 provincial regions in China. Thirdly, through analyzing the empirical results, specific policy recommendations are put forward, which can provide reference for managing the DE development, energy consuming, and carbon neutrality.

The remaining sections of this paper are structured as below. Section 2 reviewed the existing literature. Sections 3 introduces the methods. Variables selection and data sources are explained in Section 4. Section 5 presents empirical results and discussion. Section 6 draws conclusions and put forward policy recommendations.

2. Literature review

Currently, there exist arguments about the influence of the DE on energy consumption. Some literature indicated that the development of the DE will positively influence energy, which can bring energy-saving effect, while some scholars hold views that the digitalization process will promote energy consuming increase, which leads to energy-consumption effect.

For energy saving effect, with the process of digitalization, the industrial economy's fundamentals have been changed by digital techniques, such as AI, blockchain, cloud computing, and big data. Digital techniques are increasingly playing the driving role of enterprises innovation [22]. With the integration of digital techniques and industries, traditional enterprises management, industries production, and operation mode have changed. Through big-data analysis, enterprises can make accurate decisions, decrease management costs, and optimize business process [23]. Moreover, with the integration of digital techniques and daily life, online shopping and medical care change people's behaviors, which decrease traffic trips and lower energy consumption (Noussan et al., 2020). Popkova pointed out that the development of digital technology can improve management efficiency which can accelerate the realization of sustainable development [24]. Cao et al. explained that the digital finance can greatly enhance energy and environmental performance through improving technological efficiency rather than scale [25]. [26]. Verified that digital technology can increase electricity using efficiency [26]. Hao et al. thought that the emergence of the Internet has altered conventional energy consuming pattern, bringing about a reduction in energy intensity [27]. Xu et al. illustrated that the DE can decrease energy intensity by propelling technique innovation, speeding up the human capital accumulation, and improving economic structure [18]. Ren et al. argued that digitalization can promote energy intensity decrease by economic growth, financial development, research and development input, and economic structure upgrading [15].

For energy consuming effect, scholars thought that the DE depends on the internet expand. And the expansion of the DE will promote the growth of information and communication technology (ICT) industry, ICT equipment manufacture and utilization, and digital infrastructure construction [26]. However, they are all considered to be energy-intensive. And data centers and stations are energy-consuming equipment. And the expansion of the Internet will expand the use of electronic items, these devices are also energy consuming (Qin et al., 2022). Schien thought that digital infrastructure and services are the significant driving force for electricity consuming [28]. It has also been discovered that the electricity demand will increase with the Internet development [29,30]. There exist evidences supporting that Internet access will make electricity demand increasing greatly. Coyne et al. [14] and Jin et al. [31]proved that the digitalization mainly relied on information and communication infrastructure which is energy consuming. Kim et al. also discussed about the energy consuming brought by digital development. They thought the advantages of digitalization are improving electrification of human consumption modes, hence, their dependence on energy will increase [32]; 2021b).

Existing literature also refuted the viewpoint that digitalization can decrease energy demand through increasing energy efficiency. Lange et al. implied that the digitalization enhanced energy efficiency which made energy consuming become lower. Nevertheless, the development of ICT and economic growth brought by the digitalization would cause more incremental energy using [33]. Salahuddin discussed that the digital technology can decrease energy consuming in the short term, while the rebound effect caused by the digitalization will boost energy demand in the long term [34,35].

Considering about the complicated relationship between the DE and energy consuming, this paper deeply researched on the nonlinear correlation between the DE and energy intensity of 30 provincial regions in China. And the influencing mechanism is investigated from economic scale and structure, society structure, technological innovation, and opening degree.

3. Methods

3.1. PSTR model

The model of this research was established according to the PSTR model proposed by Gonzalea et al. [36]. The superiority of this model is that it can better handle the problem of jumping change before and after the door limit in Hansen's panel threshold model. A continuous transformation function has been introduced into the model which can make model parameters gradually change with the vary of transformation variables, hence, it is more consistent with actual economy [37]. Besides smooth transformation, the PSTR model can efficiently capture the heterogeneity between different parts and is suitable for multi-section data research. The PSTR model is established as

$$Energy_{i,t} = \beta_0 + \beta_1 Dige_{i,t} + \sum_{j=1}^{r} \beta_{2j} Dige_{i,t} \times G_j(q_{i,t}, \gamma, c) + \beta_z Z_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $Energy_{i,t}$ is the explained variable representing the energy consumption intensity of provincial region i in period t. β_0 is the constant term of the function. $Dige_{i,t}$ is the DE development level of provincial region i in period t, which is deemed as the core explanatory variable in our research. β_1 is the correlation coefficient of the DE development level on energy intensity, which is deemed as the core parameter. $\beta_{2,j}$ is the coefficient of the non-linear part. $Z_{i,t}$ indicates a series of control variables. β_z is the coefficient of control variables. $\varepsilon_{i,t}$ is the random disturbance term. $q_{i,t}$ is the conversion variable. $G_j(q_{i,t}, \gamma, c)$ is the transformation function, which is a continuous, bounded function of a transformation variable $q_{i,t}$. And the value of the conversion function is normalized in the interval of [0, 1]. $\gamma > 0$ represents the slope coefficient, which determines the speed at which model conversion occurs. The larger the value of γ, the greater the slope of the transformation function, demonstrating the larger the conversion speed. $c = (c_1, c_2, \ldots c_m)$ is an m-dimensional positional parameter vector, also known as a threshold value, which represents the location where model transformation occurs. The transformation function G_j is generally expressed in the form of a Logistic function as

$$G_j(q_{i,t}, \gamma, c) = \left\{1 + \exp\left[-\gamma \prod_{z=1}^{m} (q_{i,t} - c_z)\right]\right\}^{-1}, \gamma > 0, c_1 \leq \ldots \leq c_m \tag{2}$$

Because G_j is a continuous function, when G_j continuously changes within the [0,1] interval, the regression coefficient will complete a continuous and stable transformation within the interval $[\beta_1, \beta_1 + \sum_{j=1}^{r} \beta_{2j}]$. Moreover, in the PSTR model, values of two critical parameters m and r should be determined. m represents the number of positional parameters, and Gonzalea believes that a value of 1 or 2 for m is sufficient to be representative. r represents the amount of conversion functions.

