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How heterogeneous industrial agglomeration impacts energy efficiency subject to technological innovation:Evidence from the spatial threshold model☆

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ABSTRACT

The relationship between industrial agglomeration (IA) and energy efficiency (EE) is significant for China to promote high-quality urban economic development and achieve China's dual carbon goals. Since technological innovation (TI) and green TI (GTI) are vital elements in the evolution of socioeconomic change and green development, this study employs a spatial threshold model to explore the technology innovation dependency of the influence of heterogeneous IA on EE based on prefecture-level city panel data of the manufacturing sector from 2006 to 2014 in China. This study finds that diversified IA (DIA) has a spatial threshold impact on EE subject to TI or GTI, while specialized IA (SIA) does not. DIA has significant positive direct, spillover, and overall effects on EE at the high TI and GTI thresholds. The distance attenuation feature is evident in the spatial spillover effect of DIA on EE. DIA impacts EE through its spatial effects on labor pooling, knowledge spillovers, and input sharing. The findings offer insights into the development of IA patterns and the enhancement of EE.

1. Introduction

In the context of China's dual pressures of economic growth demands and environmental conservation challenges, promoting energy efficiency is essential for sustainable development (Gao et al., 2022). Over the past 12 years, China has remained the world's largest consumer of primary energy, with its consumption rising from 1.47 billion tons of standard coal in 2000 to 5.41 billion tons in 2022, marking a compound annual growth rate of 6.10% (National Bureau of Statistics, 2000, 2022). As energy consumption continues to rise, the urgency to enhance energy efficiency has become paramount. Studies have shown that industrial agglomeration significantly contributes to improving energy efficiency by facilitating the pooling of resources and collective innovation, offering a strategic pathway to optimize energy use. The government has committed to supporting the development and application of energy-efficient technologies within industrial clusters through financial backing from national science and technology plan projects and innovation fund projects.

The interaction between industrial agglomeration and energy efficiency has garnered extensive global attention, supported by numerous empirical studies exploring this complex relationship (Otsuka et al., 2014; Zhao and Lin, 2019; Tanaka and Managi, 2021; Peng et al., 2023). Researchers have enriched the analysis by considering additional variables such as technological innovation, energy usage rates, patterns of agglomeration, and changes in industrial structure, either as moderating or threshold factors (Liu et al., 2022; Peng et al., 2023). Technological innovation, especially in green technologies, often leads to the development of more efficient production processes and machinery, reducing energy consumption per unit of output. It is crucial to investigate whether technological and green technological innovations play significant roles in shaping how industrial agglomerations impact energy efficiency. Additionally, agglomeration externalities such as labor

Abbreviations: DEA, data envelopment analysis; DIA, diversified industrial agglomeration; EE, energy efficiency; GTFEE, green total-factor energy efficiency; GTI, green technological innovation; IA, industrial agglomeration; PTM, panel threshold model; SBM, slacks-based measure; SDM, spatial Durbin model; SFA, stochastic frontier approach; SIA, specialized industrial agglomeration; TI, technological innovation; TFEE, total-factor energy efficiency..

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pooling, input sharing, and knowledge spillover have been extensively studied (Marshall, 1890; Glaeser et al., 1992; Rosenthal and Strange, 2001; Duranton and Puga, 2004; Jofre-Monseny et al., 2011; Faggio et al., 2020). The applicability of these externalities to the effects of industrial agglomeration on energy efficiency remains an area for further exploration, especially since the manufacturing sector is traditionally one of the most energy-intensive industries.

Given these considerations, the primary objective of this study is to explore the relationship between industrial agglomeration and energy efficiency, particularly focusing on how technological innovation and green technological innovation influence this dynamic. The study also aims to analyze the differences in the impacts of diversified and specialized industrial agglomeration on energy efficiency. To achieve this goal, the research initially employs a panel threshold model, using technological innovation and green technological innovation as threshold variables, to investigate the presence of threshold effects and examine the differences. This paper then explores whether both diversified and specialized industrial agglomerations have pronounced spatial relationships with energy efficiency. While a spatial econometric model can capture the spatial spillover effect of industrial agglomeration on energy efficiency, the influence from neighboring regions might vary based on different levels of technological innovation and green technological innovation. Based on the regression results from the panel threshold model and the spatial econometric model, this study employs a spatial threshold model to investigate the asymmetric spatial interaction relationships caused by different levels of technological innovation and green technological innovation. Furthermore, this paper unveils the mechanisms behind the varying impacts of heterogeneous industrial agglomeration. Mechanisms such as labor pooling, input sharing, and knowledge spillovers represent the principal routes by which industrial agglomeration fosters technological innovation and boosts energy efficiency. These mechanisms not only enhance the collaborative synergy among firms but also promote the clustering of innovative resources and the swift spread of knowledge, thereby powering the enhancement of energy efficiency. Consequently, understanding how these mechanisms function across different types of industrial agglomeration is vital for formulating effective industrial and energy policies, pushing the economy toward a more sustainable, efficient, and greener future.

In contrast to prior research, the main contributions of this research can be outlined as follows. First, although prior research has delved into the threshold or spatial spillover impact of either specialized or diversified industrial agglomeration on energy efficiency, few have incorporated two types of agglomeration into a single research framework. It remains uncertain whether the effects of agglomeration economies on energy efficiency stem from either specialized industrial agglomeration or diversified industrial agglomeration. Accordingly, this paper builds a conceptual framework to illustrate the mechanism of the threshold and spatial effect of heterogeneous industrial agglomeration on energy efficiency by examining the spatial threshold influence between them, yielding differentiated outcomes that accord with reality. Second, researchers who have studied the threshold effect of industrial agglomeration on energy efficiency have considered economic levels or industrial agglomeration as threshold variables (Zheng and Lin, 2018; Wu and Lin, 2021). Such researchers have typically neglected the influence of industrial agglomeration on energy efficiency guided by technological innovation or green technological innovation. Studies that ignore these limitations may produce inaccurate conclusions, posing significant risks to policymaking and practice. Therefore, this study considers the dependency of technological innovation and green technological innovation on the spatial threshold effect of specialized and diversified industrial agglomeration on energy efficiency. Furthermore, it delves into the variances between them under varying levels of technological and green technological advancements. Third, although existing research has investigated the spatial spillover effect of heterogeneous industrial agglomeration on energy efficiency, the potential for spatial attenuation and regional boundaries remains undisclosed. To fill this gap, this paper employs a spatial weight matrix incorporating threshold distances to determine the regional boundaries of spillover effects. The findings reveal the relationship and mechanisms between heterogeneous industrial agglomeration and energy efficiency, offering both theoretical insights and actionable guidance for China's pursuit of energy-efficient economic expansion.

The remainder of this paper is organized as follows. Section 2 reviews the literature and summarizes relevant studies on industrial agglomeration and energy efficiency. Section 3 proposes the research hypotheses and establishes the conceptual framework. Section 4 introduces the data and methodology. Section 5 presents the empirical results. Section 6 provides the conclusion and policy implications.

2. Literature review

2.1. Measurement of EE

EE refers to using less energy to produce at least an equal number of services or useful outputs (Patterson, 1996). Currently, EE is typically measured using two distinct indicators: single-factor EE and total-factor EE. The conventional single-factor EE, determined by the energy used to produce one unit of output, fails to consider the substitution impacts of capital, labor, and other non-energy elements. Thus, total-factor EE (TFEE) serves as a more comprehensive measure that encapsulates both economic and environmental dimensions (Hu and Wang, 2006). Techniques for computing TFEE fall into two categories: parametric approaches, represented by the stochastic frontier approach (SFA), and non-parametric methods, exemplified by data envelopment analysis (DEA). Compared with SFA, DEA offers notable benefits such as minimizing subjectivity, simplifying computational algorithms and reducing mistakes (Zheng, 2021). Initially introduced by Charnes et al. (1978), the DEA framework was expanded by Zhou and Ang (2008a) to include undesirable outputs. Nevertheless, DEA fails to provide detailed analyses of efficient decision-making units, particularly when considering slack and undesirable outputs. To address this limitation, Tone (2001) proposed a slacks-based measure (SBM) model, which sidesteps the biases from angular and radial measures and considers the impact of undesirable outputs during production, accurately capturing the core principles of efficiency evaluation (Zheng, 2021; Gao et al., 2023). Consequently, numerous researchers have adopted the SBM model to evaluate EE (Ang et al., 2015; Zhang and Chen, 2022). The conventional computation of TFEE neglects undesirable output pollutants, resulting in imprecise outcomes (Zhou and Ang, 2008b). Consequently, several researchers have incorporated environmental elements into the TFEE computation, defining it as green TFEE (GTFEE) by taking into account both energy usage and pollutant discharges (Wu et al., 2020b; Li and Ma, 2021; Wu et al., 2021; Zhou and Qi, 2022; Wang and Shao, 2023; Gao et al., 2022, 2023).

2.2. IA and EE

Researchers have extensively studied factors impacting EE, including urbanization and industrialization (Sadorsky, 2013), industrial policies (Zheng and Lin, 2017), technical progress (Tao et al., 2016), IA (Zheng and Lin, 2018) and environmental regulation (Cui and Cao, 2023). Among these factors, the significance of IA has emerged as a key determinant of EE. However, the relationship between heterogeneous IA and EE in the manufacturing sector remains insufficiently explored. In the manufacturing sector, IA refers to the geographical concentration of manufacturing sectors and related industries, resulting in a continuous aggregation of manufacturing-related capital elements (Krugman, 1991; Porter, 1998; Zheng and Lin, 2018). To date, scholars have yet to agree on the relationship between IA and EE.

From a linear analysis perspective, researchers believe that IA has different effects on EE. In the paper and pulp sector of Japan, IA has played a role in enhancing EE. However, a contrasting impact was noted in the cement sector (Tanaka and Managi, 2021). Zhang and Tu (2022) found that the IA of manufacturing sector hinders the enhancement of enterprises' TFEE.

From a non-linear analysis perspective, a threshold analysis is employed to examine the non-linear relationship between IA and EE. Zheng and Lin (2018) posited that in China's paper industry, IA has a positive impact on EE once it surpasses a specific threshold. Zhao and Lin (2019) concluded that in China's textile sector, the correlation between IA and TFEE follows an inverted U-shaped curve. Moreover, Peng et al. (2023) identified an inverted N-shaped relationship between SIA and EE, while observing an N-shaped connection between DIA and EE. Compared to a previous study that used IA as a threshold variable, Wu and Lin (2021) considered economic level as the threshold variable and found that with economic growth, the beneficial impact of IA on EE became more pronounced. Numerous studies have highlighted the link between TI and GTI while investigating the relationship between IA and EE. Liu et al. (2017) asserted that IA promotes TI by fostering both scientific breakthroughs and corporate technological advancements, which notably enhance EE. Wu et al. (2020a, 2020b) proposed that the agglomeration of agricultural industries can foster technological and knowledge dissemination, leading to the adoption of energy-saving agricultural methods and enhanced EE. Yang et al. (2022) posited that GTI would mediate the relationship between IA and improvements in EE.

