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Assessing the Impact of Regional Industrial Relocation in China:

Based on the Information Taken From a Multi-Regional Input-Output Analysis

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ABSTRACT

Through innovative application of the multi-regional input-output model (MRIO) and spatial econometric methods, this paper investigates the trends, scale, and environmental impacts of China's industrial relocation, providing new information from an input-output perspective. The findings indicate that the relocation of China's industrial sector has exhibited a distinctive trend of moving "westward" and "northward," while the service sector has demonstrated a tendency to cluster in several developed regions. Moreover, the authors have identified that the energy efficiency in net inflow regions and other regions is affected differently by industrial relocation. Specifically, the net inflow of the industrial sector positively impacts the energy intensity of local provinces, but negatively affects neighboring provinces. Conversely, the net inflow of the service sector has the opposite effect. The research enriches the understanding of China's industrial relocation and provides targeted implications to further prove the high-quality of China's industrial relocation.

KEYWORDS

Energy Intensity, Industrial Relocation, Industrial Sector, Input-Output Analysis, Spatial Econometric Model

INTRODUCTION

In recent decades, fossil energy as a primary driver of economic growth has contributed to numerous environmental issues (Xuehui Li & Lin, 2013; Thuiller, 2007). As a result, governments worldwide have implemented various measures to reduce energy consumption, focusing on reducing energy intensity (Xu & Lin, 2019; Zhu & Lin, 2020). Many countries have set reducing energy intensity as a central goal of their energy conservation and emission reduction plan.

China is the world's largest carbon emitter and is crucial in mitigating climate change. In 2020, China pledged to attain near-zero carbon emissions by 2060, which means that China needs to achieve huge energy efficiency improvements in the next decades. However, uneven regional development has

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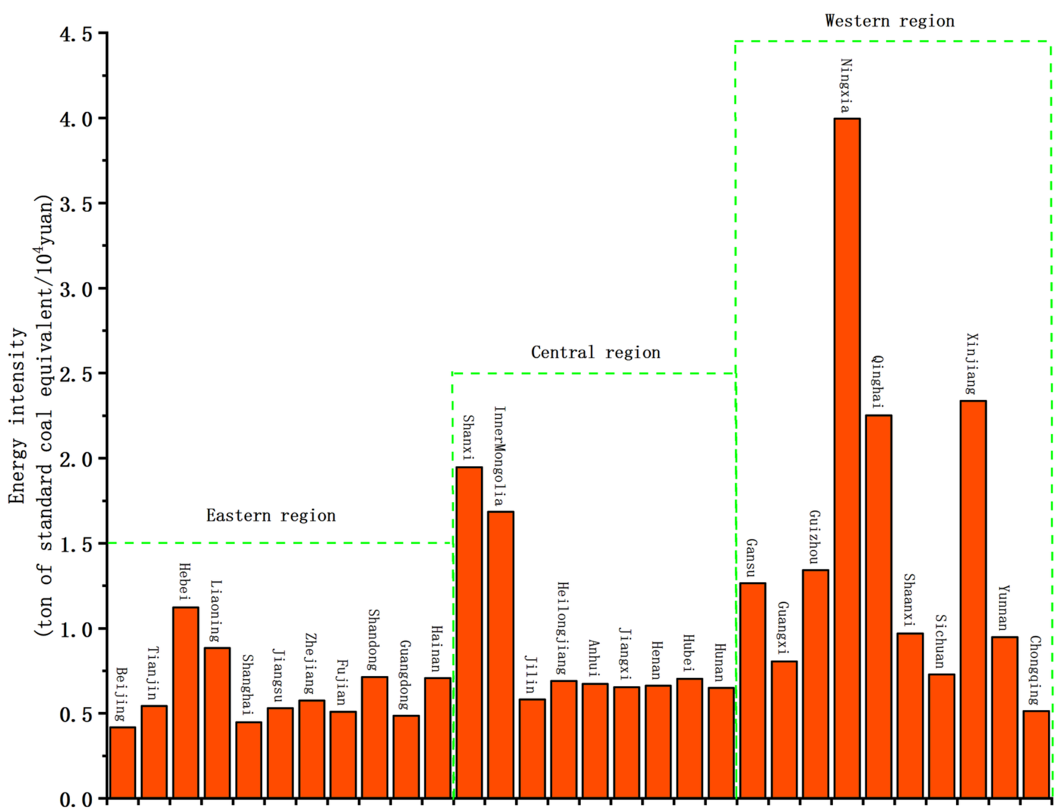
resulted in significant gaps in energy intensity among different regions in China. While the eastern region has achieved a significant reduction in energy intensity through leveraging green technologies and industrial upgrading (Chen et al., 2019; Chen & Lin, 2021), energy intensity in central and western regions is still relatively high due to backward modes of economic development (Figure 1). This regional disparity poses a significant challenge to achieving China's carbon neutrality target (Zheng et al., 2020a).