3.2. Linearity test

Before establishing the PSTR model, a linearity test needs to be conducted. The PSTR model can only be established under the context that the data sequences are non-linear. The linearity test can determine the value of m in the transformation function G_j. The null assumption of linearity test is supposed as $H_0 : r = 0$ or $H_0 : \beta_2 = 0$. Nevertheless, under such assumption, unrecognizable parameters will be generated in the PSTR model. Hence, Gonzalea et al. [32] solve this problem by proposing the null assumption as $H_0 : r = 0$. Simultaneously, to avoid the identification issue, Taylor series expansion was employed for $G_j(q_{i,t}, \gamma, c)$ when $r = 0$, which is expressed as:

$$y_{i,t} = \mu_i + \beta_0^{'} x_{i,t} + \beta_1^{'} x_{i,t} q_{i,t} + \cdots + \beta_m^{'} x_{i,t} q_{i,t}^{m} + \mu_{i,t}^{'} \tag{3}$$

In Equation (3), $\beta_0^{'}$, $\beta_1^{'} \cdots \beta_m^{'}$ are generated by r and they are constant. $\mu_{i,t}^{'} = \mu_{i,t} + R_m \beta_1^{'} x_{i,t}$. R_m is the remainder of Taylor expansion. Thus, the null assumption of the linearity examination is the same as $H_0 : \beta_1^{'} = \cdots = \beta_m^{'} = 0$. If the null assumption is accepted, the PSTR model is inappropriate to be established. Otherwise, if the null assumption is rejected, the data sequences are nonlinear and the PSTR model is reasonable to be built.

3.3. No remaining non-linearity test

The conduction of no remaining non-linearity test of the PSTR model aims at examining whether the residual term μ_i still includes obvious nonlinear components. The concept of this examination is the same as the linearity examination. The null assumption is written as: $H_0 : \beta_1^{'*} = \cdots = \beta_m^{'*} = 0$. If this assumption is accepted, the PSTR model has fully captured the non-linear correlation among data sequences. Otherwise, the model is unreasonable.

3.4. Operation process

The specific operation process of the PSTR model is illustrated as follows.

Step 1. Stability test

To prevent the occurrence of false regression, this paper first uses the panel unit root test methods to test the data stationarity of each variable.

Step 2. Linearity test

Before using the PSTR model for estimation, it is necessary to first conduct a linear test to test whether the development of the DE has a non-linear impact on energy consumption intensity under the influences of different transformation variables. Three statistics, LM, LMF, and LRT, are used to conduct the examination. Only if the test results reject the original hypothesis $H_0 : r = 0$, a PSTR model can be constructed.

Step 3. Remaining non-linearity test

The purpose of the remaining non-linearity test is to determine the optimal number of r in the transformation function of the PSTR model. If the original assumption $H_0 : r = 1$ is accepted, it is considered appropriate to set only one transformation function for the model. If the original assumption is rejected, it means that the model needs to set multiple conversion functions.

Step 4. The number of positional parameters determination

After determining the number of transformation functions, it is necessary to further determine the number of positional parameter m for each PSTR model's transformation function. It is essential to perform PSTR estimation under m = 1 and m = 2, respectively, and determine the optimal number of location parameter m based on AIC and BIC information criteria.

4. Data

The explained variable is energy consumption intensity, which is represented by the ratio of energy consumption to real GDP. The core explanatory variable is the development level of the DE. Through reviewing existing literature and related reports, we found that there is no uniform standard for the measurement of the DE. Through referring to some literature [12,38–40] researching on the comprehensive evaluation of the DE development level, the indicators used to represent the development level of the DE in our research are listed in Table 1. The indicators are selected from four perspectives including digital infrastructure, integrated development, social benefits, and electronic-commerce, containing 14 indicators. The final values of the DE development level are calculated by entropy method which is shown in Supporting Information A.

For conversion variables, real GDP, urbanization rate, the proportion of secondary industry in GDP, research & development (R&D) funds for industrial enterprises above designated size, and foreign direct investment (FDI) are selected as the conversion variables for the established Models 1–5. For real GDP, economic scale and activities are often deemed as one of the significant factors influencing energy consumption. He et al. (He, 2020) indicated that a positive relationship exists between economic growth and electricity using. Thus, real GDP of 30 provincial regions from 2013 to 2021 are calculated taking GDP in the year of 2000 as basic period values, which is taken as the conversion variable in Model 1. Since urbanization level and energy consumption have a causal correlation and high urbanization level can be the significant driver of energy consumption increasing (Hongyun et al., 2021), urbanization rate represented by the ratio of urban population in total population is selected to be the conversion variable in Model 2. As the industrial development and energy consumption are inseparable and it has been proved that the adjustment of economic structure can promote the energy consumption increasing (Shi et al., 2022), the proportion of secondary industry in GDP is employed to be the conversion variable in Model 3. Technological innovation is generally regarded as the main factor to restrain the growth of energy consuming (Fang et al., 2019), hence, R&D funds for industrial enterprises above designated size is selected to be the conversion variable representing scientific and technological progress in Model 4. Under the context of economic globalization, opening degree of domestic market is gradually deemed as a critical factor to promote energy consuming, hence, FDI is chosen as the conversion variable in Model 5.

All the data of energy intensity, the DE development level, and five conversion variables of 30 provincial level regions in China from 2013 to 2021 are collected from the State Statistics Bureau, China Energy Statistical Yearbook, China Statistical Yearbook, and Statistical yearbook of provinces (autonomous regions, municipalities). The descriptive statistics of each variable are listed in Table 2.

Table 1
Indicators used to represent the development level of the DE.

