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Can industrial agglomeration alleviate energy poverty? Evidence from China

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ABSTRACT

This study determines whether industrial agglomeration can solve energy poverty (ENPO) by applying a provincial dataset (2002–2019) to assess the potential effect of industrial agglomeration on ENPO. Additionally, this study conducts an in-depth exploration of provincial heterogeneity and its influence mechanisms. The conclusions are as follows: ① Industrial agglomeration is negatively correlated with ENPO; by implication, enhancing industrial agglomeration is a driving force for reducing ENPO. ② The alleviating effect of industrial agglomeration on ENPO in the midwestern region is considerably higher than that in the eastern region, and the ENPO alleviation effect of the high agglomeration region is better than that in the low agglomeration region. ③ Foreign investment and energy efficiency have a mediating role, that is, they are valid transmission pathways for industrial agglomeration to solve the ENPO issue. Relevant policy suggestions for reducing ENPO by accelerating industrial agglomeration are proposed by drawing on the above three conclusions.

1. Introduction

Industrial agglomeration refers to the gradual convergence of elements such as capital and labor, a high concentration of industries, and continuous refinement of the social division of labor in specific geographic regions. These are inevitable trends when an industry develops to a particular stage and becomes common in various sectors (Liu et al., 2017; Zheng and Lin, 2018). Since reform and opening-up in 1978, and the subsequent improvement of the economic market system and support for national preferential policies, the spatial agglomeration features of economic factors have become increasingly significant. This is particularly the case in the eastern coastal areas, especially in the Pearl River Delta, Yangtze River Delta, and Jing-Jin-Ji region, where many industrial enterprises are concentrated (Chen et al., 2020). These areas have promoted the formation of a center-edge industrial agglomeration mode (Hong et al., 2020). With the vigorous implementation of strategies such as "The Rise of the Central Region", and "The Development of the Western Region", many central and western regions began to establish industrial parks, causing industries to cluster in specific geographic areas and spreading industrial agglomeration from the southeast coast throughout the entire country. In 2017, the report of the 19th National Congress of the Communist Party of China pointed out that deepening supply-side structural reform requires allocating and adjusting supply-side elements, such as labor, land, capital, and system innovation, and optimizing investment and the financial and industrial structure. In-depth research and the realization of regional industrial agglomeration development will be one of the long-term issues that local governments will face.

Industrial agglomeration facilitates the frequent flow of production factors, and energy, as a particular form of factor input, will inevitably be affected by rapid industrial agglomeration (Tanaka and Managi, 2021). However, as a significant problem that needs to be solved urgently, academics have primarily neglected the influence of industrial agglomeration on energy poverty (ENPO), although establishing the extent of such influence is a significant obstacle in the energy field. ENPO is a considerable obstacle for all economies in attempting to achieve overall poverty alleviation because it severely restricts the sustainable growth of mankind and has inflicted serious harm to the economy, society, and the environment (Burlinson et al., 2021; Crentsil et al., 2019; Li et al., 2022b). As the world's largest developing country, China faces more complex and severe energy chal-

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lenges. With the energy system's deepening reform, complete and extensive electricity coverage has been accomplished, improving the overall ENPO situation (Dong et al., 2021; Lu et al., 2022). Although China has made breakthroughs in alleviating poverty with low-carbon fuels and green cookware, natural gas infrastructure development in rural areas has been hampered by dispersed housing and poor transportation. Moreover, rural households are reluctant to pay high electricity prices and instead use free firewood and straw, making it arduous for rural regions to break free from ENPO (Xia et al., 2022; Zhang et al., 2023; Zhao et al., 2021). The Chinese government is strongly committed to improving people's livelihoods and realizing shared prosperity by eliminating ENPO, taking several policy initiatives to achieve these aims (Qin et al., 2022).

The existing literature approaches ENPO by measuring it (Halkos and Gkampoura, 2021; Okushima, 2016) and investigating its environmental (Hassan et al., 2022), economic (Acharya and Sadath, 2019; Amin et al., 2020), and health effects (Kyprianou et al., 2019; Li et al., 2022a). These studies have achieved significant results. Although the existing literature examines the determinants of ENPO, such as financial development (Nguyen et al., 2021), energy efficiency (Al-Tal et al., 2021; Li et al., 2021a), technological progress (Wang et al., 2022c; Zhao et al., 2022), and digital adoption (Wang et al., 2022b), few scholars have tested the underlying influence of industrial agglomeration on eradicating ENPO. As a frontier trend of conserving resources and improving efficiency, assessing whether rapid industrial agglomeration is an effective solution to China's ENPO provides new directions and evidences for seeking new channels and approaches to eradicate poverty using low-carbon and clean fuels. Accordingly, this study applies provincial data from 2002 to 2019 to quantitatively evaluate the causal link between industrial agglomeration and ENPO. Additionally, this study explores the provincial heterogeneity and transmission pathways of foreign investment and energy efficiency.

This study further supplements the literature on ENPO from three perspectives. First, this study is the first to examine the potential role of continuous industrial agglomeration in achieving comprehensive poverty alleviation in China's energy sector. This investigation addresses the lack of understanding regarding the correlation between industrial agglomeration and ENPO and aims to provide new directions and ideas for solving the ENPO issue. Second, the sample of this study is divided into subsamples to empirically examine the heterogeneous impacts of industrial agglomeration on reducing ENPO. This discussion is conducive to effectively formulating practical policies in different regions to promote initiatives that address ENPO. Third, our study creatively investigates whether FDI and energy efficiency are effective channels for industrial agglomeration to affect ENPO; this is important for exploring the specific mechanism between industrial agglomeration and ENPO.

The remaining sections are organized as follows. The following section thoroughly examines relevant literature and elaborates on the process of industrial agglomeration on ENPO. Section 3 presents the econometric model and sample data, and Section 4 reports the empirical findings and analyzes the intrinsic meanings. The last section concludes with a set of policy recommendations.

2. Influence mechanism and research hypothesis

2.1. Direct effect analysis

The main issue in China with regards to ENPO is the accessibility of renewable energy sources and the capacity to procure electricity. The gradual industrial agglomeration directly affects ENPO through its external effects, which mainly include shared infrastructure, a shared labor market, and economies of scale. First, constructing social infrastructure necessitates allocating substantial resources and energy as an impetus. In contrast, firms located in industrial agglomeration zones can mitigate resource wastage, decrease production costs and share fees, and provide more energy for residents to meet their daily life needs by sharing public infrastructure in the region, effectively alleviating ENPO (Han et al., 2018; Karathodorou et al., 2010).