Industrial relocation is widely recognized as the main reason for regional disparities in energy intensity within China (Li, Pan, & Yuan, 2022; Wu & Lin, 2021). The impact of industrial relocation on energy intensity is complex. On the one hand, industrial relocation may lead to the agglomeration of energy-intensive industries in some specific regions, which can increase local energy intensity. On the other hand, industrial relocation can promote industrial synergy, technology diffusion, and economies of scale, thereby decreasing regional energy intensity (Tanaka & Managi, 2021). Additionally, industrial relocation is a bidirectional phenomenon that involves the relocation-out and relocation-in of corresponding industries in different areas simultaneously, resulting in a dual impact on energy intensity at the national level (Lin & Wang, 2023). However, the existing literature has mainly focused on the emissions transfer driven by industrial relocation, with limited attention paid to the industrial relocation itself. Therefore, the actual situation of China's industrial relocation and its relationship with energy intensity remains uncertain.

Since 2000, the Chinese government has implemented a range of regional economic policies, such as the "Rise of Central China," "Western Development," and "Revitalization of the Northeast," aimed at addressing imbalanced regional economic development and optimizing the national industrial layout.

Figure 1. Provincial energy intensity in 2019



Industrial relocation has emerged as a key means for achieving these goals Chen & Lin, 2021; Mi et al., 2021). For the more developed eastern regions of China, the outflow of certain industries, particularly the outflow of some energy-intensive industries, can redirect their surplus economic capacity to other regions and enhance the quality of local development (Ge, Cai, & Song, 2022; Han, Zhang, Huang, Peng, & Wang, 2021). For the less developed central and western regions, the inflow of capital and labor-intensive sectors can lead to significant investments and employment, rapidly promoting local economic growth (Zheng, Deng, Li, & Yang, 2022). Despite the significant impact of industrial relocation on China's regional economy and environment, the trend, scale and environmental impact of China's industrial relocation is still largely unknown. However, a comprehensive understanding of China's industrial relocation is of practical importance for designing and adjusting future industrial policies in the country. The current study seeks to answer three crucial questions: (1) What is the scale and trend of industrial relocation in China? (2) How does industrial relocation affect regional energy intensity? (3) Are there any spatial spillover effects associated with industrial relocation?

Furthermore, close spatial influences and links exist between China's different regions, which have a crucial impact on the feasibility and cost of inter-regional industrial relocations. Traditional econometric methods, such as OLS and fixed effect models, cannot capture such spatial correlations and thus may lead to biased estimation results (Anselin & Griffith, 1988; Tobler, 1970). Therefore, this paper adopts the spatial econometric model to investigate the relationship between industrial relocation and regional energy intensity, which can better capture the spatial spillover effects of industrial relocations and reveal their regional heterogeneity.

In this study, we focus on the relocation of China's three major economic sectors. Using the MRIO model and the latest multi-regional input-output tables, we comprehensively analyze of the trend and scale of industrial relocation among China's 30 provinces between 2006 and 2018. The findings reveal that the relocation of China's industrial sector has exhibited a distinctive trend of moving "westward" and "northward," while the service sector has demonstrated a tendency to cluster in several developed regions. Next, the Spatial Durbin model (SDM) is employed to examine the spatial spillover effect of industrial relocation on regional energy intensity. We find that the impact of industrial relocation on energy intensity has significant regional heterogeneity. That is, the net inflow of the industrial sector will increase the energy intensity of the inflowing region but will decrease the energy intensity of other regions. Moreover, the services sector's effect is just the opposite. However, on the whole, the total effects of these two sectors on energy intensity are both insignificant. This insignificance indicates that China's current industrial relocation has yet to fully realize its potential to enhance resource allocation efficiency at the national level.