No consensus has been reached regarding spatial spillover effects. IA has the potential to enhance EE both locally and in adjacent areas (Liu et al., 2017). China's agricultural EE has exhibited clear spatial gradients and correlations, and agricultural IA had an overall positive impact on it (Wu et al., 2020a, 2020b). In the service sector, both SIA and DIA have notable positive direct impacts on the EE of the service sector, along with substantial spatial spillover benefits (Wang et al., 2022). Han et al. (2018) argued that while SIA and DIA did not notably influence the city's own EE, they considerably lowered the EE of surrounding cities from 2003 to 2010.

In light of the varied findings and methodologies present in existing literature, a pronounced gap is evident in fully comprehending the impact of IA on EE. Current studies, with their focus on linear and non-linear analyses, provide valuable insights but fall short of encapsulating the multifaceted nature of the IA-EE relationship. Additionally, the literature presents inconsistent results concerning the spatial spillover effects of IA on EE, indicating a complex, context-sensitive interplay. This diversity in outcomes underscores the necessity for a more sophisticated and nuanced method of analysis. Furthermore, the potential roles of TI and GTI as intermediaries in this relationship are yet to be thoroughly examined. This study, therefore, proposes the utilization of a spatial threshold regression model to delve into the effects of IA on EE. By employing this model, the research aims to explore the differences in the impact of DIA and SIA on EE and unravel how heterogeneous IA influences EE across varying degrees of TI and GTI, thereby addressing the aforementioned gaps in the literature.

Focusing specifically on the manufacturing sector—where the dynamics between IA and EE are notably complex and not entirely unraveled—this study aspires to enhance the existing body of knowledge. It will do so by offering a more comprehensive understanding of the IA-EE interconnection within this sector through detailed spatial threshold analysis. Additionally, the research will explore the roles of TI and GTI as potential mediators in the IA-EE equation and shed light on the spatial spillover effects of IA on EE. These insights are expected to yield significant implications for policymaking, particularly in tailoring region-specific and sector-specific industrial development strategies. This study, therefore, not only fills a critical gap in current research but also paves the way for informed decisions in industrial and environmental policy domains.

3. Conceptual framework

3.1. Agglomeration externalities

Existing research indicates that IA has a non-linear effect on EE (Zheng and Lin, 2018; Wu and Lin, 2021; Peng et al., 2023). For the present study, this paper incorporates both SIA and DIA into a conceptual framework, highlighting the agglomeration externalities.

From the SIA perspective, positive externalities include matching, learning, and sharing effects within the industry (Duranton and Puga, 2004). Regarding the matching effect, enterprises can readily access the necessary workforce from a labor pool tailored to their requirements. Simultaneously, skilled workers can identify roles aligned with their expertise in the local market. This positive effect not only diminishes recruitment expenses but also enhances labor market efficiency (Han et al., 2018), which is beneficial for the promotion of EE. Regarding the learning effect, SIA connects enterprises within a region, forming a cohesive network. Through this network, shared learning among enterprises diminishes innovation risk and cultivates a setting conducive to creativity, thereby enhancing EE (Du and Li, 2019). Regarding the sharing effect, enterprises within the agglomeration areas of similar fields benefit from shared specialized facilities, such as eco-friendly utilities and equipment dedicated to EE and environmental preservation, leading to resource conservation and efficient energy use (Han et al., 2018).

Negative externalities include the competition effect, congestion effect, increased vulnerability, and limited innovation brought about by highly specialized industries (Henderson, 2003). In highly agglomerated industries, excessive competition among enterprises may lead to price wars and excessive use and waste of resources, which is detrimental to efficient energy use. Moreover, the increased demand for resources and services can lead to congestion in various forms, such as transportation bottlenecks, the overuse of public utilities, and increased competition for limited resources, which can result in inefficiencies in energy use (Brakman et al., 1996; Brülhart and Mathys, 2008; Liu et al., 2017). Additionally, if a specific sector is affected by external shocks, such as an economic recession, technological changes, or policy changes, the entire region may be severely impacted because it relies too heavily on a specific sector in the context of SIA. Therefore, enterprises find it difficult to create a stable environment that focuses on energy conservation and environmental protection. Simultaneously, enterprises might often adhere to established models and technologies rather than embracing innovation or trying fresh approaches. Such resistance hinders the enhancement of EE.

From the DIA perspective, positive externalities include matching, learning, and sharing effects among industries. Regarding the matching effect, DIA helps form a more mature factor market. Diversified industries and enterprises help workers find jobs that match their skills more easily, improve the degree of labor matching, and reduce search costs (Andersson et al., 2007). DIA can also speed up the flow of factors like capital, innovation, and energy among regions (Røyne et al., 2015), boosting the efficiency of factor allocation. Regarding the learning effect, complementary knowledge spillovers among industries can promote the generation and diffusion of cutting-edge energy conservation knowledge through the flow of information (Weidenfeld et al., 2014). This, in turn, strengthens interindustry relationships, minimizes unnecessary resource wastage, and increases EE. Regarding the sharing effect, by sharing basic infrastructure, such as transportation, telecommunications, and environmental protection, DIA can reduce fixed and transaction costs, bolstering the benefits of scale economies and improving EE (Han et al., 2018; Shen and Peng, 2021). Considering the negative externalities of competition and congestion, excessive DIA may lead to disproportionate competition and congestion, which may result in enterprises competing for limited resources or market share, traffic congestion, rising housing prices, and increased infrastructure pressure, ultimately resulting in the inefficient use of energy and a decline in EE.

The impact of SIA and DIA on EE may differ according to the level of TI or GTI. The equipment and methods used in the production process in regions with lower TI or GTI level may not be highly efficient. Enterprises in these regions may lack the ability to innovate and fully utilize the advantages of agglomeration to boost EE. Even if companies are geographically close, information and knowledge dissemination may be limited in these regions, which restricts the impact of heterogeneous IA on EE. It's worth noting that the absence of advanced GTI might result in resource wastage, which could be especially pronounced in regions with highly agglomerated industries. Conversely, regions with advanced TI or GTI levels possess cutting-edge technology and equipment and stronger research and development capabilities, which is favorable for the diffusion of technology and information. Under such circumstances, enterprises can not only drive individual enterprises to improve EE but also influences other enterprises through the network effect of IA. Therefore, it is reasonable to assert that TI and GTI guides the influence of SIA and DIA on EE, whether that influence is positive or negative. Hence, this paper focuses on TI and GTI as threshold variables and examine how it alters the relationship between industrial clustering and EE at different TI and GTI thresholds. The threshold effect of SIA and DIA on EE relies on their trade-off effect (Fig. 1).

Accordingly, this paper posits that:

Hypothesis 1. SIA and DIA may have distinct threshold effects on EE, subject to TI or GTI.

3.2. The mechanism of the spatial spillover effect and its regional boundary

3.2.1. The mechanism of the spatial spillover effect

The idea that economic activity agglomeration promotes factor productivity and economic growth can be traced back to Marshall (1890). Agglomeration externalities are conducive to improving the production efficiency of factors and bring about better production performance for firms (Flyer and Shaver, 2003). Although DIA and SIA have different manifestations, they both affect EE of neighboring areas through labor pooling, input sharing, and knowledge spillovers (Jofre-Monseny et al., 2014) (Fig. 2).

Polarization effect: (1) **Labor pooling.** Firms located in the same market or industrial zone can efficiently access required labor from a collective pool of workers in response to shifts in product market demand. Within regions of industrial agglomeration, the labor market might intensify in competitiveness due to heightened demand, consequently drawing in an increased influx of a highly skilled and experienced workforce(Marshall, 1890; Glaeser et al., 1992). (2) **Input sharing.** In areas of industrial agglomeration, dominant industries and their supply chains become increasingly interdependent due to geographical and economic proximity. This results in strengthened connections within specific sectors. (3) **Knowledge spillovers.** In agglomerated areas, the proximity of firms and institutions fosters a rich environment for rapid knowledge exchange and innovation. This leads to a clustering of high-tech industries, creating a competitive environment where advanced knowledge is intensely shared within the cluster (Rosenthal and Strange, 2001; Jofre-Monseny et al., 2011; Faggio et al., 2020).

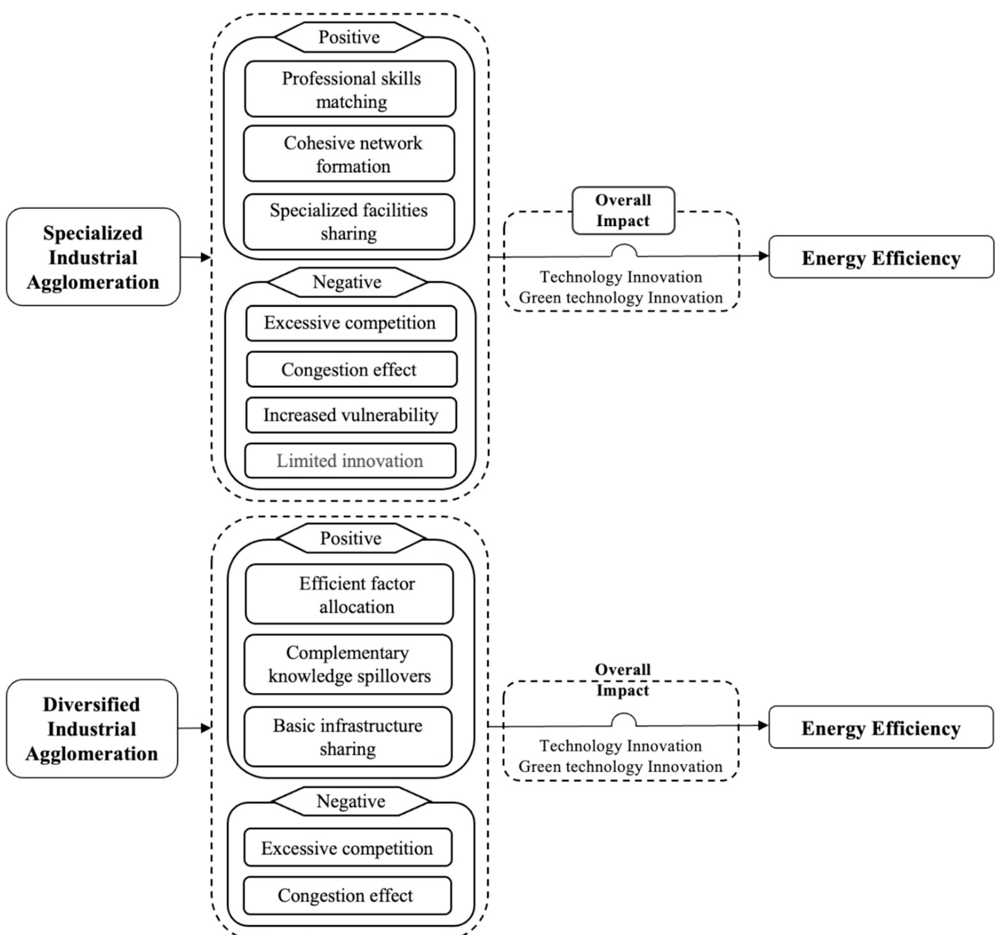

Fig. 1. The threshold mechanism of heterogeneous industrial agglomeration on energy efficiency.