Perspectives	Indicators
Digital infrastructure	Telephone penetration ratio
	Number of Internet broadband access users
	Long distance optical cable line length
	Number of websites per 100 enterprises owned
Integrated development	Software business income
	Express business income
	Total post and telecommunications business
	Income from information technology services
	Express quantity
Social benefits	Average wage of urban employees in information transmission, computer services and software industries
	Employment of urban units in information transmission, software and information technology services
Electronic-commerce	Electronic-commerce sales amount
	Electronic-commerce purchase amount
	Proportion of enterprises with electronic-commerce transactions

5. Results and discussion

5.1. Stability test

To prevent the occurrence of false regression, the panel unit root test methods, such as Levin, Lin and Chu (LLC test) (Levin et al., 2002), and Im, Pesaran and Shin (IPS test) [41], are employed in our research to test the data stationarity of each variable. The test results listed in Table 3 show that energy intensity, the development level of the DE , real GDP, urbanization rate, the proportion of secondary industry in GDP, R&D funds for industrial enterprises above designated size, and FDI in our research are stable at a significance level of 1%. Therefore, the PSTR model can be established based on these variables.

5.2. Linearity test

After ensuring all variables are stable, it is necessary to conduct a linear test (original hypothesis $H_0 : r = 0$) to examine whether the development level of the DE has a non-linear impact on energy intensity under the influence of different transformation variables. According to the linear test results illustrated in Table 4, the P-values of the three statistics LM, LMF, and LRT of the five models are all less than 5%, which means that the original hypothesis is significantly rejected at the 5% significance level, indicating that the development level of the DE has a significant nonlinear impact on energy consumption intensity, and the modeling of PSTR in our investigation is reasonable.

5.3. Remaining non-linearity test

After proving that the development level of the DE has a non-linear impact on energy intensity under the influence of five selected transformation variables, the optimal number of r in the transformation function should be determined by the remaining non-linearity test. According to the remaining non-linearity test results illustrated in Table 5, the P-values of the three statistics LM, LMF, and LRT of the five models are all larger than 10%, which demonstrates the original assumption $H_0 : r = 1$ should be accepted at 10% significance level. Thus, it is reasonable to set only one conversion function in the PSTR model.

5.4. The number of positional parameters determination

After determining the optimal number of r in the transformation function, we need to testify the number of positional parameter m for each PSTR model's transformation function. The PSTR estimation is conducted under $m=1$ and $m=2$, respectively, and optimal number of location parameter m is determined based on AIC and BIC information criteria. According to the test results of AIC and BIC depicted in Table 6, it is demonstrated that $m=1$.

5.5. Regression results of the PSTR model

After determining the number of transformation functions r and the number of positional parameters m, five PSTR models can be constructed. The least squares method is used to estimate the parameters to obtain the regression coefficients of the explanatory variables under different mechanisms. The regression results are shown in Table 7. It can be seen that the regression coefficients of Models 1–5 are significant at the 1% level.

Table 2
The descriptive statistics of each variable.

Variable	Symbol	Obs	Unit	Mean value	Std. Dev	Minimum value	Maximum value
Energy Intensity	EI	270	Ton standard coal/10ˆ4 yuan	1.8066	3.8496	0.3686	25.4647
The development level of the DE	DE	270	–	0.1111	0.0731	0.0018	0.4597
Real GDP	GDP	270	Trillion yuan	1.8780	1.5445	0.0535	7.7743
Urbanization rate	UR	270	–	0.6088	0.1148	0.3789	0.8960
The proportion of secondary industry in GDP	STR	270	–	0.4090	0.0824	0.1583	0.5500
R&D funds for industrial enterprises above designated size	R&D	270	100 billion yuan	0.4083	0.5243	0.0065	2.9022
Foreign direct investment	FDI	270	100 billion yuan	0.4834	0.4561	0.0002	1.7985

Table 3
Panel data unit root test results.

Variables	L.L&C	IPS	Conclusions
EI	−3.8936 (0.0074)[a]	3.7278 (0.0067)[a]	Stationary
DE	−4.0442 (0.0056)[a]	−3.8332 (0.0070)[a]	Stationary
GDP	−3.9135 (0.0019)[a]	−3.5491 (0.0021)[a]	Stationary
UR	−3.7136 (0.0051)[a]	−3.5271 (0.0043)[a]	Stationary
STR	−3.5216 (0.0002)[a]	−3.3145 (0.0024)[a]	Stationary
R&D	−3.9263 (0.0025)[a]	−3.5728 (0.0024)[a]	Stationary
FDI	−3.2314 (0.0005)[a]	−4.2527 (0.0000)[a]	Stationary

Notes: the values in brackets indicate the probability values. If the probability values are less than the specified level of significance, it means the null hypothesis ought to be rejected.
a: Denotes 1% level of significance.
b: Denotes 5% level of significance.

Table 4
Linearity test results.

Model	Conversion variable	Original hypothesis $H_0 : r = 0$		
		LM	LMF	LRT
Model 1	GDP	15.103 (0.000)[a]	14.161 (0.000)[a]	15.542 (0.000)[a]
Model 2	UR	12.866 (0.000)[a]	11.959 (0.001)[a]	13.183 (0.000)[a]
Model 3	STR	6.175 (0.000)[a]	5.351 (0.000)[a]	6.234 (0.000)[a]
Model 4	R&D	5.175 (0.023)[b]	4.67 (0.032)[b]	5.225 (0.022)[b]
Model 5	FDI	4.555 (0.033)[b]	4.101 (0.044)[b]	4.594 (0.032)[b]

Notes: the values in brackets indicate the probability values.
[a] Denotes 1% level of significance.
[b] Denotes 5% level of significance.

Table 5
The remaining non-linearity test results.

Model	Conversion variable	Original hypothesis $H_0 : r = 1$		
		LM	LMF	LRT
Model 1	GDP	0.002 (0.967)	0.001 (0.970)	0.002 (0.967)
Model 2	UR	0.026 (0.872)	0.023 (0.880)	0.026 (0.872)
Model 3	STR	0.013 (0.812)	0.018 (0.803)	0.02 (0.824)
Model 4	R&D	0.084 (0.771)	0.074 (0.786)	0.084 (0.771)
Model 5	FDI	0.083 (0.774)	0.073 (0.788)	0.083 (0.774)

Notes: the values in brackets indicate the probability values.

Table 6
Results of AIC and BIC for positional parameters determination.