This paper may deliver the following marginal contributions to existing literature: Firstly, using an input-output analysis framework, this paper provides an in-depth examination of the trend and scale of industrial relocation across China's 30 provinces during 2006-2018. Previous literature based on MRIO models has focused primarily on emissions transfers and lacked attention to industrial relocation. This paper extends the existing studies about China's industrial relocation by providing new insights into understanding it. Secondly, considering the close spatial correlations between China's regions, this paper employs spatial econometric models to investigate the relationship between industrial relocation and regional energy intensity, which can better grasp the spatial spillover effect of industrial relocation and obtain more accurate estimation results. This method can also draw richer conclusions than traditional econometrics models by decomposing the regression results. Finally, according to the empirical results, we proposed targeted policy recommendations to promote high-quality industrial relocation in China.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Early studies on industrial relocation mainly focused on international industrial relocation and widely discussed its driving factors and relocation patterns (Akamatsu, 1962; Vernon, 1966). These studies depict industrial relocation as an orderly circular economy process. However, industrial relocation can occur between countries and regions (Peng, Zhu, & Cui, 2023; Zheng, 2021), particularly for countries with significant regional differences, such as China, where the scale and impact of its domestic industrial relocation between its various regions exceed its industrial relocation with other countries (Lin & Wang, 2023; Zhou et al., 2018). China's domestic scholars have attempted to quantify industrial relocation from various perspectives, such as regional industrial output value, changes in industrial structure, and the number of industrial parks (Li et al., 2022; Song, Zhang, Xu, & Elshkaki, 2023; Wang, Sun, Lv, & Wang, 2022; Wu & Lin, 2021). However, these methods may be prone to significant measurement errors, as changes in industry structure and output are not precisely equivalent to the scale of industrial relocation but are also influenced by local economic output and demand structure. Additionally, these measurements usually reflect only the relative degree of industrial relocation and fail to capture the absolute scale of such relocations, leaving the actual state of China's industrial relocation largely unknown.

In contrast to traditional methods that assess industrial relocation through changes in industrial structure, the MRIO model utilizes matrix operations to distinguish between output used for intermediate inputs and external trade, enabling more accurate measurements of industrial relocation and providing valuable insights into its absolute scale. However, existing literature based on the MRIO analysis framework primarily focuses on emission transfer and lacks a comprehensive analysis of industrial relocation (Mi et al., 2017; Mi et al., 2021; Zheng et al., 2020a). To address this gap, this paper employs the MRIO model to analyze the inter-provincial relocations of China's three major sectors, which can accurately capture the overall trend and absolute scale of industrial relocations in China.

Energy intensity refers to the amount of energy consumed per unit of output and is one of the important indicators for assessing energy efficiency. Generally, a higher energy intensity indicates that more energy is required per unit of output, typically implying a lower level of energy efficiency. In comparison, a lower energy intensity indicates that less energy is required per unit of output, typically implying higher energy efficiency. Since the beginning of the 11th Five-Year Plan, China has been setting energy intensity reduction targets as part of its national plan. Therefore, understanding the influencing factors of energy intensity is relevant to achieving China's energy saving and emission reduction targets. The existing literature on energy intensity mainly focuses on its influencing factors, generally summarized in three aspects: the economic, structural, and technological factors. As for the economic factor, numerous studies have shown that China's economic growth and energy intensity demonstrate an inverted U-shaped relationship, which aligns with the "Kuznets Curve" theory of the environment (Shokoohi, Dehbidi, & Tarazkar, 2022; Zhang, Chen, & Wang, 2022). Besides, many scholars have emphasized the significant impact of economic structure, particularly the industrial and urbanization structures, on regional energy intensity. For instance, some scholars argue that a region's industrialization level is positively related to the local energy intensity (Wang, Sun, Reiner, & Wu, 2020; Wang et al., 2022). Zhu and Lin (2020) find that China's new urbanization can contribute to a decrease in energy intensity. Moreover, technological innovation is widely considered to be the key to reducing energy intensity and improving energy efficiency (Liu, Zhang, Adebayo, & Awosusi, 2022; Uddin, Pan, Saima, & Zhang, 2022; Zheng, 2021). Besides the main factors above, macro factors such as foreign direct investment and regional environmental regulations can also influence China's regional energy intensity (Lee & Ho, 2022; Zhang & Song, 2021).