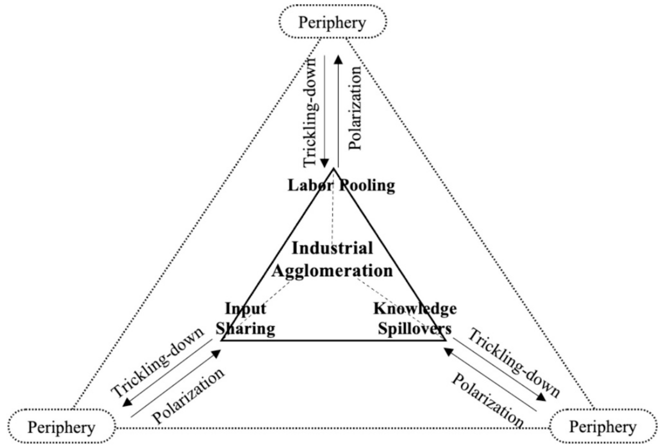

Fig. 2. The spatial spillover mechanism of heterogeneous industrial agglomeration on energy efficiency.

Trickle-down effect: (1) **Labor pooling.** As industries in these clustered areas grow, their expansion often necessitates outreach into neighboring areas for additional labor resources. This creates new job opportunities in these peripheral regions, promoting skills development and potentially attracting industries that complement the core-agglomerated sectors. Over time, this process can lead to a more balanced distribution of skilled labor across a broader geographic area, aiding in regional economic development and reducing labor market disparities (Faggian et al., 2019). (2) **Input sharing.** As the main industries in these clusters grow, their demand for a diverse range of inputs also increases, fostering the development of related or new industries in surrounding regions. This expansion not only enhances input sharing within the core agglomerated areas but also extends these benefits to a broader geographical scope, promoting overall regional development and economic integration (Quigley, 1998; Frenken et al., 2007). (3) **Knowledge spillovers.** As innovations developed in agglomerated regions begin to mature, they spread outward, reaching broader areas. This dissemination can be facilitated through various mechanisms like business expansions, worker mobility, and inter-firm collaborations. Over time, this leads to a more even distribution of knowledge and expertise, fostering regional development and reducing disparities in knowledge and innovation across different areas(Vernon Henderson, 2007).

Thus, this paper presents the undermentioned hypothesis:

Hypothesis 2. Heterogeneous IA exerts spatial spillover effects on EE.

3.2.2. *The regional boundary of the spatial spillover effect*

Spatial spillovers follow the law of distance attenuation and exhibit significant characteristics: the intensity of the spatial spillover declines with an increase in spatial distance. The primary justifications for this include: (1) **Geographic constraints.** Although modern communication technology has greatly reduced the impact of geographic distance, geographic neighbors are often more likely to share information and best practices for improving EE (Helsley and Strange, 1990). Simultaneously, companies located farther away may face higher transportation and logistics costs, which could affect the implementation of energy-efficient measures (Autant-Bernard and LeSage, 2011). (2) **Local protectionism.** Local authorities may intentionally establish systemic obstacles that hinder the unobstructed flow of factors of production and technology between areas. This action curtails the optimal distribution of resources and hampers the synchronized growth of industries in various regions (Fujita and Thisse, 2003). (3) **Environmental regulation.** Different regions may have varying environmental protection standards that can either inhibit or encourage the adoption of energy-efficient technologies and practices (Wang et al., 2023).

Thus, this paper hypothesizes that:

Hypothesis 3. The spatial threshold effects of heterogeneous IA on EE have regional boundaries.

4. Data and methodology

4.1. *Variable selection*

4.1.1. *Explained variable (GTFEE)*

This study utilizes the undesirable SBM model to evaluate the GTFEE of 280 cities from 2006 to 2014. Tone (2001) proposed the SBM model, which takes into account undesirable outputs. Additionally, it incorporates the effects of undesirable outputs into the production process, offering a more nuanced and accurate assessment of GTFEE. However, this model fails to decompose the efficiency value of an effective decision-making unit. Therefore, Tone (2004) introduced an enhanced super-efficiency SBM model for undesirable outputs, ensuring no information loss regarding the effective decision-making unit. Specifically, for k decision-making units, each with l input, S_1 desirable outputs, and S_2 undesirable outputs, this can be presented as matrix $X = (x_{ij}) \in R_{l\times k}$, $Y^g = \left(y^g_{ij}\right) \in R_{S_1\times k}, Y^b = \left(y^b_{ij}\right) \in R_{S_2\times k}$. The relaxation vectors for desirable and undesirable output are represented as $S^g \in R_{S_1}$, and $S^b \in R_{S_2}$, respectively. The vector w represents the weight assigned to the corresponding variable. The model that considers undesirable outputs is:

$$\rho^* = \frac{\frac{1}{l}\sum_{i=1}^{l}\frac{\overline{x}}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \tag{1}$$

$$s.t.\begin{cases} \overline{x} \geq Xw \\ \overline{y^g} \leq Y^g w \\ \overline{y^b} \geq Y^b w \\ w \geq 0, \overline{x} \geq x_0, \overline{y^g} \leq y_0^g, \overline{y^b} \geq y_0^b \end{cases} \# \tag{2}$$

The assessment of GTFEE primarily encompasses input, desirable output, and undesirable output. Table 1 lists the specific index selection and their measurements. The input-related variables include capital stock, labor force, and energy consumption of prefecture-level cities. The perpetual inventory method is employed to gauge capital stock. The number of employees is used to measure the labor force. Energy consumption encompasses the use of natural gas, liquefied petroleum gas and electricity, all converted to the equivalent of 10,000 tons of standard coal. Using 2006 constant prices, the desirable output is denoted by the real GDP. Undesirable outputs are quantified using indicators such as industrial wastewater discharge, industrial sulfur dioxide, and industrial smoke and dust emissions.

Table 1
Construction of indicators for the GTFEE.

Category	Indicators	Measurement
Input	Capital stock	Capital stock
	Labor force	Number of employees in the whole society at the end of the year
	Energy consumption	Consumption of natural gas, liquefied petroleum gas and electricity
Desirable output	Real GDP	Real GDP using 2006 constant prices
Undesirable output	Wastewater	Industrial wastewater discharge
	Sulfur dioxide	Industrial sulfur dioxide
	Smoke and dust	Industrial smoke and dust emissions

Before delving into the formal empirical analysis, this study presents the spatial distribution of GTFEE in the manufacturing sector across China's prefecture-level cities for the years 2006 and 2014. Fig. 3 discloses that, in 2006, the GTFEE in the majority of regions fell within the low to moderate category, situated between 0.2 and 0.6. A handful of regions, chiefly in the central and southern coastal zones, demonstrated high levels of GTFEE. Propelled by the unequivocal energy conservation and emission reduction objectives established by the Chinese government throughout the "Eleventh Five-Year Plan" and the "Twelfth Five-Year Plan," there has been a notable uptick in the GTFEE across most prefectural cities within the manufacturing industry. By the year 2014, areas registering GTFEE values between 0.2 and 0.4 witnessed a substantial decline, ceding ground to regions where GTFEE escalated to the 0.4 to 0.6 bracket, particularly in the southeastern coastal regions and Northeast China. Zones with high-level GTFEE have seen a modest increment, with Northeast China in particular experiencing pronounced enhancements. Regions with low GTFEE remained largely in the central and southwestern sectors. Furthermore, the study highlights a distinct intercity variation in GTFEE across the nation.

4.1.2. Core explanatory variables (SIA and DIA)

The core explanatory variables encompass SIA (SIA_i) and DIA (DIA_i). According to Combes (2000), the formulas for SIA and DIA are as follows:

$$SIA_i = \sum_s \left| \frac{E_{is}}{E_i} - \frac{E_s^{'}}{E^{'}} \right| \tag{3}$$

$$DIA_i = \sum_s \frac{E_{is}}{E_i} \left[\frac{1 \Big/ \left(\sum_{s^{'}=1, s^{'} \neq s}^{n} \left(E_{is^{'}} / (E_i - E_{is}) \right)^2 \right)}{1 \Big/ \left(\sum_{s^{'}=1, s^{'} \neq s}^{n} \left(E_{s^{'}} / (E - E_s) \right)^2 \right)} \right] \tag{4}$$

where E_{is} and $E_{is^{'}}$ are the employment of manufacturing sectors s and $s^{'}$ in prefecture-level city i, respectively. E_i is the total employment in prefecture-level city i. $E_s^{'}$ denotes the total employment in the manufacturing sector s across the nation, excluding the workforce in city i. $E^{'}$ denotes the total employment for all cities nationwide, excluding the workforce in city i. E_s and $E_{s^{'}}$ are the total employment of sectors s and $s^{'}$, respectively. E represents the country's total employment.

4.1.3. Threshold variables (TI and GTI)

TI and GTI are employed as threshold variables to assess the impacts of SIA and DIA on GTFEE at various thresholds. Commonly used proxy indicators for assessing the level of TI include the number of invention patent applications, the number of granted invention patents, and investment in research and development (Uddin et al., 2022; Su et al., 2022; Chen et al., 2023). This study uses the number of invention patent applications as a metric to gauge TI level. Moreover, this paper selects the number of green invention patent applications to measure the level of GTI based on the Green Patent Classification (IPC) code provided by the World Intellectual Property Office (WIPO) (Abdullah et al., 2016). Owing to the zero values in the data on invention and green patents for some cities, this paper processes the logarithm of the data by adding 1.

4.1.4. Mechanism variables

Labor pooling (LP). Referring to Drucker and Feser (2007), this study quantifies the accessibility of specialized labor resources by summing the labor force available in the fundamental industrial sectors of adjacent cities. LP_i indicates the likelihood of procuring specialized labor.

$$LP_i = \sum_{j=1}^{n} \left[\sum_{p, sign\left(\frac{E_{jp}/E_v}{E_p/E} - 1 \right) > 0} \left(\frac{E_{jp}/E_j}{E_p/E} - 1 \right) \right] d_{ij}^{-\delta} \tag{5}$$

where E_{jp} and E_j denote the employment numbers in industry p of city j and the total employment in the area, respectively, while E_p and E refer to the nationwide employment in industry p and the total employment across the country, respectively. The term d_{ij} represents the distance between two cities, with δ being the distance decay parameter, with its value specifically assigned a value of 1 in this study.