Model	Conversion variable	*m* option	AIC	BIC	Optimal value of *m*
Model 1	GDP	m = 1	−3.107	−3.054	m = 1
		m = 2	−3.096	−3.029	
Model 2	UR	m = 1	−1.648	−1.595	m = 1
		m = 2	−1.637	−1.57	
Model 3	STR	m = 1	−1.627	−1.593	m = 1
		m = 2	−1.521	−1.572	
Model 4	R&D	m = 1	−1.635	−1.582	m = 1
		m = 2	−1.624	−1.557	
Model 5	FDI	m = 1	−1.949	−1.896	m = 1
		m = 2	−1.555	−1.489	

5.6. Analysis of the impact of conversion variables on the relationship between the development of DE and energy intensity

(1) Analysis of the impact of real GDP on the relationship between the development of DE and energy intensity

Model 1 discusses the change of the influence coefficient of the development of the DE on energy intensity as the real GDP changes. As can be seen from Table 7, there is a single threshold value of $c=1.2250$ for Model 1. And the coefficient of the linear part of the development level of the DE is $\beta_1 = 0.9828 > 0$, while the coefficient of the non-linear part is $\beta_2 = -0.5633 < 0$. Therefore, the theoretical range of the influence coefficient of the development of the DE on energy intensity is [0.4195, 0.9828], and an invert U shape curve exist between the development level of DE and energy intensity under the influence of real GDP.

The change curve of the conversion function and impact coefficient is shown in Fig. 1. With the continuous change of real GDP, the conversion function smoothly transforms in the interval [5.3148 *10ˆ(−16), 1]. Moreover, the impact coefficient of the development of the DE on energy intensity is smoothly converting between high and low regimes, and in practice its value range is [0.4195, 0.9828], which is close to the theoretical value. When the real GDP is less than 1.2250 trillion yuan, the development of the DE has a significant positive impact on energy intensity, with a maximum impact coefficient of 0.9828. When the real GDP is greater than 1.2250 trillion yuan, the positive impact of the development of the DE on energy intensity gradually decreases to 0.4195 which is already the theoretical minimum. However, it can be seen from the Supporting Information Figure B3 that by the end of 2021, the real GDP of Shanxi, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang have not crossed the threshold value. With the mode transformation of economic growth, the optimization of the industrial and energy structure, and the enhancement of the driving force for economic development, the real GDP of these provinces will increase annually, and will cross the threshold value, hence, the impact coefficient of the development of the DE on energy intensity will constantly approach the inflection point of the inverted U-shaped curve, and enter a downhill stage.

Table 7
Regression results of PSTR model.

Model			Model 1	Model 2	Model 3	Model 4	Model 5
Conversion variable			Real GDP	UR	STR	R&D	FDI
Explanatory variable: the development level of the DE	β_1	Estimated value	0.9828***	0.9335***	1.1332***	1.2368***	1.1254***
		t statistic	−7.7609	−4.2432	5.2372	−4.4374	−4.0760
	β_2	Estimated value	−0.5633***	−0.8096***	−0.9862***	−0.7324***	−0.6483***
		t statistic	7.4956	3.4737	3.4281	3.9127	3.5276
Influence coefficient	$\beta_1 + \beta_2$		0.4195	0.1239	0.1470	0.5044	0.4771
Positional parameter	c		1.2250	0.5993	0.2700	0.093	0.3530
Slope coefficient	γ		30.0229	77.0561	6.2187	60.71	8.8697
Sum of squares of residuals	RSS		11.508	49.514	30.232	50.138	36.629

Notes: ***: Denotes 1% level of significance.

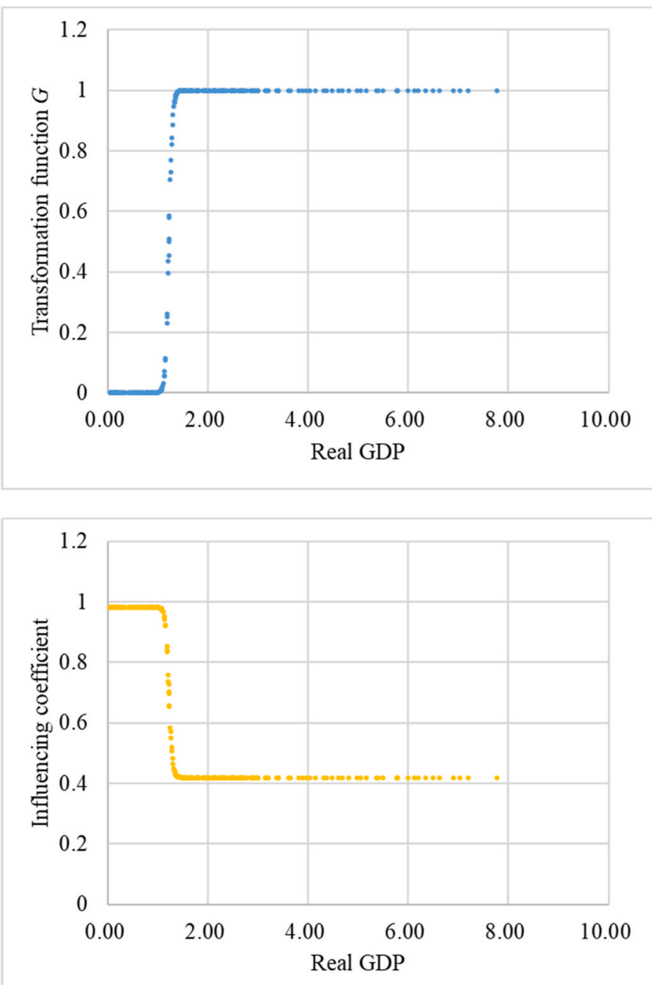

Fig. 1. Smooth transformation diagram of transformation function and influence coefficient of Model 1.