However, there is still a debate regarding the impact of industrial transfer on energy intensity. Some scholars argue that industrial transfer may lead to the relocation of energy-intensive industries from developed to less developed regions, resulting in a "pollution haven" effect (Cheng, Li, & Liu, 2020; Wei, Liu, & Zhang, 2019) and higher energy intensity (Xue et al., 2022). On the other hand, other scholars maintain that industrial relocation can improve energy efficiency through technology transfer, scale effect, and resource integration (Li et al., 2022; Wu, You, Ren, & Gan, 2022). In addition, many studies of the relationship between industrial relocation and energy use ignored the spatial spillover effect of industrial relocation (Chen, Xu, & Yang, 2017; Li, Huang, Yang, Chuai, & Wu, 2017; Xin-gang & Fan, 2019; Zhao & Yin, 2011). But in fact, the net inflow of an industry in one region also means the net outflow of that industry in another region. Ignoring this spatial correlation will likely lead to biased estimates (Anselin & Griffith, 1988; Elhorst, 2014).

In China, the agricultural sector has a much lower total energy consumption and output than the industrial and service sectors. Therefore, its impact on energy intensity may be relatively small (Muhammad, Pan, Agha, Umar, & Chen, 2022). As the main consumer of fossil energy, the industrial sector has a higher energy intensity than the other two sectors (Li & Lin, 2014; Muhammad et al., 2022; Zhang & Wang, 2021). Hence, the net inflow of the industrial sector may increase local energy intensity. However, despite the service sector's high energy consumption (mainly secondary energy), it strongly drives the regional economy. Therefore, the net inflow of the service sector is likely to reduce local energy intensity. Based on the preceding discussion, the first hypothesis of this paper is as follows:

Hypothesis 1: The net inflow of the industrial sector may increase local energy intensity, while the net inflow of the service sector may reduce local energy intensity.

Industrial relocation in China is bidirectional, with the inflow of an industry in one region being accompanied by the outflow of the same industry in other regions (Liu, Liu, & Liu, 2011). This phenomenon is common between developed and less developed regions, with developed areas relocating their energy-intensive industries to less developed regions. While this may lead to an increased energy conservation burden on less developed regions, it can also reduce energy intensity in developed areas to a certain extent (Lin & Wang, 2023). Therefore, the environmental implications of industrial relocation may also be bidirectional. Thus, the second hypothesis of this paper is as follows:

Hypothesis 2: Industrial relocation has opposing effects on the energy intensity of the industrial inflow region and that of other regions.

METHODOLOGY AND DATA

Multi-Regional Input-Output Model

The MRIO model, proposed by Isard (1951), is a widely used method for analyzing economic links between regions based on inter-regional trade data. This model has been continuously developed and improved and is commonly used for measuring emission transfer and industrial relocation (Mi et al., 2017; Mi et al., 2021; H. Zheng et al., 2020a).

Our study applies the MRIO model to measure industrial relocation among regions in China. In this model, we are supposing an economy with r regions and s sectors. For region m, its total output can be represented as x_i^m; its intermediate input from sector i to region n's sector j is x_{ij}^{mn}; the product provided by sector i in region m for final demand in region n as Y_i^{mn}. The relationships between x_i^m, x_{ij}^{mn}, and Y_i^{mn} are as follow:

$$\mathrm{x}_i^m = \sum\nolimits_{r,m\neq n} \sum\nolimits_{s,i\neq j} x_{ij}^{mn} + \sum\nolimits_{r,m\neq n} Y_i^{mn} \tag{1}$$