Knowledge Spillovers (KS). Inter-regional knowledge spillovers originate from several mechanisms, including the demonstration and imitation processes among innovative enterprises and their counterparts. This process entails acquiring knowledge and replicating practices through the integration of skilled professionals and state-of-the-art equipment. Additionally, it encompasses structured cooperation in scientific research and associated ventures among various firms. The sources of

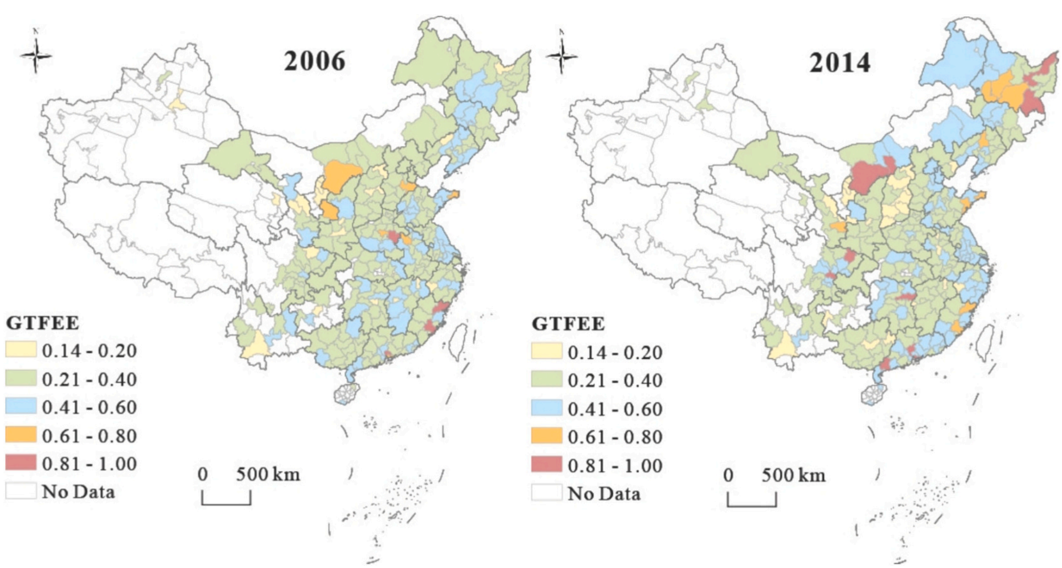

Fig. 3. Spatial evolution of GTFEE.
Note:This map is produced using the standard map obtained from the Ministry of Natural Resources standard map service website, bearing the approval number GS (2020)4619, with no alterations made to the original base map, similarity hereinafter.

knowledge spillover are related to research activity investment. In this paper, the regional research activity expenditure U_j is used to construct the indicator *KS* for knowledge spillovers experienced by city *i* from other cities.

$$\mathrm{KS_i} = \sum_j \frac{\mathrm{U_j}}{\mathrm{d_{ij}^{\delta}}} \tag{6}$$

Input sharing (IS). In this study, we calculate the input sharing by applying weights to the availability of intermediate inputs in the manufacturing sector, as outlined by Drucker and Feser (2012). The weighting is based on the ratio of employment in all specified target industries *k* within city *i* to the overall employment in the manufacturing sector.

$$\mathrm{IOL_i} = \sum_k \frac{\mathrm{E_{ki}}}{\mathrm{E_i}} \left[\sum_j \left(\sum_m \frac{\mathrm{E_{mj} r_{mk}}}{\mathrm{r_{Mk}}} \right) \mathrm{d_{ij}^{-\delta}} \right] \tag{7}$$

where E_{mj} represents the number of employees in industry *m* of the manufacturing sector in city *j*, r_{mk} represents the complete consumption coefficient between industry *m* of the manufacturing sector and the target industry *k* in the studied city, and r_{Mk} is the complete consumption coefficient of the target industry *k* in the studied city for all manufacturing industries. E_{ki} is the number of employees in the target industry *k* in city *i*, and E_i is the number of employees in all manufacturing industries in city *i*. The values of r_{mk} and r_{Mk} are derived from the input-output tables, where the complete consumption coefficients for 2006–2009 are obtained from the 135-sector IO table of 2007, and those for 2010–2014 are from the 139-sector IO table of 2012.

4.1.5. Control variables

This paper draws upon prior research(Li and Lin, 2014; Yu et al., 2019; Feng et al., 2019; Pan et al., 2020; Peng et al., 2023; Cui and Cao, 2023), selecting urbanization ratio, industrial structure, foreign direct investment, environmental protection investment, and fiscal revenue as control variables.

4.1.6. Data sources

This paper utilizes panel data of 280 prefecture-level cities. Energy-related data for the dependent variables are sourced from the China Energy Statistical Yearbook. The primary explanatory variables are derived from the China Industrial Enterprise Database, with an emphasis on manufacturing entities bearing a three-digit industry code between 130 and 420, spanning from 2006 to 2014. When processing data from the China Industrial Enterprise Database, this paper refers to the processing methods of Cai and Liu (2009). First, this paper retains enterprises that exceed a predetermined scale. Specifically, this paper excludes firms with a principal business revenue of <5 million RMB before 2010 and those with a principal business revenue of <20 million RMB from 2011 onward from the analysis. Second, this paper excludes observations with fewer than 30 employees. Third, this paper excludes observations with missing or negative values related to the study variables. Fourth, this paper eliminates observations that do not conform to Generally Accepted Accounting Principles (GAAP). Finally, this paper applies 1% winsorization to the key indicators. Threshold variable data is sourced from the State Intellectual Property Office and the WIPO Green Patent List. Control variable information is extracted from the China City Statistical Yearbook. This sample data covers the years 2006 to 2014 due to the availability of data from the China Industrial Enterprise Database. Table 2 shows the variable definitions and descriptive statistics.

4.2. Model setting

4.2.1. Panel threshold model (PTM)

Hansen (1999) developed the PTM that has become the predominant approach for investigating the threshold effect between different variables. This model offers the following four key benefits. Initially, it is unnecessary to establish non-linear equations to depict the interrelations among the variables. Second, the threshold's magnitude and count are solely determined by empirical data. Third, the model provides a theorem for the asymptotic distribution, which facilitates the computation of the parameter confidence intervals. Finally, bootstrap techniques can be employed to gauge the statistical significance of the identified thresholds (Hansen, 1996). Consequently, this paper employs a PTM to explore the impact of heterogeneous IA on EE using the levels of TI and GTI as threshold variables. The expressions for the threshold models are as follows:

$$\begin{aligned} \mathrm{GTFEE_{it}} = {} & \gamma_1 \mathrm{IA_{it}} \mathrm{I}(\mathrm{ThV_{it}} \le \omega_1) + \gamma_2 \mathrm{IA_{it}} \mathrm{I}(\omega_1 < \mathrm{ThV_{it}} < \omega_2) \cdots\cdots \\ & + \gamma_n \mathrm{IA_{it}} \mathrm{I}(\omega_{n-1} < \mathrm{ThV_{it}} \le \omega_n) + \\ & \gamma_{n+1} \mathrm{IA_{it}} \mathrm{I}(\mathrm{ThV_{it}} > \omega_n) + \delta \mathrm{X_{it}} + \mathrm{c_i} + \mu_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where $i(i = 1, 2\cdots\cdots n)$ represents a prefecture-level city and $t(t = 1, 2\cdots\cdots T)$ denotes the year. The dependent variable is GTFEE, and the core explanatory variables are SIA and DIA. *ThV* specifies the threshold variable (TI or GTI). $\omega_1, \omega_2, \cdots\cdots \omega_{n-1}, \omega_n$ are the different threshold values, and the coefficients $\gamma_1, \gamma_2, \cdots\cdots \gamma_{n-1}, \gamma_n$ correspond to the effects

Table 2
Variable definitions and descriptive statistics.

Types	Variables	Definition	Data source	Obs	Mean	Std
Explained variable	GTFEE	Undesirable output super-efficiency energy efficiency	China Energy Statistical Yearbook, City Statistical Yearbook	2520	0.558	0.212
Core explanatory variables	SIA	Formula 3	China Industrial Enterprises Database	2520	0.840	0.108
	DIA	Formula 4	China Industrial Enterprises Database	2520	0.324	0.156
Threshold variables	TI	The logarithm of number of invention patent applications	State Intellectual Property Office	2520	5.131	1.764
	GTI	The logarithm of number of green invention patent applications	State Intellectual Property Office, WIPO Green Patent List	2520	3.068	1.687
Mechanism variables	Labor pooling	Formula 5	China Industrial Enterprises Database	2520	0.012	0.008
	Knowledge spillovers	Formula 6	China Industrial Enterprises Database	2520	0.060	0.297
	Input sharing	Formula 7	China Industrial Enterprises Database	2520	0.060	0.033
Control variables	Urbanization ratio	The proportion of the urban population in the total population	City Statistical Yearbook	2520	0.478	0.164
	Industrial structure	The proportion of added value of the tertiary industry to the secondary industry	City Statistical Yearbook	2520	0.787	0.366
	Foreign direct investment	The proportion of FDI to GDP	City Statistical Yearbook	2520	0.003	0.003
	Environmental protection investment	Investment in pollution control	City Statistical Yearbook	2520	80.740	21.562
	Fiscal Revenue	The proportion of the fiscal revenue to GDP	City Statistical Yearbook	2520	0.159	0.076

of heterogeneous IA at varying levels of the threshold variable. $I(\bullet)$ is an index function, with its value contingent on the threshold variable (either TI or GTI) and the threshold values $\omega_1, \omega_2, \cdots\cdots \omega_{n-1}, \omega_n$. X stands for the set of control variables specific to a prefecture-level city. The terms c_i, μ_t and ε_{it} represent the city- fixed effect, time-fixed effect, and stochastic error term, respectively.

4.2.2. The spatial Durbin model (SDM)

IA and EE exhibit a pronounced spatial relationship (Liu et al., 2017; Wu et al., 2020a). This study employs a spatial panel model to empirically identify the spatial effects of heterogeneous IA on GTFEE. The SDM includes the spatial error term from both the spatial lag model and the spatial error model. Further, this approach integrates the dependent variable into the regression analysis, emphasizing the spatial interplay between the explanatory and dependent variables, thereby enhancing its explanatory power (Pace and Kelley, 2009). The SDM is expressed as follows:

$$\mathrm{GTFEE_{it}} = \eta_1 \sum_{j=1}^{n} \mathrm{W_{ij}GTFEE_{it}} + \beta \mathrm{IA_{it}} + \eta_2 \sum_{j=1}^{n} \mathrm{W_{ij}IA_{it}} + \zeta \mathrm{X_{it}} + \eta_3 \sum_{j=1}^{n} \mathrm{W_{ij}X_{it}} + \phi_i + \pi_t + \varepsilon_{it} \tag{9}$$

where η_1 represents the impact of local GTFEE on the GTFEE of adjacent regions, η_2 denotes the spatial regressive coefficient of heterogeneous IA, and W is the binary weight matrix. The equation below defines the spatial weight matrix:

$$\mathrm{W_{ij}} = \begin{cases} 1, \text{region i and region j are neighbors} \\ 0, \text{otherwise\#} \end{cases} \tag{10}$$