(2) Analysis of the impact of urbanization rate on the relationship between the development of DE and energy intensity

Model 2 analyzes the change of smooth transition of the impact coefficient for the development of DE on energy intensity with the urbanization rate changes. From Tables 7 and it can be seen that there is a single threshold value of *c=0.5993* for Model 2. The linear coefficient of the development level of the DE is $\beta_1 = 0.9335 > 0$, while the coefficient of the non-linear part is $\beta_2 = -0.8096 < 0$, so the theoretical range of the coefficient of influence for the development of the DE on energy intensity is [0.1239, 0.9335], and there exist an invert U shape curve between the development level of DE and energy intensity under the influence of urbanization rate.

Fig. 2 shows the change curve of the conversion function and the influence coefficient. The minimum value of the conversion function is *G=0.0000042*, and the maximum value is *G=0.9999*. A smooth transition is achieved between the minimum and maximum values. With the continuous improvement of the urbanization rate, the impact coefficient of the development of the DE on energy intensity smoothly transforms between high and low regimes, with a value ranging in the interval [0.1241, 0.9335] in practice. When the urbanization rate is lower than 0.5993, the development of the DE has a significant positive impact on energy intensity, with the maximum impact coefficient of 0.9335.

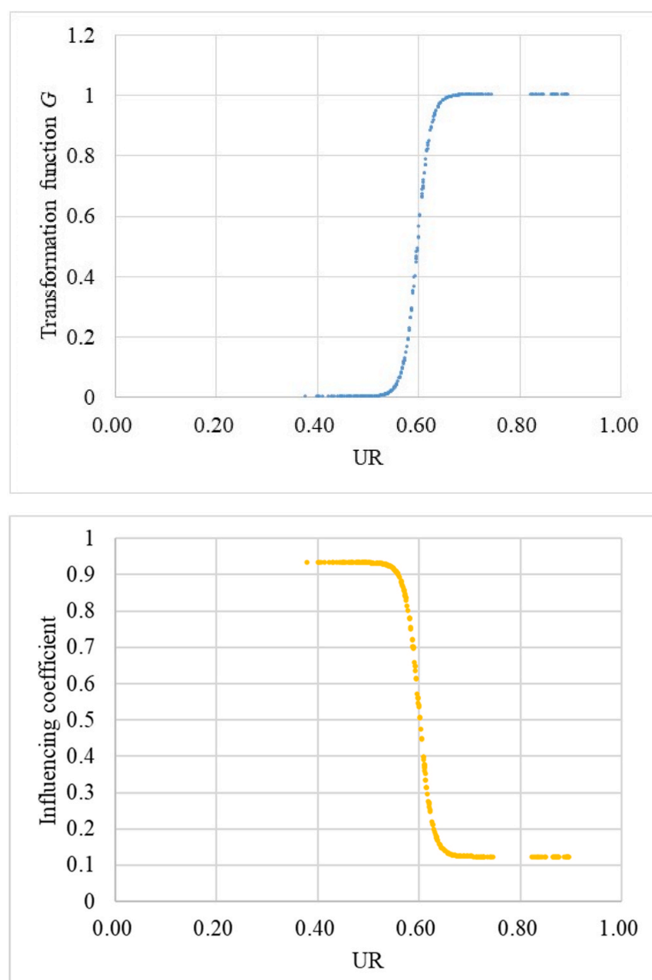

Fig. 2. Smooth transformation diagram of transformation function and influence coefficient of Model 2.

Nevertheless, when the urbanization rate is higher than 0.5993, the positive impact of the development of the DE on energy intensity gradually weakened, and the impact coefficient eventually decreased to $0.1241 > 0$, other than the theoretical minimum value of 0.1239. The primary reason is that the urbanization rate in most provincial regions in China was still within the low regime in 2013–2021. From the Supporting Information Figure B4, it can be seen that by the end of 2021, the urbanization rate level of Anhui, Henan, Guangxi, Sichuan, Guizhou, Yunnan, Gansu, and Xinjiang has not yet crossed the threshold level. Therefore, these provinces should accelerate the urbanization process and make the urbanization rate higher than the threshold earlier. Therefore, the value of the conversion function will increase to the theoretical value of 1, and the value of the impact coefficient will continue to decrease from 0.1241 to the theoretical value of 0.1239.

(3) Analysis of the impact of economic structure on the relationship between the development of DE and energy intensity

Model 3 analyzes the smooth transition of the impact coefficient of the development of the DE on energy intensity as the proportion of the secondary industry in GDP changes. As can be seen from Table 7, there is a single threshold value of $c=\mathit{0.2700}$ for Model 3, and the linear coefficient of the development level of the DE is $\beta_1 = 1.1332 > 0$, while the non-linear coefficient is $\beta_2 = -0.9862 < 0$, so the theoretical range of the coefficient for the influence of the DE development on energy intensity is [0.1470, 1.1332]. And an invert U shape curve exists between the development level of DE and energy intensity under the influence of the change of the proportion of the secondary industry in GDP.

Fig. 3 depicts the change tendency of the conversion function and the influence coefficient. The minimum value of the conversion function is G = 0.1492, and the maximum value is G = 0.8428, between which a smooth transition can be achieved. As the proportion of the secondary industry in GDP continues to increase, the impact coefficient of the development of the DE on energy intensity is smoothly conversing between high and low regimes, with a value ranging in the interval [0.3021, 0.9861] in practice. When the proportion of the secondary industry in GDP is higher than 0.2700, the positive promotion effect of the development of the DE on energy intensity is significant, with a maximum impact coefficient of 0.9861. When the proportion of the secondary industry in GDP is lower than 0.2700, the positive promotion effect of the DE development on energy intensity gradually weakens, and the impact coefficient ultimately decreases to 0.3021, but it is still far higher than the theoretical minimum value of 0.1470. This is because from 2013 to 2021, the proportion of the secondary industry in GDP in most provincial areas is still within the high regime, and the development of the tertiary industry is still insufficient. From the Supporting Information Figure B5, it can be seen that in 2021, the proportions of secondary industry in GDP of Beijing, Shanghai, and Hainan are lower than the threshold. Therefore, other provincial regions should focus on optimizing the economic and industrial structure, increasing the proportion of the tertiary industry so as to cross the threshold as soon as possible. Only then will the value of the conversion function continue to increase from 0.8428 to the theoretical value of 1, and the value of the impact coefficient can decrease from 0.3021 to the theoretical value of 0.1470.