Second, spatial industrial agglomerations are highly attractive to talent from other regions. Increased industrial agglomeration is often accompanied by improved labor employment, helping to form an efficient, specialized, and high-quality labor market and reducing the search costs of finding suitable labor for businesses in the agglomeration region. The flow of high-quality workers between various companies in the agglomeration region facilitates the spread of new information and technology, enhancing production technology and efficiency. On the one hand, this can significantly save energy and offer ample clean fuel for domestic energy procurement and payment. On the other hand, it can improve labor wages and the ability to purchase clean energy, which will alleviate regional ENPO issues.

Third, several enterprises in agglomeration regions take advantage of their geographical proximity to engage in vertical and horizontal cooperation through joint ventures and alliances, conducting collaborative endeavors such as research and development (R&D), sales, and production, reducing unit production costs and decreasing factor consumption, including energy. Notably, the specialized division of labor brought about by the agglomeration economy makes more energy available for investment in enterprises with higher productivity, enhancing the efficiency of energy allocation, minimizing energy use, and increasing the reserve of energy needed by residents in daily life (Liu et al., 2017). Accordingly, we hypothesize the following.

Hypothesis I: Gradual industrial agglomeration is a vital factor for strengthening poverty alleviation in the energy sector.

2.2. Indirect effect analysis

Recently, experts have discussed the optimal path toward reducing ENPO from an investment perspective. For instance, by reviewing three separate academic governance perspectives, Gregory and Sovacool (2019) analyzed why private enterprises have yet to be enthusiastic about the proposition that the private sector should finance the development of essential electricity capacity in sub-Saharan Africa. Thus, we are interested in exploring further the following questions: Is foreign investment a transmission pathway through which industrial agglomeration influences ENPO? Relevant studies indicate that many factors affect the choice of foreign investment location, among which policy and industrial agglomeration are the primary determinants (Luo et al., 2008). Industrial agglomeration in a host country can significantly decrease production costs and reduce uncertainty, effectively attracting foreign enterprises' investment (Guimarães et al., 2000).

On the one hand, foreign-invested enterprises have brought medium- and high-end technology, advanced management experience, and mechanical equipment to the agglomeration area and renovated existing high-energy facilities under the supervision of foreign investors, enhancing production efficiency, decreasing energy use, and alleviating ENPO. On the other hand, the entry of foreign enterprises intensifies market competition. Enterprises strengthen their investment in innovation to reduce production costs and enhance the competitive advantage, generate green technologies, decrease energy usage, and help mitigate environmental pollution and degradation.

In addition to foreign investments, improving energy efficiency is considered a valid channel through which industrial agglomeration influences ENPO. As Liu et al. (2017) and Tanaka and Managi (2021) highlighted, the technological spillover effect of industrial agglomerations is a crucial determinant of improving energy efficiency. More specifically, the frequent exchanges and cooperation between different enterprises in the industrial agglomeration area and their upstream and downstream enterprises in the industrial chain promote the dissemination of knowledge, technology, and information (Li et al., 2021b). Market competition pressure force enterprises to widely apply technologies in production processes and ensure efficient energy use (Zheng and Lin, 2018). Fylan et al. (2016) and Rosenow et al. (2013) concluded that increasing the energy efficiency reduces the ENPO.

Regarding national economic production, improving energy efficiency often involves reducing energy consumption per unit of output or increasing production per unit of energy. Such measures can reserve more energy for household consumption when demand exceeds supply (Dong et al., 2022). In the context of household life, improving energy efficiency implies that high-carbon energy, such as coal and firewood, can be completely burned, and clean energy, such as electricity, can be vigorously applied, further confirming the positive impact of energy efficiency on reducing ENPO. Accordingly, we hypothesize the following.

Hypothesis II: Introducing FDI and improving energy efficiency are essential transmission mechanisms for continuous industrial agglomeration that will accelerate the alleviation of ENPO.

According to the analysis above, this study presents the specific mechanism of the transmission of rapid industrial agglomeration on ENPO (Figure 1).

3. Model and data

3.1. Model specification

This study identifies the underlying impact of industrial agglomeration on poverty reduction initiatives in the energy industry. This study constructs a multiple econometric model, with industrial agglomeration as the core independent variable and ENPO as the dependent variable for empirical regression, as follows.

$$\mathrm{EPA}_{it} = f(\mathrm{Aggl}_{it}, \mathrm{Pgdp}_{it}, \mathrm{Ind}_{it}, \mathrm{Tec}_{it}, \mathrm{Edu}_{it}, \mathrm{Gap}_{it}) \tag{1}$$

Where, the subscripts of variables i and t represent the cross-sectional unit and time unit, respectively. EPA and Aggl refer to ENPO and industrial agglomeration, respectively. Pgdp, Ind, Tec, Edu, and *Gap* indicate economic growth, industrial upgrading, technological innovation, education level, and income gap, respectively, which are the control variables to alleviate the interference of confounding variables in multiple regression on the estimation results. $f(\cdot)$ denotes the function relation.

Additionally, to drastically eliminate estimation errors caused by heteroscedasticity and data dimension differences, all variables in Equation (1) are logized, as shown in Equation (2).

$$\ln \mathrm{EPA}_{it} = \alpha_0 + \alpha_1 \ln \mathrm{Aggl}_{it} + \sum_{k=2}^{6} \alpha_k \ln \mathrm{Control}_{it} + v_i + \mu_t + \varepsilon_{it} \tag{2}$$

Where, α_0 represents the constant term, and α_i $(i = 1, 2, 3, ..., 6)$ refers to the parameters that require assessment. Control is a vector of Pgdp, Ind, Tec, Edu, and Gap. v_i and μ_t denote individual and time fixed effects, respectively. ε_{it} is a random error term. Continuous industrial agglomeration in China is expected to be an essential solution to ENPO.