4.2.3. The spatial threshold model

While a basic SDM can capture the spatial spillover effect of IA on GTFEE, the influence from neighboring regions might differ based on varying levels of TI or GTI. If this paper overlooks the differences in spatial coefficients and uses only the constant-coefficient SDM, its parameter estimation is often biased and cannot reflect the true spatial interaction relationship. Thus, if TI or GTI is employed as a threshold variable, the constructed spatial threshold model can depict the asymmetric spatial interaction relationships caused by different TI or GTI levels. This paper adopts spatial threshold model pioneered by Yuan et al. (2020) to address the indivisibility of the threshold effect and spatial spillover effect of heterogeneous IA on GTFEE. The spatial threshold model is expressed as follows:

$$\begin{aligned} GTFEE_{it} = {} & \rho \sum_{j=1}^{N} W_{ij} GTFEE_{it} + \alpha_1 IA_{it} \bullet d_1(IA_{it} \le \omega_1) \\ & + \alpha_2 IA_{it} \bullet d_2(\omega_1 < IA_{it} < \omega_2) \cdots\cdots + \alpha_n IA_{it} \bullet d_n(\omega_{n-1} < IA_{it} \le \omega_n) + \\ & \alpha_{n+1} IA_{it} \bullet d_{n+1}(IA_{it} > \omega_n) + \xi X_{it} + \beta_1 WIA_{it} \bullet d_1(IA_{it} \le \omega_1) \\ & + \beta_2 WIA_{it} \bullet d_2(\omega_1 < IA_{it} < \omega_2) \\ & \cdots\cdots + \beta_n WIA_{it} \bullet d_n(\omega_{n-1} < IA_{it} \le \omega_n) \\ & + \beta_{n+1} WIA_{it} \bullet d_{n+1}(IA_{it} > \omega_n) + \theta WX_{it} + \psi_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{11}$$

When heterogeneous IA lies within a specific threshold range, the expression in parenthesis holds true, and $d(\bullet)$ is set to 1; if not, $d(\bullet)$ is set to 0. In the spatial threshold model, $\alpha_1, \alpha_2, \cdots\cdots \alpha_{n-1}, \alpha_n$ represent the estimated coefficients for the direct effect, while $\beta_1, \beta_2, \cdots\cdots \beta_{n-1}, \beta_n$ signify the estimated coefficients for the spatial spillover effect of heterogeneous IA on GTFEE.

5. Results and discussion

5.1. The analysis of the spatial threshold effect

5.1.1. The threshold effect of heterogeneous IA on GTFEE

As depicted in Table 3, a single threshold for TI meets the 5% significance test, suggesting that there is a single threshold for the effect of SIA on GTFEE. Conversely, the single threshold of GTI does not meet the criteria for the significance test; thus, SIA does not show a threshold effect on GTFEE in this case (Table 4). Based on the findings from the threshold effect tests presented in Tables 5 and 6, when either TI or GTI is used as the threshold variable, DIA exhibits a single threshold influence on GTFEE in both scenarios, albeit with distinct threshold values. The estimated single-threshold values are 6.293 and 3.932, respectively. Since the control variables are not the primary focus of this research, their regression outcomes are not elaborated. Hence, only the core explanatory variables' regression results are presented in this paper.

Table 7 displays regression results derived from PTM estimation. Observing Columns (1) and (2), it is evident that the estimated coefficient for DIA, when evaluated using the high-dimensional fixed effect model, is notably positive. This suggests that DIA plays a role in enhancing GTFEE. However, SIA has no significant impact on GTFEE. As depicted in Column (3), even though a single-threshold effect is evident,

Table 3
TI threshold effect tests for SIA.

	Threshold value	F-value	*P*-value	Critical value		
				1%	5%	10%
Single threshold	6.310	33.360	0.020	38.935	26.830	20.236
Double threshold	6.161 6.930	3.380	0.957	30.072	21.835	18.564
Triple threshold	2.773	5.490	0.750	24.168	17.032	15.485

Table 4
GTI threshold effect tests for SIA.

	Threshold value	F-value	P-value	Critical value		
				1%	5%	10%
Single threshold	4.318	12.190	0.260	30.079	22.388	17.476
Double threshold	3.892 5.210	6.330	0.507	19.348	14.555	12.244
Triple threshold	4.585	2.990	0.817	16.958	12.803	10.552

Table 5
TI threshold effect tests for DIA.

	Threshold value	F-value	P-value	Critical value		
				1%	5%	10%
Single threshold	6.293	49.570	0.003	39.130	25.843	20.967
Double threshold	6.293 7.222	9.120	0.530	28.678	21.205	18.187
Triple threshold	7.249	6.800	0.577	26.223	17.817	15.273

Table 6
GTI threshold effect tests for DIA.

	Threshold value	F-value	P-value	Critical value		
				1%	5%	10%
Single threshold	3.932	26.200	0.023	33.144	22.183	18.751
Double threshold	3.932 4.890	12.030	0.180	19.877	16.830	14.159
Triple threshold	1.609	3.920	0.823	20.003	15.623	12.852

Table 7
Estimation results of PTM.

	(1)	(2)	(3)	(4)	(5)
	FE		PTM		
SIA	−0.027				
	(0.035)				
DIA		0.054*			
		(0.030)			
SIA (TI≤6.310)			−0.031		
			(0.035)		
SIA (TI>6.310)			0.014		
			(0.035)		
DIA (TI≤ 6.293)				0.010	
				(0.031)	
DIA (TI>6.293)				0.114***	
				(0.032)	
DIA (GTI≤3.932)					0.018
					(0.031)
DIA (GTI>3.932)					0.095***
					(0.031)
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

the influence of SIA on GTFEE remains non-significant across all TI levels when TI is chosen as the threshold variable. This observation is consistent with the outcomes from the 2SLS regression, suggesting that SIA does not significantly affect GTFEE. According to Columns (4) and (5), DIA has no significant impact on GTFEE when TI is less than or equal to 6.293. When this threshold is exceeded, the regression coefficient becomes significantly positive. Similarly, when GTI is less than or equal to 3.932, DIA has no significant impact on GTFEE. Once surpassing this threshold, the coefficient turns notably positive. Therefore, up to a specific level of TI in a prefecture-level city, the progression of DIA has no discernible effect on GTFEE. Beyond that point, however, its positive influence becomes evident. This outcome is reasonable because when TI or GTI is at a lower level, DIA might not be able to leverage positive externalities like technology dissemination and knowledge transfer that aid in enhancing EE. However, when they reach a certain degree, the promotional effect of DIA on GTFEE emerges.

The above conclusions strongly support Hypothesis 1, which posits differences in the threshold effects of SIA and DIA on GTFEE under different mechanisms. A possible explanation may be that although SIA offers positive externalities (such as matching, learning, and sharing effects) leading to efficient energy use through enhanced labor efficiency, reduced innovation risks, and shared facilities, the negative externalities brought about by SIA (including excessive competition, congestion, increased vulnerability, and limited innovation) offset the positive externalities mentioned above under different TI or GTI levels. Hence, this paper cannot determine the impact of SIA on EE in the manufacturing sector. Moreover, both the central and various local governments in China have repeatedly emphasized in policy reports the importance of creating a diversified industrial ecosystem. There is a strong encouragement for urban areas to foster diverse industrial growth and undergo strategic upgrades, aimed at bolstering industrial competitiveness. Consequently, these policy initiatives can be seen as a driving force behind the noticeable impact of diversified agglomeration on enhancing energy efficiency. Additionally, Capello (2006) highlighted that while both SIA and DIA economies can potentially enhance urban factor productivity, cities characterized by competitive and diverse agglomeration structures tend to benefit more from shared infrastructure and economies of scale compared to those with monopolistic and specialized structures. Consequently, the beneficial externalities of DIA influence GTFEE, but this influence is distinctly modulated by varying levels of TI or GTI.

Table 8
Moran's I index of GTFEE from 2006 to 2014.

Year	Moran's I	Year	Moran's I	Year	Moran's I
2006	0.068***	2009	0.134***	2012	0.149***
2007	0.095***	2010	0.156***	2013	0.179***
2008	0.121***	2011	0.138***	2014	0.164***

Note: ***p < 0.01, **p < 0.05, *$p < 0.1$.

5.1.2. *The spatial spillover effect of heterogeneous IA on GTFEE*

In spatial econometric models, the spatial autocorrelation test serves as an initial step to assess the distribution traits of specific variables across geographical areas. Typically, Moran's I is employed in empirical studies to gauge spatial autocorrelation. Table 8 reveals that for the 280 cities, the Moran's I value for GTFEE consistently exceeded zero and is statistically significant at the 1% level throughout 2006–2014. This indicates a robust spatial spillover of GTFEE across the cities under study, manifesting as a positive spatial correlation. The scatter plots of Moran's I for EE in 2006 and 2014 are illustrated in Fig. 4. All observations are evenly distributed across all quadrants. The distribution of observations in 2014 is more dispersed than that in 2006.

Statistical tests are conducted in this study to ascertain the appropriate model. Through the application of LM, LR, and Hausman tests, we determine the model structure suitable for the regression analysis.

When either the LM-lag or LM-error test is significant, it suggests that the conventional non-spatial panel model is unsuitable, necessitating the use of spatial model. If both tests are significant, the robustness of the LM-lag and error should be examined. When all four tests are significant, both the spatial lag model and spatial error model are appropriate, but further LR and Wald tests are needed to confirm the suitability of the SDM. The Hausman test is then used to decide between fixed and random effects models. The LM, LR, Wald, and Hausman test results for the effects of SIA and DIA on GTFEE are presented in Columns (1) and (2) of Table 9, with both models being significant at the 1% level. Consequently, a two-way fixed effect SDM is adopted in this study.

The total effect is divided into two segments. The first segment, termed the direct effect, elucidates the influence of SIA and DIA on GTFEE within the specific region. The second segment, known as the indirect or spillover effect, highlights the ramifications of SIA and DIA on GTFEE in neighboring regions due to spatial correlation. As displayed in Table 10, SIA does not exhibit direct, spatial, or total effects on GTFEE. Simultaneously, the findings show that DIA has no direct effect but a spillover effect with a coefficient of 3.646, which is statistically significant. This suggests that an increase in DIA in one region will lead to an increase in GTFEE in adjacent regions. Additionally, based on the estimation outcomes of the total effect, DIA notably enhances GTFEE. Contrary to expectations, the findings above contradict Hypothesis 2, and the reasons why SIA may not impact GTFEE in local and neighboring areas could be as follows. First, SIA can result in a rigid supply chain, making adaption to market or technological changes difficult. Second, governments might adopt one-size-fits-all policies for specialized agglomeration zones, neglecting the unique needs and differences of individual enterprises or industries. Third, while enterprises in homogeneous competition might be driven to innovate, this might not necessarily lead to knowledge acquisition and technological spillover, which could hinder regional EE (Rhee et al., 2014). Additionally, capital might become overly concentrated in specific enterprises or projects, leaving other potential ventures starved of necessary investment. Last, intense industrial agglomeration can have environmental consequences, such as land degradation and water resource overexploitation. These factors can disrupt positive outcomes in areas like supply chain collaboration, policy direction, capital and talent flow, and environmental and social impacts of SIA. This could explain the observed insignificant regression results, which might be attributed to polarization and trickle-down effects. Additionally, from the perspective of government policies, enhancing industrial energy efficiency is a key focus of Chinese

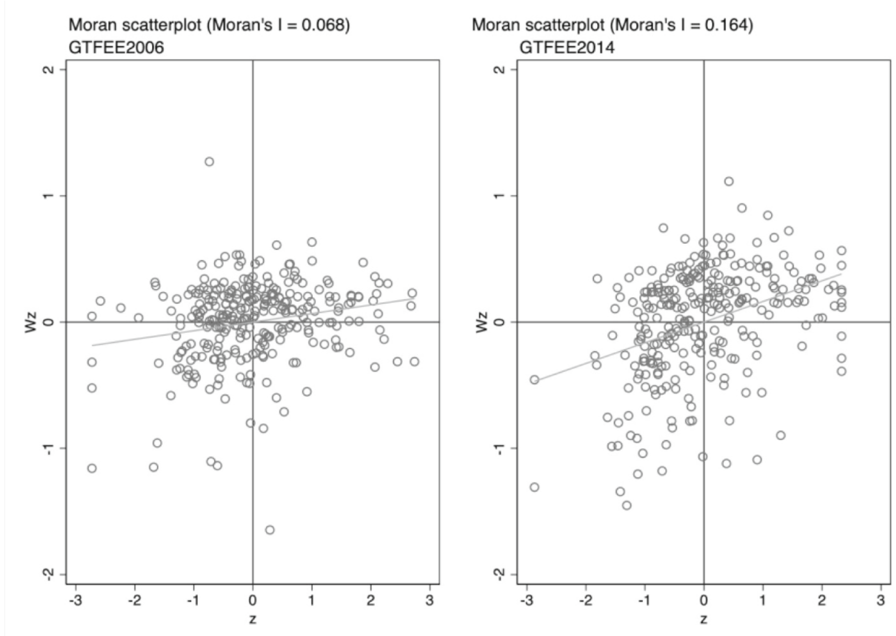

Fig. 4. Scatter plots of the local Moran's I index for GTFEE in 2006 and 2014.