(4) Analysis of the impact of R&D on the relationship between the development of DE and energy intensity

Model 4 analyzes the smooth transition of the impact coefficient of the DE development on energy intensity as R&D changes. From Tables 7 and it can be seen that there is a single threshold value of c = 0.0930 for Model 4, and the linear coefficient of the development level of the DE is $\beta_1 = 1.2368 > 0$, while the coefficient of the non-linear part is $\beta_2 = -0.7324 < 0$. Therefore, the theoretical range of the coefficient of influence for the development of the DE on energy consumption intensity is [0.5044, 1.2368], and there exist an invert U shape curve between the development level of DE and energy intensity under the influence of R&D.

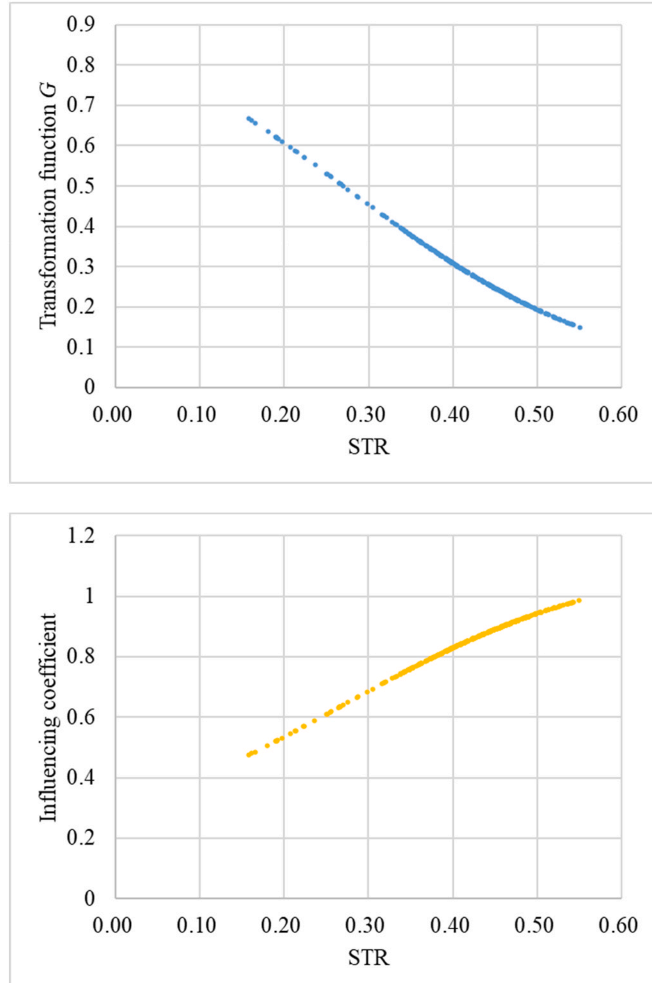

Fig. 3. Smooth transformation diagram of transformation function and influence coefficient of Model 3.

The change tendency of the conversion function and the influence coefficient is illustrated in Fig. 4. The minimum value of the conversion function is G = 0.0052, while the maximum value is G = 1, and a smooth transition is achieved between them. With the continuous improvement of R&D, the impact coefficient of the development of the DE on energy consumption intensity smoothly converses between high and low regimes, with values ranging from 0.5044 to 1.2330 in practice. When R&D is lower than 0.0930, the development of the DE has a significant positive impact on energy intensity, with the maximum impact coefficient of 1.2330. When R&D is higher than 0.0930, the positive impact of the development of the DE on energy intensity gradually weakens. The influence coefficient finally decreased to $0.5044 > 0$, which is close to the theoretical minimum value. This is because from 2013 to 2021, R&D in most provincial regions was already in the high regime with a high level of technological innovation. From the Supporting Information Figure B6, it can be seen that until the end of 2021, only Jilin, Heilongjiang, Shanghai, Guangxi, Hainan, Gansu, Qinghai, Ningxia, and Xinjiang's R&D levels have not yet crossed the threshold. Therefore, these provincial regions should strengthen investment in scientific and technological innovation to enable R&D to cross the threshold as earlier as possible, so that the value of the conversion function will increase to the theoretical value of 1, and the value of the impact coefficient will reach 0.5044. Hence, technical progress can play a positive role in

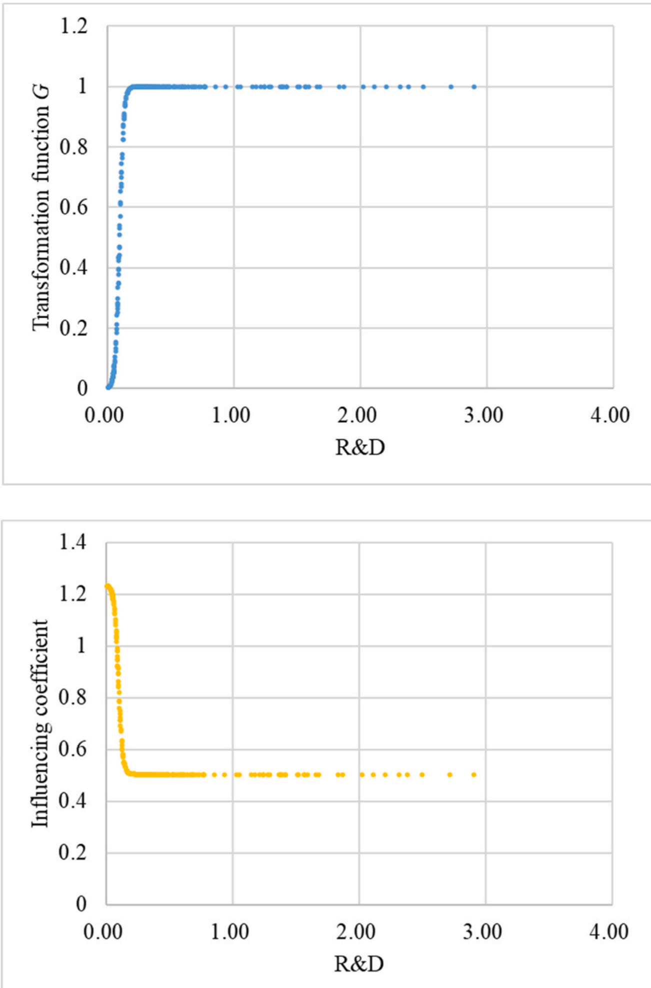

Fig. 4. Smooth transformation diagram of transformation function and influence coefficient of Model 4.