As analyzed in Section 2, the potential roles of foreign investment and energy efficiency in industrial agglomerations in affecting ENPO activities. Thus, this study verifies this viewpoint using the mediating effect model to conduct the estimated analysis; the specific models are as follows.

$$\ln M_{it} = \beta_0 + \beta_1 \ln \mathrm{Aggl}_{it} + \sum_{k=2}^{6} \beta_k \ln \mathrm{Control}_{it} + v_i + \mu_t + \varepsilon_{it} \tag{3}$$

$$\ln \mathrm{EPA}_{it} = \xi_0 + \xi_1 \ln \mathrm{Aggl}_{it} + \xi_2 \ln M_{it} + \sum_{k=3}^{7} \xi_k \ln \mathrm{Control}_{it} + v_i + \mu_t + \varepsilon_{it} \tag{4}$$

Where, M represents the mediating variables (i. e., FDI and EE). β_0 and ξ_0 refer to the constant terms. β_i $(i = 1, 2, 3, ..., 6)$ and ξ_i $(i = 1, 2, 3, ..., 7)$ indicate the regression parameters. The variables and other parameters adhere to the equation in Equation (2).

The specific test procedures for the stepwise regression coefficient method of the mediating effect model are as follows.

(1) This study first estimates Equation (2) to test the total effect of gradual industrial agglomeration on ENPO in the absence of mediating variables; that is, it verifies whether the industrial agglomeration coefficient in Equation (2) is significant. Thus, Equations (3) and (4) can be further tested.

(2) The second step estimates Equations (3) and (4). Notably, the indirect impact of industrial agglomeration on ENPO is established for the test coefficients of industrial agglomeration in Equation (3) (i.e., β_1), and the mediating variable (i.e., ξ_2) is simultaneously significant in Equation (4). The industrial agglomeration coefficient in Equation (4) also shows a direct effect.

3.2. Variable selection

3.2.1. Dependent variable

The variable energy poverty (denoted as EPA) was measured using a composite index comprising four aspects (i.e., accessibility, completeness, cleanliness, and affordability). It was obtained following the work of Zhao et al. (2022). The specific indicators are shown in Figure 2. Using the enhanced entropy method, the subindexes of ENPO—accessibility index (EPA_1), completeness index (EPA_2), cleanliness index (EPA_3), and affordability index (EPA_4)—are also obtained. On this basis, this study further plotted the time trend and

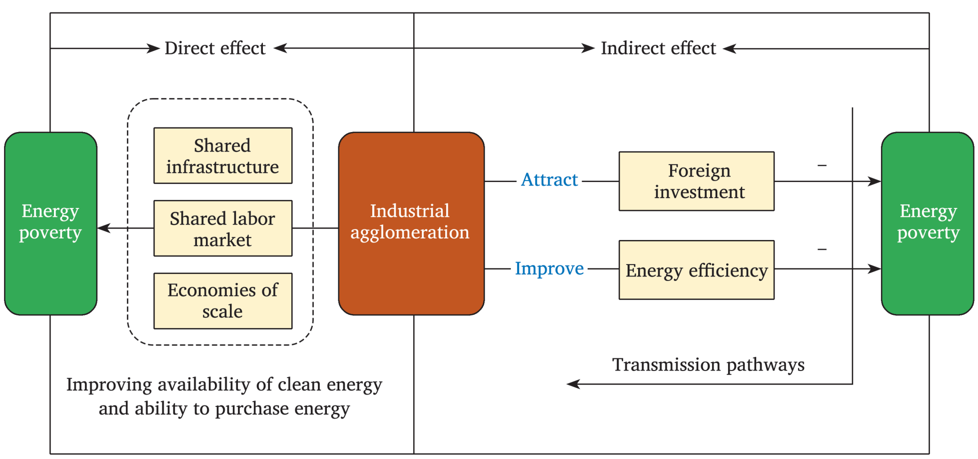

Figure 1. The influence mechanism between industrial agglomeration and ENPO

spatial pattern of ENPO in Figure 3. Obviously, China's initiatives to address the ENPO problem have made outstanding progress during the sample period, and have alleviated the energy problem to a certain extent.

3.2.2. Independent variable

The measures of the industrial agglomeration (denoted as Aggl) have been the subject of considerable research, and using proxies for industrial agglomeration exhibits significant differences. This study applies Chen et al.' s (2019) location entropy to gauge the industrial agglomeration level, which is shown in Equation (5) as follows.

$$\mathrm{Aggl}_{it} = \frac{I_{it}/I_t}{L_{it}/L_t} \tag{5}$$

Where, Aggl represents the industrial agglomeration level, and I_{it} and I_t indicate the number of employees in the urban units of the manufacturing industry in province i and the whole country in year t, respectively. L_{it} denotes the number of urban unit employees in all industries in province i at year t, whereas L_t denotes the number in the entire country at year t. Based on this equation, we obtain the level of industrial agglomeration in China's 30 provinces from 2002 to 2019.

3.2.3. Mediating variable

Energy efficiency (denoted as EE) is a mediating variable. Numerous scholars have supported the active role of energy efficiency in solving ENPO (Fylan et al., 2016; Rosenow et al., 2013). As an effective determinant, this variable is measured by the ratio of the total consumption of the fossil-energy-transformed standard coal based on the conversion coefficient used in primary energy use.