Table 9
Identification test of spatial econometrics model.

	(1)	(2)
LM-Lag	732.470***	887.028***
R-LM-Lag	4.900***	2.668***
LM-Error	1065.448***	1224.502 ***
R-LM-Error	337.878***	340.142***
LR-SDM-SAR	81.470***	122.800***
LR-SDM-SEM	4870.580***	4871.310***
Wald-SDM-SAR	36.310***	36.310***
Wald -SDM-SEM	46.320***	46.320***
Hausman	163.15***	141.250***

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 10
Estimation results of SDM.

		(1)	(2)
Direct effect	SIA	−0.019	
		(0.034)	
	DIA		0.008
			(0.030)
Spillover effect	SIA	−0.625	
		(1.315)	
	DIA		3.646***
			(1.264)
Total effect	SIA	−0.645	
		(1.320)	
	DIA		3.653***
			(1.266)
	Control variables	Yes	Yes
	Time fixed effect	Yes	Yes
	City fixed effect	Yes	Yes
	Observations	2520	2520

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

government policies from 2006 to 2014, emphasizing industrial energy conservation and green development. These initiatives likely influenced IA and EE. SIA may not significantly boost energy efficiency due to limited technology and knowledge sharing. Conversely, DIA could effectively elevate energy efficiency through cross-innovation and collaboration across various industries and technologies, aligning with China's goals for optimizing industrial structures and promoting green development.

5.1.3. The spatial threshold effect of heterogeneous IA on GTFEE

Based on previous research, SIA has neither a threshold effect nor a spatial effect on GTFEE. In contrast to SIA, DIA exhibits both threshold and spatial spillover effect. Consequently, this study employs the spatial threshold model to explore the spatial threshold influence of DIA on GTFEE.

Regarding the direct effect results: When TI is less than or equal to 6.293, the estimated coefficient of DIA is significantly negative. This implies that DIA has a negative impact on local GTFEE at a low-level TI. When the TI level is >6.293, the regression coefficient is 0.171, which is significant at the 1% confidence level. It is evident that at a high-level TI phase, DIA promotes local GTFEE. When GTI is chosen as the threshold variable, DIA notably enhances local GTFEE only when GTI exceeds 3.932 (Table 11). Despite the Chinese government's ongoing commitment to technological modernization and sustainable development, cities with lower TI or GTI levels often still depend on outdated, less efficient technologies due to limited funding for newer advancements and a lack of key infrastructure like smart grids. This reliance on traditional, energy-intensive industries in low-tech areas hampers the

Table 11
Estimation result of spatial threshold model.

	(1)	(2)	(3)
	Direct effect	Spillover effect	Total effect
DIA (TI≤ 6.293)	−0.107**	−0.028	−0.135
	(0.042)	(0.304)	(0.307)
DIA (TI>6.293)	0.171***	0.452***	0.622***
	(0.040)	(0.168)	(0.168)
DIA (GTI≤3.932)	−0.069	−0.239	−0.309
	(0.045)	(0.297)	(0.301)
DIA (GTI>3.932)	0.112***	0.850***	0.962***
	(0.039)	(0.229)	(0.232)
Control variables	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

full realization of the positive externalities from DIA in enhancing GTFEE. However, as TI or GTI levels surpass certain thresholds, aligning with governmental initiatives for eco-friendlier and advanced industrial structures, DIA begins to optimize the industrial framework. This transition, propelled by swift integration of green technologies, further amplifies DIA's positive influence on local GTFEE.

Regarding the spillover effect results: When TI or GTI is relatively low, DIA has no impact on the GTFEE of neighboring areas. Above the threshold, the effect shifts to being statistically significant. When TI exceeds 6.293, the coefficient is 0.452, with a significance level of 1%. Similarly, when GTI exceeds 3.932, the coefficient becomes 0.850. Thus, DIA helps improve GTFEE in adjacent areas up to some stage of TI or GTI (Table 11). Low-tech areas struggle to generate spillover effects on neighboring regions' GTFEE due to limited technology diffusion, resource dispersion, inadequate infrastructure, incomplete industrial chains, or unfavorable policies. In high-tech areas, however, these constraints are mitigated. Therefore, diversified clustering can yield spillover effects, positively impacting neighboring regions' energy efficiency. As for GTI, it marks a transformative shift in the realm of environmental conservation technologies (Liu and Li, 2022). To stay competitive, enterprises must ramp up their research and development expenditures and enhance their green production methodologies (Wang, 2023). Given the elevated costs associated with GTI and the complexities in disseminating it, the spatial spillover influence of DIA on GTFEE is constrained when GTI is below the threshold. Yet, surpassing this threshold activates spillover effects. Additionally, given that China's green development policies typically favor more technologically advanced areas, regions with lower GTI may struggle to fully benefit from these policies, thereby facing challenges in leveraging DIA to improve GTFEE.

Regarding the total effect results: The total effect comprises both direct and spillover effects, and the rationale behind this phenomenon can be inferred from the preceding analysis. The overall impact of DIA on GTFEE is positive in regions with high levels of TI or GTI. Specifically, when TI exceeds 6.293, the estimated coefficient is 0.622, passing the 1% significance test. Notably, the total effect of DIA on GTFEE becomes significant only when GTI surpasses 3.932. In regions with elevated GTI levels, DIA demonstrates a pronounced positive impact on GTFEE. This suggests that increases in TI or GTI contribute to the positive trajectory of GTFEE (Table 11).

5.2. The analysis of the regional boundary of the spatial spillover effect

As previously stated, IA facilitates EE improvements in other regions through spatial spillover, which adheres to the law of spatial distance decay. A question worth pondering is whether the impetus created by IA via spatial spillover extends to all sampled regions or remains restricted solely to adjacent areas. Using a threshold distance matrix, this study investigates the spatial spillover effects under different distance constraints. The matrix eliminates areas within distance *d* by setting different distance thresholds, identifying the spatial spillover of regional economic growth without considering the spatial relationships of areas within that distance. This approach further tests whether wealth generation in affluent areas has a global or local effect on the prosperity of other regions. The detailed configuration of the spatial weight matrix is outlined below.

$$W_{ij} = \begin{cases} \dfrac{1}{d_{ij}}, d_{ij} \geq d \\ 0, d_{ij} < d\# \end{cases} \tag{12}$$

Given that only a limited number of region pairs have geographical distances shorter than 20 km, this study sets 20 km as the starting point. We then progress in 20 km increments, noting the spatial spillover coefficients in the regression outcomes at each distance threshold. Fig. 5 shows that across varying distance thresholds, the spatial spillover displays a distinct decay pattern with distance. This distance decay isn't linear but exhibits a wave-like diminishing trajectory. Additionally, the spatial spillover effects' boundary of DIA on GTFEE shifts based on the stages of the threshold variables. In areas where TI > 6.293, the boundary is 120 km. For those where GTI > 3.932, the boundary is 200 km.

In regions where TI exceeds 6.293, there is an upward trend in the spatial spillover effect within a 60 km radius. This is attributed to the dense concentration of innovation activities and the close-knit network of collaboration among enterprises, research institutions, and universities. The proximity of these entities fosters a robust environment for effective knowledge sharing and resource pooling. It is this intense interactivity and collaboration within a confined geographical space that amplify the spillover effect, leading to a noticeable increase within this radius. This scenario aligns well with the strategic objectives of China's "Twelfth Five-Year Plan", which proposes leveraging dominant enterprises, industrial clusters, and major projects to implement an

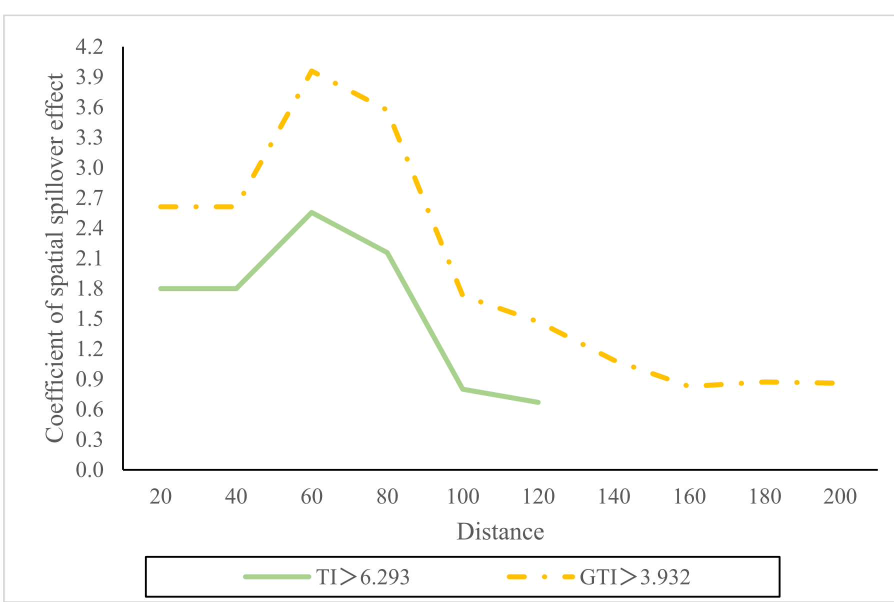

Fig. 5. The attenuation process of the spatial spillover effect.

industrial innovation development project. The plan's emphasis on fostering innovation through the concentration of resources and collaboration in key areas resonates with the observed outcomes in regions with high TI. Beyond this, from 60 to 120 km, the spatial spillover effect experiences a fluctuating decline. This pattern can be attributed to the diminishing intensity of direct innovation transmission and collaboration opportunities as the distance from the core of technological innovation increases. Although innovation continues to spread across this broader area, the impact and frequency of such spillover fluctuate due to variations in geographic distribution, industry structures, and the strength of economic linkages between regions.