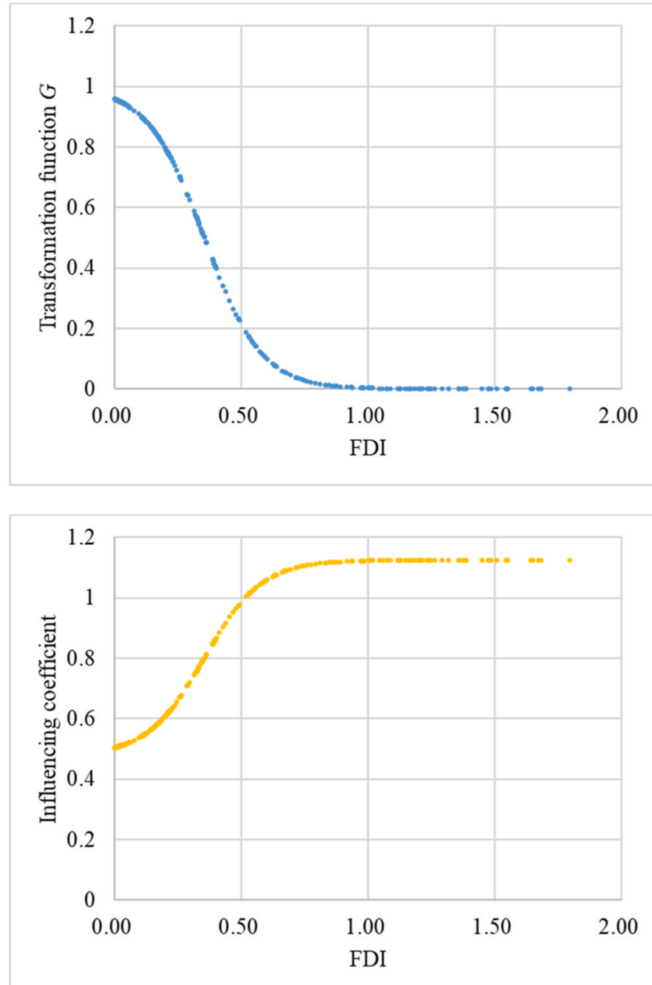

Fig. 5. Smooth transformation diagram of transformation function and influence coefficient of Model 5.

promoting energy utilization efficiency.

(5) Analysis of the impact of FDI on the relationship between the development of DE and energy intensity

Model 5 depicts the smooth transition of the impact coefficient of the DE development on energy intensity as FDI changes. From Table 7, we can discover that a single threshold value of $c=0.3530$ exists for Model 5, and the linear coefficient of the DE development level is $\beta_1 = 1.1254 > 0$, while the coefficient of the non-linear part is $\beta_2 = -0.6483 < 0$. Therefore, the theoretical range of the impact coefficient of the DE development level on energy intensity is [0.4771,1.1254]. And there exist an invert U shape curve between the development level of DE and energy intensity under the influence of FDI.

Fig. 5 demonstrates the change curve of the conversion function and the influence coefficient. The minimum value of the conversion function is G = 0.00027, and the maximum value is G = 0.9581, between which a smooth transition is achieved. With the continuous improvement of FDI, the impact coefficient of the DE development on energy intensity is smoothly transforming between high and low regimes, with a value ranging from 0.5042 to 1.1254 in practice. When FDI is higher than 0.3530, the positive promotion effect of the DE development on energy intensity is significant, with a maximum impact coefficient of 1.1254. When FDI is lower than 0.3530, the positive promotion effect of the DE development on energy intensity gradually weakens, and the impact coefficient ultimately decreases to 0.5042, but is still higher than the theoretical minimum value of 0.4771. This is because from 2013 to 2021, the FDI of most of the provincial regions were in the high regime. From the Supporting Information Figure B7, it can be discovered that only Beijing, Hebei, Zhejiang, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, and Shanxi's FDI are higher than the threshold. In order to achieve the goals of carbon peak and carbon neutrality and reduce energy intensity, these provincial regions should control the growth of FDI and improve energy utilization efficiency. Thus, the value of the conversion function can be increased from 0.9581 to the theoretical value of 1, thereby reducing the value of the impact coefficient from 0.5042 to theoretical value of 0.4771.

The empirical analysis of Models 1–5 established on the basis of five transformation variables demonstrates that there exist invert U shape curves between the development level of DE and energy intensity under the influence of real GDP, urbanization rate, the proportion of secondary industry in GDP, R&D, and FDI. While the development level of the DE is relatively low, the promoting effect of the DE on energy intensity increases steadily. The possible explanation for this phenomenon is that the original development of the DE should be accompanied by extensive infrastructure construction. And some researchers pointed out that the energy consumption of large digital infrastructure, such as data centers, is high ([14,31]. Additionally, the communications industry is energy intensive. Hence, at the beginning of the DE development, energy consumption gradually increases with the construction of the DE infrastructure.

While the development level of the DE gradually rises, the energy intensity will cross the peak and begin to fall. This phenomenon may be explained by the fact that when the DE develops to a certain level, the energy-saving effect will be brought by technological progress, resources optimal allocation and other reasons. Hence, the position effect of the DE on energy intensity becomes weaken [42].

5.7. Discussion on endogeneity

A close nexus exists between the economy and energy consumption which has been proved by many researches. In the established PSTR model, there will be an endogenous risk if a two-way causal relationship between the DE and energy intensity. Hence, to reduce the endogenous risk, it is necessary to re-estimate the PSTR model with the DE lagging by one period. Since the DE_{t-1} will influence DE_t, while the EI_t cannot influence the DE_{t-1}, thus selecting the DE_{t-1} as the explanatory variable can somewhat mitigate the potential endogenous risk resulted from the existence of two-way causation. The re-estimation results of Models 1–5 are listed in Table 8. And the results show that even after considering the endogenous issue, the coefficients are significant. The findings prove the reliability of the established PSTR model results.