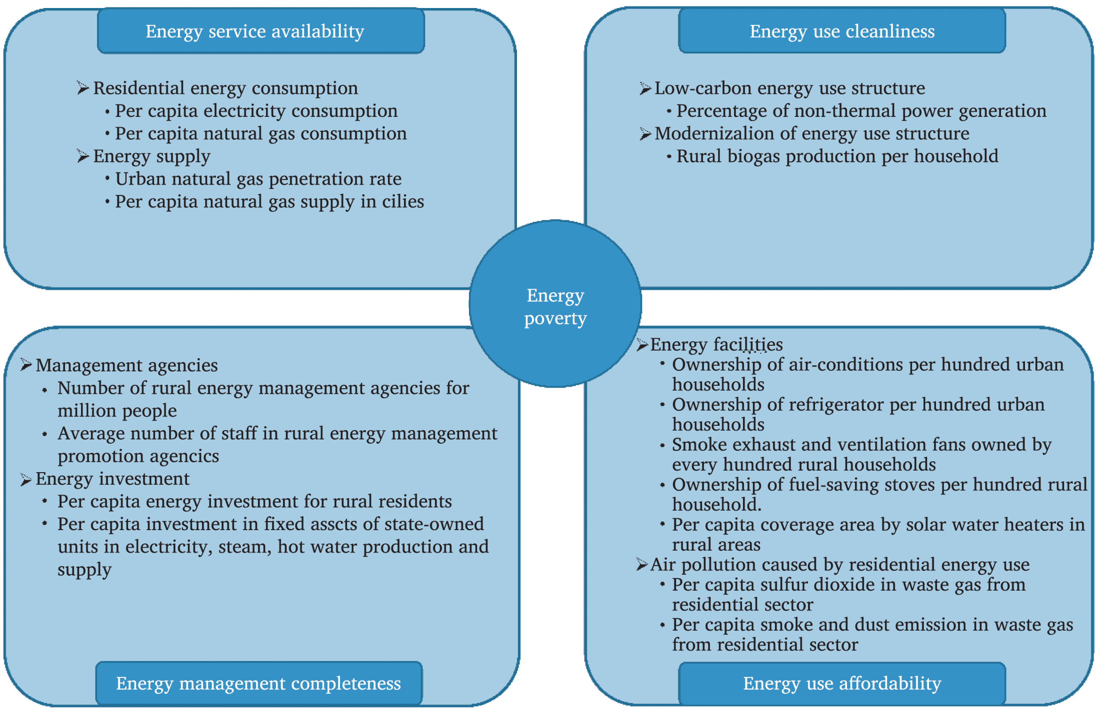

Figure 2. The specific indicators of China's ENPO

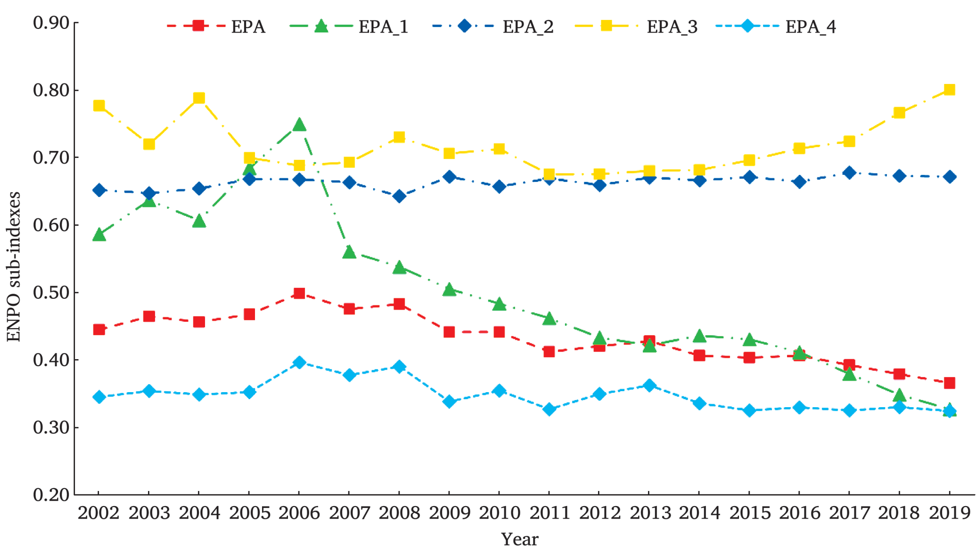

Figure 3. The time trend chart of ENPO and its sub-indexes

Foreign investment (FDI) is a mediating variable. The accelerated pace of foreign investment provides capital and technical support to facilitate the growth of China's emerging energy sector, creating more job opportunities for residents and improving households' ability to purchase clean fuel and kitchenware. Thus, the empirical model incorporates this indicator, which is assessed by the aggregate investment of foreign-invested businesses.

3.2.4. Control variable

Regarding the control variables, economic growth (denoted as Pgdp) is primarily used per capita gross domestic product in each province. Industrial upgrading (expressed as Ind) is assessed by comparing the output value of tertiary industry to that of secondary industry, technological innovation (indicated as Tec) is approximated by the number of authorized domestic patent applications, education level (expressed as Edu) is surrogated by the proportion of students in high school or above in the total population, and income gap (denoted as Gap) applies mainly to the ratio of urban residents' disposable income to rural residents' disposable income.

3.3. Data sources and correlation analysis

This study employs a sample dataset from China's 30 provinces (Data from Hong Kong, Macao and Taiwan, as well as Xizang are excluded). The dataset covers the period from 2002 to 2019. ENPO data are mainly from the *China Energy Statistical Yearbook* (CESY, 2020), the *China Population and Employment Statistical Yearbook* (CPESY, 2020), and the *China Statistical Yearbook* (CSY, 2020), whereas the statistical data on energy efficiency are from CESY (2020). CSY (2020) provides data on foreign investments and all the control variables. The detailed definitions and statistical information about the variables are presented in Table 1.

Before performing the official benchmark regression study on the connection between industrial agglomeration and ENPO, conducting correlation analysis on the variables is imperative to avoid estimation distortion or difficulty in accurate estimation caused by multicollinearity. Table 2 lists the results of correlation analysis, suggesting that industrial agglomeration, economic growth, industrial upgrading, technological innovation, and education adversely affect ENPO. This provides preliminary evidence of the nexus between variables.

This study carefully calculates the independent variables' variance inflation factor (VIF) to further examine whether the model has multicollinearity problems (Table 2). If the test value of VIF is greater than 10, the severe multicollinearity among the explanatory variables significantly affects the parameter estimate of the regression equation, affecting the empirical results quantitatively and qualitatively. The VIF statistical test values in Table 2 are all below 10, implying that the model does not have serious multicollinearity problems.

Table 1
Definitions and descriptive statistics of the selected variables

Categories	Variables	Definitions	Obs.	Mean	Std. Dev.	Minimum	Maximum
Explained variable	ln EPA	Energy poverty alleviation gauged by the composite index	540	−0.904 3	0.373 7	−1.997 3	−0.119 7
Explanatory variable	ln Aggl	Industrial agglomeration assessed by the location quotient based on manufacturing employment	540	−0.221 9	0.397 4	−1.226 8	0.603 2
Mediation variables	ln EE	Energy efficiency measured by the ratio of GDP to primary energy use in each province	540	−0.298 7	0.546 4	−1.609 6	1.016 2
	ln FDI	Foreign investment gauged by the total investment of foreign-invested enterprises	540	10.604 0	1.515 7	6.551 1	14.485 0
Control variables	ln Pgdp	Economic growth measured by the per capita GDP	540	0.997 2	0.769 1	−1.126 8	2.784 1
	ln Ind	Industrial upgrading gauged by the ratio of the output value of the tertiary industry to that of the secondary industry	540	0.058 7	0.372 1	−0.640 5	1.655 2
	ln Tec	Technological evolution measured by the number of authorized domestic patent applications	540	9.081 0	1.711 1	4.248 5	13.175 7
	ln Edu	Education level assessed by the proportion of students in high school or above in the total population	540	−4.197 1	0.461 3	−5.745 3	−3.245 6
	ln Gap	Income gap measured by the ratio of urban residents' disposable income to rural residents' disposable income	540	0.647 5	0.109 1	−0.552 5	0.901 9