As previously mentioned, DIA significantly influences GTFEE in adjacent regions once a specific GTI level is achieved. Once GTI surpasses 3.932, there is a pronounced spatial spillover effect within a 60 km radius, with its coefficient showing an upward trend. The reasons for this phenomenon are the same as mentioned earlier, namely that close collaboration and knowledge sharing among these entities are more physically feasible, leading to strong spillover effects within a smaller geographical scope. Beyond 60 km, the spatial spillover effect witnesses a sharp decline. High GTI regions typically employ more advanced green technologies, which may require specific infrastructure, expertise, and higher capital investments, making it difficult for the technology to spread effectively beyond a certain geographical range.

The attenuation trajectory of the spatial spillover curve suggests that while DIA promotes EE improvement in neighboring regions via spatial spillovers, its effective range is geographically limited. Inside this range, DIA can significantly foster rapid EE growth through spatial spillovers. These conclusions strongly support Hypothesis 3.

5.3. Robustness test

This study carries out multiple robustness checks encompassing the following facets: (1) *Replacement of the spatial weight matrix*. This paper uses a K-nearest neighbor matrix as the spatial weight matrix. Columns (1) to (3) of Table 12 display the findings. (2) *Replacement of the explanatory variables*. This paper performs this test by reconstructing SIA and DIA. The formulas for SIA and DIA are as follows:

$$SIA_i = max\frac{E_{i,s}/E_i}{E_s/E} \tag{13}$$

$$DIA_i = 1\bigg/\sum_s \left|E_{i,s}/E_i - E_s/E\right| \tag{14}$$

The definitions of each variable in the above formulas are presented in Section 4.1.1. The results are listed in columns (4) to (6). (3) *Replacement* of the explained variables. This study employs non-radial directional distance functions for the calculation of EE. The input variables comprise capital stock, labor force and energy consumption, and the expected output corresponds to the real GDP of each prefecture, with the regression findings presented in columns (7) to (9). (4) *Changing the measure of threshold variables*. Following Wen et al. (2022), this study employs the number of invention patents granted as proxy variables for TI and green invention patent granted for GTI. The findings can be found listed in columns (10) to (12). The outcomes of these robustness tests align with our benchmark regression findings, thereby reinforcing the robustness of our research results.

5.4. Mechanism analysis

In the preceding section, substantial evidence is presented demonstrating the impact of heterogeneous IA on the GTFEE. The following analysis delves into potential mechanisms through which these effects manifest. In cities with lower levels of TI, the labor pooling effect is insignificant, as seen in columns (1) to (3) of Table 13. The effect is significantly positive in high-TI regions. High-tech regions exert

Table 12
Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Replacement of spatial weight matrix			Replacement of explanatory variables			Replacement of explained variables			Changing the measure of threshold variables		
	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect
DIA (TI≤ th)	−0.083*	0.139	0.056	−0.008*	0.027	0.019	−0.063*	0.132	0.069	−0.065*	−0.061	−0.127
	(0.044)	(0.102)	(0.108)	(0.005)	(0.037)	(0.037)	(0.037)	(0.214)	(0.219)	(0.035)	(0.250)	(0.255)
DIA (TI> th)	0.132***	0.357***	0.489***	0.024***	0.166***	0.189***	0.231***	0.837***	1.068***	0.264***	0.341***	0.605***
	(0.041)	(0.099)	(0.107)	(0.006)	(0.043)	(0.045)	(0.052)	(0.239)	(0.245)	(0.055)	(0.122)	(0.143)
DIA (GTI≤ th)	−0.050	0.098	0.048	−0.004	−0.027	−0.032	0.043	0.230	0.273	−0.007	0.110	0.103
	(0.045)	(0.107)	(0.115)	(0.003)	(0.027)	(0.028)	(0.034)	(0.199)	(0.205)	(0.033)	(0.112)	(0.115)
DIA (GTI> th)	0.091**	0.380***	0.471***	0.029***	0.159***	0.189***	0.313***	0.448*	0.761***	0.132*	0.400***	0.532***
	(0.039)	(0.108)	(0.119)	(0.006)	(0.051)	(0.053)	(0.062)	(0.267)	(0.273)	(0.073)	(0.118)	(0.143)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The threshold values in each regression are different, thus th is used uniformly to refer to the threshold value. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 13
The mechanism test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	LP			KS			IS		
	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect
DIA (TI≤ th)	−0.004	−0.384	−0.388	0.001	0.002	0.003	−0.009***	0.934**	0.925**
	(0.007)	(1.397)	(1.404)	(0.001)	(0.003)	(0.003)	(0.003)	(0.388)	(0.390)
DIA (TI> th)	0.008**	0.483*	0.492*	−0.255***	2.362***	2.108***	−0.016**	0.598***	0.582***
	(0.004)	(0.276)	(0.280)	(0.075)	(0.535)	(0.524)	(0.007)	(0.167)	(0.170)
DIA (GTI≤ th)	−0.004	−0.436	−0.441	0.000	−0.005	−0.005	−0.007**	0.503***	0.497***
	(0.007)	(1.436)	(1.442)	(0.001)	(0.007)	(0.007)	(0.003)	(0.176)	(0.177)
DIA (GTI> th)	0.007***	0.316***	0.323***	−0.272***	2.275***	2.004***	−0.019***	0.602***	0.582***
	(0.003)	(0.121)	(0.123)	(0.079)	(0.526)	(0.514)	(0.007)	(0.183)	(0.186)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

significant positive effects by attracting a substantial number of talented individuals to both local and neighboring areas. In contrast, low-tech regions demonstrate very limited talent attraction capabilities. For cities with higher TI or GTI, columns (4) to (6) show that the DIA of manufacturing sector benefits from spatial knowledge spillovers, boosting the GTFEE of neighboring cities. This positive effect is likely due to the enhanced interaction and exchange of ideas and innovations within these agglomerated regions. However, the direct effect is significantly negative, likely because businesses in highly innovative environments adopt more protective measures to prevent knowledge leakage, which in turn inhibits the direct flow of knowledge (Bloodgood and Chen, 2021). The positive spatial spillover effects of DIA, regardless of TI or GTI status as shown in columns (7) to (9), lead to strong input sharing of neighboring cities. These linkages facilitate efficient resource and information flow among industries, enhancing regional energy efficiency. However, the local effect of DIA in cities with lower TI or GTI is negative. Excessive industrial agglomeration may lead to a "lock-in effect," where local businesses become overly dependent on specific industries or technologies, lacking the flexibility to transform and adapt to new market supply and demand (Zizka et al., 2021).

In summary, in regions with relatively low TI, DIA tends to align with the local disadvantages in input sharing, which leads to a decrease in the

Table 14
Heterogeneity analysis.

	Direct effect	Spillover effect	Total effect	Direct effect	Spillover effect	Total effect
Panel A: heterogeneous regions	Eastern China			Central China		
DIA (TI≤ th)	−0.166**	0.258	0.092	0.006	0.724	0.729
	(0.077)	(0.269)	(0.265)	(0.050)	(0.445)	(0.449)
DIA (TI> th)	0.106*	0.395**	0.500***	0.051	−0.059	−0.009
	(0.063)	(0.175)	(0.177)	(0.063)	(0.226)	(0.225)
DIA (GTI≤ th)	−0.144**	0.322	0.178	–	–	–
	(0.067)	(0.253)	(0.250)			
DIA (GTI> th)	0.101	0.703**	0.804**	–	–	–
	(0.072)	(0.327)	(0.325)			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: heterogeneous city scales	Large cities			Small and medium-sized cities		
DIA (TI ≤ th)	−0.029	1.352***	1.324***	−0.127**	0.212	0.085
	(0.069)	(0.471)	(0.486)	(0.052)	(0.453)	(0.450)
DIA (TI > th)	0.166***	0.664*	0.830**	0.039	0.435	0.475
	(0.061)	(0.402)	(0.407)	(0.050)	(0.370)	(0.373)
DIA (GTI ≤ th)	0.038	3.697***	3.734***	–	–	–
	(0.053)	(0.856)	(0.869)			
DIA (GTI > th)	0.284***	−1.265**	−0.981*	–	–	–
	(0.094)	(0.520)	(0.554)			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: heterogeneous stages of development	2006–2010			2011–2014		
DIA (TI ≤ th)	–	–	–	0.086	−0.042	0.044
				(0.165)	(0.543)	(0.534)
DIA (TI > th)	–	–	–	0.029	5.117***	5.146***
				(0.031)	(1.797)	(1.802)
DIA (GTI ≤ th)	–	–	–	0.017	−1.083	−1.066
				(0.035)	(1.199)	(1.204)
DIA (GTI > th)	–	–	–	−0.311**	2.884***	2.573***
				(0.131)	(0.711)	(0.738)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: The threshold values in each regression are different. Thus, th is used uniformly to refer to the threshold value. There is no threshold effect in western China, and a spatial threshold regression could not be performed. ***p < 0.01, **p < 0.05, *p < 0.1. indicates that there is no threshold effect in the regression and that spatial threshold regression cannot be performed.

GTFEE of local areas. In regions with relatively low GTI, despite the significant input sharing mechanism, DIA still does not affect GTFEE. In areas with higher TI or GTI, DIA that correspond with the labor pooling, knowledge spillovers and input sharing effects are all conducive to fully leveraging agglomeration externalities, thereby generating positive spatial spillover effects on the GTFEE of neighboring cities. While DIA can lead to positive regional spillovers in terms of labor pooling, knowledge spillovers, and input sharing, the local effects in certain contexts may be unfavorable due to protective measures to prevent knowledge leakage and mismatches in local industry capabilities and needs.

5.5. Heterogeneity analysis

This paper tests the heterogeneous impacts of heterogeneous IA on GTFEE based on various regions, city scales, and stages of development. Consistent with benchmark regression results, SIA does not exhibit significant threshold effects in various subsamples, making it infeasible to report the spatial threshold regression outcomes for SIA. Therefore, this paper only reports the regression results for DIA.

5.5.1. Estimation results by regions

China's eastern, central, and western regions exhibit marked differences in economic growth, resulting in pronounced variations in IA conditions. To evaluate the regional variations in the influence of heterogeneous IA on EE, this study divides the samples into three geographical categories: eastern, central, and western China. Panel A in Table 14 presents the outcomes, illustrating China's notable regional disparities. Only when the level of TI or GTI surpasses the threshold does DIA exhibit positive spillover effect on GTFEE in eastern China. In low-tech regions, only negative direct effects are observed. Additionally, in central China, irrespective of the TI level, the direct, indirect, and total impacts of DIA are not statistically significant. When considering GTI, neither threshold nor spatial spillover effects of DIA on GTFEE are evident. Furthermore, no significant threshold or spatial spillover effects are observed in the western region.