6. Conclusions and policy implications

Under the context of realizing the goal of carbon peak and carbon neutrality, with the rapid development of the DE, it is necessary to investigate the influence of the DE on energy intensity. This research firstly evaluated the DE development level of 30 provincial regions in China from 2013 to 2021. And then the non-linear impact of the DE development on energy intensity is studied based on the PSTR model via selecting real GDP, urbanization rate, the proportion of secondary industry in GDP, R&D, and FDI as the transformation variables. The boundaries of changes in the impact of the DE development on energy intensity are analyzed from the perspective of threshold effect.

Based on the empirical analysis of Models 1–5 established on the basis of five transformation variables, it can be discovered that there exist invert U shape curves between the development level of DE and energy intensity under the influence of real GDP, urbanization rate, the proportion of secondary industry in GDP, R&D, and FDI. For R&D, except for Jilin, Heilongjiang, Shanghai, Guangxi, Hainan, Gansu, Qinghai, Ningxia, and Xinjiang, other provincial regions R&D levels have already crossed the threshold and the influence coefficient is close to the theoretical minimum value, hence, scientific and technological innovation has significantly improved energy utilization efficiency. For the real GDP, except for Shanxi, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang, other provincial regions real GDP has crossed the threshold value. For the urbanization rate, Anhui, Henan, Guangxi, Sichuan, Guizhou, Yunnan, Gansu, and Xinjiang's levels are lower than the threshold level. For the proportions of secondary industry in GDP, only that of Beijing, Shanghai, and Hainan is lower than the threshold level. And the influence coefficients of the development of the DE on energy intensity has great space to decline in Models 2 and 3 established via selecting the urbanization rate and the proportion of the secondary industry in GDP as transformation variables, as they are higher than the theoretical minimum values. Therefore, only by continuously optimizing the industrial structure and accelerating the process of green urbanization can the impact coefficient of the DE development on energy intensity continue to decline, and can it help achieve the carbon peak and carbon neutrality goals. Therefore, the policy implications for promoting the decrease of energy intensity are as follows.

Firstly, technological progress has played a positive role in improving energy efficiency and reducing carbon emissions. In order to achieve the carbon peak and carbon neutral goals and the economic growth goal, it is necessary to further increase R&D investment in the future, especially in Jilin, Heilongjiang, Shanghai, Guangxi, Hainan, Gansu, Qinghai, Ningxia, and Xinjiang. The 30 provincial regions need to continuously optimize their investment structure, focusing on supporting low-carbon energy technology research and development and digital technologies.

Secondly, as can be seen from the empirical results, the key to reducing the impact of the DE development on energy intensity lies in two aspects. First, continuously promote the green upgrading of the industrial structure. In addition to Beijing and Shanghai, other provincial regions should control the growth of industries with low added value, high energy consumption, and high emissions in the secondary industry, vigorously develop resource saving and environmentally friendly characteristic industries, and expand emerging industries and modern service industries. The second is to effectively promote the process of green urbanization, especially in Anhui, Henan, Guangxi, Sichuan, Guizhou, Yunnan, Gansu, and Xinjiang. While promoting the development of urbanization, we should attach importance to the green and low-carbon development of urbanization areas.

Thirdly, while expanding opening up degree, we should improve the level of international division of labor, actively develop modern service trade with low pollution and high added value, in order to promote unlocking the high carbon lock in economic growth.

Fourthly, while developing the digital economy, it is better to further apply the digitalization technologies in the energy field. With the rapid development of the DE, the energy consuming increase brought by the infrastructure construction of the DE may also require attentions. The innovation effect of digital technologies should be fully stimulated and the development of emerging internet techniques should be encouraged. The application of digital technologies, such as 5G, AI, big data, cloud computing, and others, should be strengthened. Hence, the digital technologies can be widely employed in energy systems via the development of "Internet Plus" smart energy and energy Internet so as to improve energy allocation efficiency and realize energy conservation and emissions reduction.

This investigation explores the relationship between the DE development level and energy intensity under different transformation variables based on the PSTR model, however, there is still some work to be improved in the future. Firstly, future work should establish a more reasonable DE evaluation index system to comprehensively evaluate the DE development level. Secondly, as data collection improves, the relationship between the DE development level and energy intensity at city

Table 8
Regression results of the re-estimated PSTR model with the DE lagging by one period.

Model			Model 1	Model 2	Model 3	Model 4	Model 5
Conversion variable			Real GDP	UR	STR	R&D	FDI
Explanatory variable: the development level of the DE	β_1	Estimated value	0.9816***	0.9312***	1.1330***	1.2362***	1.1252***
		t statistic	−7.7503	−4.2414	5.2369	−4.4348	−4.0738
	β_2	Estimated value	−0.5631***	−0.8093***	−0.9829***	−0.7312***	−0.6479***
		t statistic	7.4942	3.3779	3.4215	3.9134	3.5268
Influence coefficient	$\beta_1 + \beta_2$		0.4185	0.1219	0.1501	0.5050	0.4773
Positional parameter	c		1.2247	0.5986	0.2690	0.0928	0.3512
Slope coefficient	γ		30.0156	77.0497	6.1893	60.6923	8.3769
Sum of squares of residuals	RSS		11.312	49.438	30.192	49.893	36.264

Notes: ***: Denotes 1% level of significance.

level should be investigated. Thirdly, administrative regulation is an important factor that cannot be ignored when studying Chinese energy and environment issues. However, considering that the administrative regulations are difficult to be quantified, we have not taken it as a transformation variable in this research. In the following research, we will conduct in-depth study on the influence of the administrative regulations on energy consumption issues.

Credit author statement

Haoran Zhao: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft Preparation, and Writing-Review & Editing. Sen Guo: Data curation, Formal analysis, Writing – original draft Preparation, and Writing-Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.128867.

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