Table 2
Test results for multicollinearity and correlation checks

Variables	VIF	ln EPA	ln Aggl	ln Pgdp	ln Ind	ln Tec	ln Edu	ln Gap
ln EPA		1.000 0						
ln Aggl	1.77	−0.484 7* (0.000 0)	1.000 0					
ln Pgdp	5.98	−0.532 0* (0.000 0)	0.165 2* (0.000 1)	1.000 0				
ln Ind	1.59	−0.276 2* (0.000 0)	−0.378 5* (0.000 0)	0.380 1* (0.000 0)	1.000 0			
ln Tec	4.06	−0.626 8* (0.000 0)	0.479 3* (0.000 0)	0.780 5* (0.000 0)	0.088 8* (0.039 1)	1.000 0		
ln Edu	2.81	−0.353 0* (0.000 0)	0.150 9* (0.000 4)	0.797 2* (0.000 0)	0.233 6* (0.000 0)	0.621 7* (0.000 0)	1.000 0	
ln Gap	1.13	−0.019 8 (0.646 0)	−0.058 8 (0.172 5)	0.182 3* (0.000 0)	0.228 5* (0.000 0)	−0.013 6 (0.752 8)	0.099 3* (0.021 1)	1.000 0

Notes: * refers to $P < 0.10$; P values are in parentheses.

4. Empirical finding

4.1. Benchmark estimate

Table 3 presents the empirical findings of industrial agglomeration on eradicating ENPO based on the pooled ordinary least squares, fixed effect, system generalized method of moments (Sys-GMM), instrumental variable-GMM (IV-GMM), and approaches simultaneously. This table shows that the coefficient of industrial agglomeration (i.e., ln Aggl) is significantly negative regardless of whether control variables are added. This suggests that the continued agglomeration of various industries is a powerful solution to the problem of ENPO.

Endogeneity issues are often encountered when estimating regression models (Liu et al., 2021). As Ullah et al. (2021) highlighted, endogeneity occurs when one or more explanatory variables in a model are correlated with a random disturbance term. Omitted variables, measurement errors, and interactions between explanatory and explained variables typically generate this correlation. This leads to inconsistency and bias in the estimation results. In this case, the IV-GMM method has become an effective strategy for many scholars to deal with endogenous issues. In the last column, the statistical values of the Kleibergen–Paap rk LM test are significant at the 1% level. In contrast, those of the Kleibergen–Paap rk Wald *F* test are significantly larger than the critical value (i.e., 19.93) of the Stock–Yogo test at the 10% level. This suggests that the results of the IV-GMM method can be utilized as benchmark estimates.

Table 3 shows that the coefficient of industrial agglomeration is −0.459, indicating statistical significance at the 1% level. There are three possible reasons for the negative industrial agglomeration – ENPO nexus. First, industrial agglomeration will prompt similar enterprises to gather in specific areas, forming a large-scale supply market, saving fixed costs through infrastructure sharing, reducing variable costs through the mutual provision of complementary products and production factors, and increasing the proportion ratio of industrial output value in a virtuous circle, while impeding the progress of energy intensity (Wang et al., 2022a). Second, rapid industrial agglomeration brings enterprises closer geographically, reducing learning costs (Zhang et al., 2016). Additionally, learning about and imitating similar enterprises can decrease innovation costs, maintain competitive advantages, improve enterprises' technological imitation and innovation capabilities, and reduce total energy use through benign interaction between enterprises. This viewpoint is supported by Liu et al. (2017). Third, accelerated industrial agglomeration can facilitate the gradual evolution of labor-intensive industries into knowledge- and capital-intensive industries, with production factors increasingly flowing into sectors with higher energy utilization efficiency, bolstering the entire process of poverty reduction in the energy sector.

The regression results of the control variables show that the coefficients of economic growth, industrial upgrading, and technological

Table 3
Results of the benchmark regression

Dep. Var.	POLS estimate		FE estimate		Sys-GMM estimate		IV-GMM estimate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA
L.ln EPA					1.016^{***} (0.024)	0.855^{***} (0.060)		
ln Aggl	-0.456^{***} (0.044)	-0.453^{***} (0.035)	-0.298^{***} (0.035)	-0.309^{***} (0.043)	−0.004 (0.028)	-0.090^{***} (0.025)	-0.474^{***} (0.046)	-0.459^{***} (0.038)
ln Pgdp		-0.094^{***} (0.031)		-0.177^{***} (0.049)		-0.047^{***} (0.009)		-0.085^{**} (0.033)
ln Ind		-0.409^{***} (0.035)		-0.374^{***} (0.041)		-0.067^{***} (0.021)		-0.410^{***} (0.039)
ln Tec		-0.066^{***} (0.013)		-0.081^{***} (0.012)		−0.004 (0.009)		-0.062^{***} (0.013)
ln Edu		0.122^{***} (0.036)		0.142^{***} (0.042)		0.019^{*} (0.011)		0.085^{**} (0.040)
ln Gap		0.209 (0.149)		0.337^{***} (0.121)		0.076 (0.131)		0.150 (0.151)
_Cons	-1.005^{***} (0.014)	0.087 (0.239)	-0.970^{***} (0.014)	0.341 (0.234)	−0.002 (0.024)	−0.046 (0.140)	-1.021^{***} (0.015)	−0.069 (0.247)
Region fixed effect	No	No	Yes	Yes				
Time fixed effect	No	No	Yes	Yes				
AR(1)					−4.340 [0.000]	−3.990 [0.000]		
AR(2)					−0.190 [0.849]	−0.240 [0.813]		
Hansen test					29.360 [0.980]	24.950 [0.995]	0.633 [0.426]	0.268 [0.605]
Kleibergen-Paap rk LM statistic							180.458 [0.000]	173.006 [0.000]
Kleibergen-Paap rk Wald *F* statistic							16 000 {19.93}	9 415.395 {19.93}
R-squared	0.235	0.583	0.484	0.623			0.252	0.599
Obs.	540	540	540	540	510	510	480	480

Notes: ***, **, and * refers to $P < 0.01$, $P < 0.05$, and $P < 0.10$, respectively; robust Std. Err. is in parenthesis; *P* values are in brackets; the critical values are in braces.

innovation are significantly negative, while education level and income gap are positively associated with ENPO. Thus, achieving rapid economic growth, strengthening industrial optimization and transfer, and accelerating industrial technical innovation are effective measures for addressing ENPO. Furthermore, the positive income gap–ENPO nexus suggests that narrowing the income gap effectively alleviates ENPO; thus, government policies can accomplish the combined objectives of diminishing income disparities and reducing ENPO. The positive effect of the improved education level on ENPO is contrary to our expectations and may be caused by the active role of education.