These findings indicate that DIA does not contribute to the enhancement of GTFEE in regions with TI or GTI levels below the threshold value. Instead, the improvement in GTFEE in neighboring areas benefits from DIA in areas with a high TI or GTI level. Conversely, in central and western China, regardless of threshold effects or the levels of TI or GTI, DIA doesn't influence GTFEE in either local or neighboring regions. Potential explanations for these outcomes are as follows. First, owing to eastern China's location and economic development advantages, by offering competitive salaries and enacting enticing investment policies, IA can pull in skilled labor, capital, and other crucial resources from nearby regions. This could potentially disrupt the efficient distribution of these factors, thereby diminishing the influence of DIA on GTFEE in central and western China (Wang et al., 2022). Second, high-TI regions of eastern China often establish close supply chain partnerships with neighboring areas and enterprises that invest vastly in these surrounding regions, promoting the flow of capital and talent, which eventually helps DIA exert stronger spatial spillover effects. In local areas, intense competition among enterprises within the cluster may offset the advantages of the positive externalities of agglomeration, thus failing to enhance EE.

5.5.2. Estimation results by city scales

As industrialization progresses swiftly in China, the pace of urbanization has quickened, resulting in a significant increase in the quantity and magnitude of cities. The heterogeneity of IA, caused by differences in city scales, has different impacts on GTFEE. Based on the "Notice on Adjusting the Criteria for City Size Classification" released by the State Council in 2014, this study divides the sample into two groups: large cities with an urban permanent population of over 1 million and small and mid-sized cities with an urban permanent population of <1 million. Panel B of Table 14 shows the estimation outcomes. In cases where the TI level falls beneath the threshold, significant positive spillover and total effects exclusively manifest in large cities, while negative direct effect and insignificant spillover and total effects are observed in small and mid-sized cities. Conversely, once the TI level surpasses the threshold, significantly positive direct and spillover effects are discernible in large cities, whereas small and mid-sized cities exhibit insignificant effects. In situations where the GTI level remains beneath the specified threshold, large cities exhibit significantly positive spillover and total effects. Nevertheless, once the GTI surpasses this threshold, the direct impact of large cities becomes positive and significant, while the spillover and overall effects turn significantly negative. No discernible threshold effects exist, rendering the application of spatial threshold regression inapplicable to small and mid-sized cities. In the regression of DIA on GTFEE, there are no observable threshold effects associated with GTI. Consequently, the utilization of spatial threshold regression is not applicable to small and mid-sized cities in this context.

The results indicate that in large cities, when TI or GTI is less than the threshold, DIA exhibits positive influence, contributing to spillover and total effects on GTFEE. However, such effects are not evident in small to medium-sized cities. These disparities may be attributed to factors such as the superior infrastructure, higher degree of informatization, and the gradual diffusion of concentrated capital and skilled personnel into the peripheral regions of large cities; however, such advantageous conditions are absent in small and mid-sized cities. Additionally, large cities boasting elevated TI levels exhibit significant siphoning and trickle-down effect. In small and mid-sized cities with elevated TI levels, the above-mentioned effects are not observed. In large cities with high GTI levels, under the dual pressures of TI and green development, authorities may relocate heavy-polluting industries to surrounding areas, leading to an increase in EE in the local cluster and a decline in EE in neighboring regions.

5.5.3. Estimation results by stages of development

In China, during the "Twelfth Five-Year Plan" period, there was a shift in the energy development strategy. The emphasis was placed on enhancing EE, and for the first time, a target was introduced to control total primary energy consumption. To further examine whether the relationship between IA and EE was different between "Eleventh Five-Year Plan" and the "Twelfth Five-Year Plan" periods, this paper divides the sample into two development stages: 2006–2010 and 2011–2014. Panel C in Table 14 presents the corresponding estimation outcomes. No threshold effects are observed during 2006–2010. Therefore, spatial threshold regression cannot be applied to the sample. From 2011 to 2014, DIA has significant spillover effect on GTFEE only when the level of TI or GTI exceeds the threshold. However, the direct effect is found to be statistically insignificant. The results suggest that DIA does not have an impact on GTFEE before the adjustment of energy policies. After the energy policy is revised, the local authorities' corresponding policy changes lead to a shift in the mode of IA, resulting in DIA promoting the improvement of GTFEE in neighboring areas when TI or GTI is greater than high threshold. During the period from 2011 to 2014, local governments intensified their initiatives to attract investments from industries associated with energy conservation, environmental protection, and new energy. This is driven by the objective of curbing energy consumption, which is further fueled by political motivations and competitive growth dynamics. This promotes the development of DIA, making it easier to establish forward and backward linkages between industries in areas with high TI or GTI levels. Therefore, the effects of DIA can radiate to neighboring areas. However, congestion and competitive effects in areas with high TI or GTI levels prevent DIA from positively influencing local GTFEE. Additionally, such spatial spillover effects are not observed in low-TI or low-GTI areas due to limitations in technology spillover intensity.

6. Conclusion and policy implications

6.1. Conclusion

The primary focus of this study is to examine how heterogeneous IA influences GTFEE subject to TI or GTI. To address this question, the paper conducts an empirical analysis using a spatial threshold model, utilizing data from the manufacturing sector in 280 Chinese cities during the period from 2006 to 2014. The following conclusions can be drawn:

(1) Owing to differing underlying mechanisms, the SIA and DIA of the manufacturing sector have distinct effects on GTFEE subject to TI or GTI. DIA exhibits a single-threshold and spatial effect on GTFEE. In contrast, SIA does not exhibit a significant threshold or spatial effect on GTFEE.
(2) The influence of DIA on GTFEE varies across different stages of TI or GTI. When the TI level falls below a specified threshold, DIA will decrease the local GTFEE. DIA significantly enhances the GTFEE of both local and neighboring areas when the TI level is above a certain threshold. The direct, spillover, and total spatial effects of DIA on GTFEE are significant only when entering the high-level GTI stage.
(3) The spatial effect of DIA in the manufacturing sector on GTFEE display obvious attenuation characteristics and specific regional boundaries, which are restricted by the intensity of TI or GTI.
(4) The potential mechanisms through which DIA exerts influence on GTFEE encompass labor pooling, knowledge spillovers, and input sharing.

6.2. Policy implications

(1) *Enhancements in DIA within the manufacturing industry.* Considering the overall positive impact of DIA on GTFEE in the manufacturing sector, local authorities should emphasize the significance of DIA (rather than SIA) in boosting GTFEE and strategically design the spatial arrangement of manufacturing agglomerations by leveraging the comparative advantages inherent in the local manufacturing sector. Additionally, by enhancing infrastructure and supply chains, local authorities can offer fiscal incentives and tax benefits to foster manufacturing cluster zones by drawing on top-tier talent and highly efficient manufacturing enterprises. Considering the beneficial spatial spillover effects of DIA on GTFEE within the manufacturing sector, governments should leverage these agglomeration zones as pivotal tools for initiating and bolstering ongoing dialogue mechanisms with adjacent areas. This can reinforce the cross-regional movement of conventional production factors like labor, capital, and energy. Moreover, local authorities should emphasize fostering the cross-border sharing and collaboration of expert talent, energy conservation insights, advanced eco-friendly technologies, and other premium factors to amplify the positive spatial spillover effects of manufacturing agglomeration. Although this paper does not find a significant impact of SIA on GTFEE, it is crucial to keep SIA within a manageable scope and continually monitor it to avert the negative consequences of excessive competition and congestion effects, which could undermine the positive contributions of SIA to GTFEE.
(2) *Fostering substantial technological advancements, especially in the realm of green and low-carbon technologies, within the manufacturing sector.* This study indicates that DIA enhances local and neighboring GTFEE only in areas where TI or GTI is relatively high. Only by continuously strengthening the development of TI and GTI can the enhancement of the level of DIA make a greater contribution to improving GTFEE in both local and neighboring areas. Globally, breakthroughs in energy technology are the key to addressing energy shortages and responding to climate change. Countries worldwide are increasing their research and development investments, providing companies with financial support, offering tax breaks, and granting fiscal subsidies. In recent years, China has made substantial financial investments in energy technology; however, no significant breakthroughs have been made in this field. There remains a requirement for further innovation and the advancement of energy-efficient technologies and equipment. These initiatives can serve as catalysts for manufacturing enterprises to enhance their overall EE. Simultaneously, it is essential to prioritize research and development investments in clean coal and other fossil fuel technologies. This paper emphasizes the importance of ongoing investments in new energy technologies. It underscores the need to leverage the emerging industrial prospects generated by “dual carbon” initiatives, actively foster substantial advancements in green and low-carbon technologies and secure a dominant position in the global arena of green development and low-carbon competition.
(3) *Breaking obstacles that hinder spillover effects.* Owing to the impact of geographic constraints and administrative boundaries on the spatial spillover effect of DIA, addressing issues stemming from administrative divisions is crucial. This can be achieved not only by enhancing the level of DIA but also through internal restructuring and external collaboration. Local governments should reduce barriers, such as local protectionism and environment regulation, that hinder the movement of production factors. By allowing resources to flow freely across regions, the positive impact of DIA on EE can be enhanced, leading to the optimal allocation of manufacturing resources on a broader scale. Simultaneously, governments at all levels should establish mechanisms to transform and upgrade internal industries, bolster industrial integration, and foster collaboration between sectors. This would help alleviate the challenges posed by administrative boundaries on the spatial spillover effects of Industrial Agglomeration (IA) and address the negative repercussions of administrative constraints. Achieving this can be facilitated by implementing strategies like fostering cross-scale regional collaboration and establishing regional coordination institutions.
(4) *Achieving differentiated paths for EE improvements in the manufacturing sector.* Considering the heterogeneity of regions, city scales, and development stages, it is essential to formulate relevant measures based on the actual conditions of a given region. Policies should be tailored based on regional development conditions to prevent losses from following trends. For example, eastern China should continue to leverage its TI strengths while promoting coordinated industrial growth within the region. In contrast, central and western China should prioritize TI. In terms of city scales, large cities with a high-level GTI should mitigate the excessive siphoning effects of IA on surrounding areas. Small and mid-sized cities should focus on diversifying their industries based on TI. Grounded in different development stages, China should continue to implement innovation-driven development strategies during the “Fourteenth Five-Year Plan” and beyond. The country should accelerate advancements in energy technology, diligently work toward achieving the carbon peak and carbon neutrality goals, and actively contribute to enhancing EE by optimizing IA models. Adapting strategies to suit specific local conditions, the influence of IA on EE can be effectively enhanced through mechanisms including labor pooling, knowledge spillovers, and input sharing.

Although this paper undertakes a quantitative regression analysis to explore the spatial threshold effect of heterogeneous IA on EE subject to TI or GTI in the manufacturing sector, it comes with certain limitations. The study may not have fully considered the potential impact of changes in energy or economic policies on the relationship between IA and EE. Additionally, addressing spatial dependence and potential endogeneity should be a focal point for future research.

CRediT authorship contribution statement

Yuyuan Wen: Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology. **Zilong Yu:** Writing – review & editing, Writing – original draft, Validation, Project administration, Conceptualization. **Jingjing Xue:** Writing – review & editing, Formal analysis, Data curation. **Yang Liu:** Writing – review & editing, Writing – original draft, Visualization, Software, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107686.

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