4.2. Sensitivity check

4.2.1. Applying the alternative method

In addition to using Sys-GMM and IV-GMM strategies to deal with endogenous issues, selecting an appropriate instrumental variable is also a valid measure to address this problem. These instrumental variables are called the two-stage least squares (2SLS) estimators. The instrumental variables should correlate with the endogenous variables while remaining uncorrelated with the residual term (Thomas et al., 2020). Additionally, selecting lagged first-order terms of explanatory variables for estimation can also somewhat solve the endogeneity problem. Thus, Table 4 simultaneously presents the regression results of these two approaches. In the 2SLS estimator, the IV estimation utilizes the share of local fiscal expenditure as the instrumental variable. Notably, the underidentification and weak identification of the instrumental variable tests must be performed to check the IV technique's validity. These two findings suggest that the null hypotheses of under identification and weak identification of the instrumental variables are significantly rejected in the 2SLS regression, confirming the reliability and validity of the instrumental variable selection.

The regression coefficient of L.ln Aggl in Column (2) of Table 4 is −0.301. These data demonstrate that even after correctly addressing endogeneity, industrial agglomeration's impact continues to be negative. In other words, regardless of whether the endogenous issues in the estimation process are solved, industrial agglomeration continues to influence reaching the policy alleviation targets in China's energy sector, further confirming the role of rapid industrial agglomeration in addressing households' difficulty in accessing or affording clean energy. The discussion also verifies this conclusion using the lagged first-order term of industrial agglomeration as an explanatory variable.

Table 4
Results of addressing endogenous problems

Dep. Var.	Using lag first-order term		2SLS estimation	
	(1)	(2)	(3)	(4)
	ln EPA	ln EPA	ln EPA	ln EPA
L.ln Aggl	-0.305^{***} (0.036)	-0.301^{***} (0.045)		
ln Aggl			-0.629^{***} (0.056)	-1.021^{***} (0.084)
_Cons	-0.973^{***} (0.014)	0.303 (0.243)	-1.044^{***} (0.019)	-0.952^{***} (0.290)
Kleibergen-Paap rk LM			225.682 [0.000]	136.839 [0.000]
Kleibergen-Paap rk Wald *F*			386.288 {16.38}	180.908 {16.38}
Control variables	No	Yes	No	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R-squared	0.493	0.630	0.8837	0.9093
Obs.	510	510	540	540

Notes: *** refers to $P < 0.01$; robust Std. Err. is in parenthesis; *P* values are in brackets; the critical values are in braces.

4.2.2. Using proxy variables for energy poverty

The study further identifies whether the negative industrial agglomeration-ENPO is robust by reestimaing Equation (2) and replacing the EPA into four subindexes: EPA_1, EPA_2, EPA_3, and EPA_4 (Table 5). In addition to the coefficient of ln Aggl in Column (1) being insignificant, the coefficients of ln Aggl in “2” to “8” are also all significantly negative. This indicates that the research conclusion derived from the benchmark regression remains true after replacing the explained variables, proving that industrial agglomeration's role in alleviating ENPO is stable.

Table 5
Robust results of using proxy variables for ENPO

Dep. Var.	FE estimate				IV-GMM estimate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln EPA_1	ln EPA_2	ln EPA_3	ln EPA_4	ln EPA_1	ln EPA_2	ln EPA_3	ln EPA_4
ln Aggl	−0.021 (0.052)	-0.276^{***} (0.067)	-0.480^{***} (0.060)	-0.518^{***} (0.082)	-0.337^{***} (0.055)	-0.099^{*} (0.052)	-0.325^{***} (0.060)	-0.810^{***} (0.072)
_Cons	0.693^{**} (0.283)	1.077^{***} (0.362)	-1.776^{***} (0.326)	1.913^{***} (0.448)	0.118 (0.318)	1.956^{***} (0.311)	-1.840^{***} (0.310)	0.889^{*} (0.481)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes				
Time fixed effect	Yes	Yes	Yes	Yes				
R-squared	0.764	0.375	0.491	0.569	0.688	0.210	0.444	0.532
Kleibergen-Paap rk LM statistic					173.006 [0.000]	173.006 [0.000]	173.006 [0.000]	173.006 [0.000]
Kleibergen-Paap rk Wald *F* statistic					9 415.395 {19.93}	9 415.395 {19.93}	9 415.395 {19.93}	9 415.395 {19.93}
Hansen test					2.837 [0.092]	0.733 [0.392]	0.418 [0.518]	0.156 [0.693]
Obs.	540	540	540	540	480	480	480	480

Notes: ***, **, and * refers to $P<0.01$, $P<0.05$, and $P<0.10$, respectively; robust Std. Err. is in parenthesis; *P* values are in brackets; the critical values are in braces.

Table 5
Robust results of excluding the shock of the 2008 financial crisis

Dep. Var.	FE estimate		IV-GMM estimate	
	(1)	(2)	(3)	(4)
	ln EPA	ln EPA	ln EPA	ln EPA
ln Aggl	−0.400*** (0.037)	−0.311*** (0.047)	−0.462*** (0.053)	−0.467*** (0.042)
_Cons	−0.950*** (0.015)	0.367 (0.283)	−1.037*** (0.017)	0.105 (0.272)
Control variables	No	Yes	No	Yes
Region fixed effect	Yes	Yes		
Time fixed effect	Yes	Yes		
Kleibergen-Paap rk LM statistic			149.235 [0.000]	146.220 [0.000]
Kleibergen-Paap rk Wald *F* statistic			11 000 {19.93}	6948.837 {19.93}
Hansen test			0.539 [0.463]	0.785 [0.376]
R-squared	0.469	0.570	0.887	0.940
Obs.	468	468	390	390

Notes: *** refers to $P < 0.01$; robust Std. Err. is in parenthesis; P values are in brackets; the critical values are in braces.

4.2.3. Excluding the 2008 financial crisis shock

To our knowledge, the global financial crisis of 2008 that led to economic stagnation and reduced consumer demand severely impacted residents' everyday lives (Brem et al., 2020; Jensen and Johannesen, 2017). As one of the most engaged countries in the world, China has been widely affected by the financial crisis (Liu, 2009). To eliminate the constraining impact of the financial crisis on the nexus between industrial agglomeration and ENPO, this study removes 2008 from the regression (Table 5). The coefficients of ln Aggl in the equation have a similar meaning and importance to those listed in Table 3, providing sufficient evidence for the validity of the benchmark regression findings.

4.2.4. Removing the interference of the abrupt value

In the estimation process, the more prominent special values in the sample data will cause the estimation results to vary (Yang and Greaney, 2017). The provincial-level municipalities of Shanghai, Beijing, Tianjin, and Chongqing's provincial-level municipalities are at the forefront of China's evolution and development. To this end, this study reestimates the correlation between industrial agglomeration and ENPO using the whole sample, excluding the statistics of four municipalities. Table 7 shows the empirical results. From the signals and statistical significance of the coefficients related to industrial agglomeration presented in Table 7, we conclude that the benchmark estimates are robust.

5. Further discussion

5.1. Influence mechanism analysis

The transmission mechanism analyzed in Section 2 suggests that continuous industrial agglomeration, whereas directly helping alleviate poverty in the energy sector through shared facilities and labor markets, can further accelerate eradicating ENPO by strengthening foreign investment and enhancing energy efficiency. Based on the equations constructed in Section 3.1, Table 8 presents the empirical findings of the mediation analysis.

The table presents the statistical values of the Sobel test for foreign investment and energy efficiency, which are 0.099 2 and 0.095 1, respectively. These values are significant at the 1% level, suggesting that foreign investment and energy efficiency have a mediating role. Specifically, the estimated coefficients of industrial agglomeration (i. e., ln Aggl) in Columns (1) and (2) are significantly negative and positive, respectively, while that of foreign investment (i. e., ln FDI) is negative. These empirical findings indicate that the high industrial concentration in geographic areas and the continuous convergence of industrial factors in the spatial scope attract foreign investment and establish a solid financial foundation for technological innovation and China's rapid transition of its energy industry, providing an effective and influential path for poverty reduction. Additionally, similar to the transmission channel of foreign investment, the regression parameters for industrial agglomeration (i. e., ln Aggl) in Columns (1) and (4) are −0.452 7 and 0.239 8, respectively. The actual impact of energy efficiency on ENPO in Column (5) is significantly negative, energy efficiency has an effective mediating role. Industrial agglomeration enables enterprises to be closer geographically, facili-

Table 7
Robust results of removing the interference of abrupt values

Dep. Var.	POLS estimate		FE estimate		IV-GMM estimate	
	(1)	(2)	(3)	(4)	(5)	(6)
	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA	ln EPA
ln Aggl	−0.523*** (0.042)	−0.455*** (0.040)	−0.400*** (0.037)	−0.311*** (0.047)	−0.534*** (0.044)	−0.466*** (0.043)
_Cons	−0.980*** (0.015)	0.221 (0.295)	−0.950*** (0.015)	0.367 (0.283)	−0.994*** (0.016)	0.100 (0.312)
Control variables	No	Yes	No	Yes	No	Yes
Region fixed effect	Yes	Yes	Yes	Yes		
Time fixed effect	Yes	Yes	Yes	Yes		
Kleibergen-Paap rk LM statistic					148.430 [0.000]	127.771 [0.000]
Kleibergen-Paap rk Wald *F* statistic					14 000 {19.93}	7 948.708 {19.93}
Hansen test					0.650 [0.420]	0.002 [0.961]
R-squared	0.339	0.536	0.492	0.593	0.906	0.933
Obs.	468	468	468	468	416	416

Notes: *** refers to $P < 0.01$; robust Std. Err. is in parenthesis; P values are in brackets; the critical values are in braces.

Table 8
Estimated results of internal impact mechanism

Dep. Var.	Total effect	Foreign investment		Energy efficiency	
	(1)	(2)	(3)	(4)	(5)
	ln EPA	ln FDI	ln EPA	ln EE	ln EPA
ln Aggl	−0.453*** (0.035)	1.234*** (0.087)	−0.354*** (0.040)	0.240*** (0.047)	−0.358*** (0.031)
ln FDI			−0.080*** (0.017)		
ln EE					−0.397*** (0.028)
_Cons	0.087 (0.212)	7.291*** (0.529)	0.673*** (0.242)	−1.575*** (0.282)	−0.538*** (0.185)
Control variables	Yes	Yes	Yes	Yes	Yes
Region fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Sobel test		−0.099*** (0.022)		−0.095*** (0.020)	
Proportion of total effect that is mediated		21.91%		21.02%	
R-squared	0.583	0.842	0.600	0.654	0.700
Obs.	540	540	540	540	540

Notes: *** refers to $P < 0.01$; robust Std. Err. is in parenthesis.

Table 9
Estimated results of heterogeneous analysis

Dep. Var.	Geographic heterogeneity		Agglomeration heterogeneity	
	(1)	(2)	(3)	(4)
	Eastern region	Midwestern region	Low-Aggl region	High-Aggl region
	ln EPA	ln EPA	ln EPA	ln EPA
ln Aggl	−1.249*** (0.224)	−1.279*** (0.212)	−1.206*** (0.174)	−1.701*** (0.366)
_Cons	−0.113 (0.458)	0.603* (0.362)	−0.328 (0.363)	−3.118*** (0.880)
Kleibergen-Paap rk LM	36.067 [0.000]	32.437 [0.000]	67.451 [0.000]	22.505 [0.000]
Kleibergen-Paap rk Wald F	42.542 {16.38}	35.102 {16.38}	94.899 {16.38}	23.662 {16.38}
Control variables	Yes	Yes	No	Yes
Region fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
R-squared	0.934	0.897	0.947	0.825
Obs.	198	342	216	324

Notes: *** and * denote $P < 0.01$ and $P < 0.10$; robust Std. Err. is in parenthesis; P values are in brackets; the critical values are in braces.

tating significant interactions between businesses and market competitiveness, compelling these businesses to engage in technical innovation. Industrial agglomeration also encourages enterprises to learn through imitation to retain market share, promote and expand environmental protection and energy conservation industries, and contribute to improving energy efficiency.

5.2. Heterogeneity analysis

5.2.1. Geographic heterogeneity

The previous sections emphasize the importance of the impact of industrial agglomeration on addressing ENPO in the benchmark regression analysis, concluding that industrial agglomeration has a significant and beneficial function. However, the benchmark regression aims to assess the potential significance of industrial agglomeration on the decrease in fuel poverty in China in the context of the country's objective of alleviating comprehensive poverty. Given the variations in physical topography, resource conditions, and industrial focus among different provinces in China, it is not feasible to confirm the positive role of industrial agglomeration from only a holistic perspective. Consequently, this study aims to determine whether industrial agglomeration and ENPO show significant heterogeneity across different regions. Thus, the whole sample is divided into the eastern and the midwestern regions. The specific provinces in these categories are listed in Table A1.

The empirical findings are presented in Table 9. The coefficients of industrial agglomeration are negative in the eastern and midwestern regions; however, the estimated parameter of industrial agglomeration in the midwestern area is slightly larger than that in the eastern area. This may be because the eastern region is relatively low in ENPO, influenced by its favorable geographical location and robust economic foundation. In contrast, the midwestern region has a relatively high ENPO. Moreover, increased population density resulting from industrial concentration in the eastern region will lead to fierce competition among enterprises and a prominent technology imitation effect. However, industries in the midwestern region are experiencing significant growth, and enterprises' enthusiasm for innovation is high, improving energy consumption efficiency and alleviating poverty in the energy industry.

5.2.2. Agglomeration heterogeneity

In reality, the development level of industrial agglomeration varies across different regions. Therefore, considering that the influence of industrial agglomeration on ENPO might differ depending on the extent of industry clustering, the overall sample is subdivided into two subsamples of high industrial agglomeration region (High-Aggl region) and low industrial agglomeration region (Low-Aggl region) for empirical regression. The results are displayed in Table 9. The coefficients of industrial agglomeration in the High-Aggl and Low-Aggl regions are notably negative, suggesting that the concentration of companies effectively decreases ENPO. This finding further supports the benchmark results' reliability.

6. Conclusion and policy implication

Our study empirically investigate the underlying role of industrial agglomeration in reducing ENPO by applying statistical data from China's 30 provinces from 2002 to 2019. We also explore whether the effects of industrial agglomeration on ENPO differ across various provinces and the mediating roles of foreign investment and energy efficiency. The main findings of this study are summarized as follows.

(1) Rapid industrial agglomeration hurts ENPO. In other words, the actual findings from the benchmark regression show that the coefficient of industrial agglomeration is significantly harmful. Four sensitivity checks further verify this conclusion.

(2) Industrial agglomeration negatively correlates with ENPO in both the eastern and midwestern regions, and its impact on ENPO in the midwestern region is stronger and more pronounced in the eastern region. Moreover, accelerated industrial agglomeration effectively alleviates ENPO in both the low-Aggl and high-Aggl regions, and the mitigating impact of industrial agglomeration in the high-Aggl region on ENPO is higher than that of the low-Aggl region.

(3) The empirical findings from the mediating analysis establishes a mediating role of foreign investment and energy efficiency. The continuous convergence and concentration of various industries, while directly reducing ENPO, foreign investment, and energy efficiency, will further strengthen the total poverty eradication in the energy industry.

Based on the findings mentioned above, a series of policy recommendations are subsequently proposed.

First, the negative relationship between industrial agglomeration and ENPO shows that it is crucial to solve the ENPO problem by enhancing it. More specifically, all provinces should take the market as a guide, speed up concentrating high-standard industrial parks, establish and improve relevant supporting facilities, formulate and issue preferential policies to attract powerful enterprises, and simplify enterprises' entry procedures and processes, triggering the cluster effect of industrial parks. Additionally, fully harnessing the positive impact of gradual industrial agglomeration, local governments should prioritize developing high-quality industries, reject low-quality and blind clustering, and overcome obstacles that impede the movement of production factors, such as regional protectionism and market fragmentation, and focus on matching development among enterprises.

Second, the empirical conclusions of the heterogeneity analysis imply that significant provincial heterogeneity exists in different provinces. The impact of industrial agglomeration on ENPO in the midwestern and high-Aggl regions is more significant. Thus, when local governments aim to formulate strategies or measures to promote the continuous agglomeration of regional industries, they should combine the region's unique characteristics and the leading sectors to offer preferential policies and capital subsidies for industrial agglomeration following local conditions and establish relevant enterprise clusters. Moreover, local governments should protect innovative achievements through intellectual property rights and special publications, guide healthy competition among enterprises, and actively create a healthy competitive industrial environment. Furthermore, enhancing the efficacy of the government service function, boosting the construction of relevant facilities, changing the current situation in which enterprises in traditional high-tech development zones cannot form effective industrial chains, emphasizing the regional agglomeration and industrial collaboration of related enterprises, realizing economies of scale and intensive production, effectively improving the energy efficiency of enterprises, and alleviating issues of insufficient supply and excessive payment in the field of energy is imperative

Third, the findings on the mediating impact indicate that foreign investment and energy efficiency are effective for reducing ENPO through industrial agglomeration. In other words, attracting foreign investment and improving energy efficiency are the driving forces to solve the issue of ENPO. Therefore, local governments must persist in implementing diverse favorable policies to intensify their efforts to attract foreign investment. Simultaneously, they should raise the environmental entry threshold for foreign investment and limit the entry of foreign enterprises with high pollution and energy use. Finally, promoting technology diffusion through business cooperation and increasing the R&D of environmentally friendly technologies is imperative, thereby improving energy utilization efficiency.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A.

Table A1
The specific provinces of the different categories

Category	Provinces
Eastern region (11 provinces)	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Midwestern region (19 provinces)	Shanxi, Inter Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
Low-Aggl region (18 provinces)	Beijing, Hebei, Shanxi, Inter Mongolia, Heilongjiang, Anhui, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
High-Aggl region (12 provinces)	Tianjin, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Fujian, Jiangxi, Shandong, Henan, Hubei, Guangdong

Table A2
Abbreviation list

Abbreviations	Full name
CESY	*China Energy Statistical Yearbook*
CPESY	*China Population and Employment Statistical Yearbook*
CSY	*China Statistical Yearbook*
ENPO	Energy poverty
FE	Fixed effect
GDP	Gross domestic product
IV	Instrumental variable
IV-GMM	Instrumental variable-Generalized method of moments
OLS	Ordinary least squares
R&D	Research and development
2SLS	Two stage least squares
Sys-GMM	System generalized method of moments
VIF	Variance inflation factor