$$a_{ij}^{mn} = x_{ij}^{mn} \ / \ x_j^n \tag{2}$$

We express the above relationship in matrix form:

$$\begin{pmatrix} X_1 \\ \vdots \\ X_m \end{pmatrix} = \begin{pmatrix} A_{11} & \cdots & A_{1m} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mm} \end{pmatrix} \begin{pmatrix} X_1 \\ \vdots \\ X_m \end{pmatrix} + \begin{pmatrix} Y_1 \\ \vdots \\ Y_m \end{pmatrix} \tag{3}$$

$$X = AX + Y \tag{4}$$

$$X = (I - A)^{-1} Y \tag{5}$$

In Equation (5), A denotes the direct consumption coefficient matrix; I denotes the identity matrix. In this way, we can write the region m's total industrial inflow (IF) as follows:

$$IF^m = \sum_{r,n \neq m} X^{nm} \tag{6}$$

Similarly, we can write the region m's total industrial outflow (OF) as follows:

$$OF^m = \sum_{r,n \neq m} X^{mn} \tag{7}$$

where, IF^m refers to the sum of output produced by region *m* for the final demand of other regions, while OF^m refers to the sum of the output produced by other regions for the final demand of region *m*. *X* is an industrial transfer matrix.

Finally, region m's net inflow is equivalent to the inflow minus outflow, which can be expressed as:

$$NF^m = OF^m - IF^m \tag{8}$$

It should be noted that the net industrial inflow (NF^m) reflects more comprehensive information about industrial relocation than the other two indicators (IF^m *and* NF^m). This indicator contains both the information from IF^m and the information from NF^m, thus reflecting the net transfer trend of the industries in a region. Therefore, we adopt the net industrial inflow as a proxy indicator of industrial relocation.

Ceads database has only published China's MIRO tables for 2007,2010,2012, 2015 and 2017. Zheng et al. (2020b) proposed a novel method to extend the MRIO tables. This enabled us to obtain data for other years, which can be expressed as follows:

$$\begin{aligned} \mathrm{X}_{2013} &= \frac{2}{3} L_{2012} (FS_{2012} FV_{2013}) + \frac{1}{3} L_{2015} (FS_{2015} FV_{2013}) \\ \mathrm{X}_{2014} &= \frac{1}{3} L_{2012} (FS_{2012} FV_{2014}) + \frac{2}{3} L_{2015} (FS_{2015} FV_{2014}) \\ \mathrm{X}_{2016} &= \frac{1}{2} L_{2015} (FS_{2015} FV_{2016}) + \frac{1}{2} L_{2017} (FS_{2017} FV_{2016}) \end{aligned} \tag{9}$$

In equation (9), FS_t represents the final demand structure for year t, L_t is the Leontief inverse matrix for year t. FV_t denotes the final demand for year t. Here, the final demand data are obtained from China Statistical Yearbook. In the same way, we can also acquire the data for the rest years (the structure of final demand in 2006 and 2018 refers to 2007 and 2017, respectively), hence calculating the scale of industrial relocation in China's 30 provinces from 2006-2018.

Spatial Econometrics Model and Data

Tobler (1970) and Anselin and Griffith (1988) noted that spatial correlation widely exists between regions. Ignoring such spatial correlation might result in biased estimation results. With this in mind, we adopt spatial econometric models to investigate the influences of industrial relocation on energy intensity.

Spatial econometric models can be specified in various forms according to different kinds of spatial correlations (Elhorst, Lacombe, & Piras, 2012). In this paper, we mainly consider three following forms (Elhorst, 2014):

$$ei_{it} = \alpha + \rho \sum_j w_{ij} ei_{it} + \beta_1 firt_{it} + \beta_2 \sec t_{it} + \beta_3 thirt_{it} + \gamma X_{it} + u_i + \delta_t + \varepsilon_{it} \tag{10}$$

$$ei_{it} = \alpha + \beta_1 firt_{it} + \beta_2 \sec t_{it} + \beta_3 thirt_{it} + \gamma X_{it} + u_i + \delta_t + \lambda \sum_j w_{ij} \varepsilon_{jt} + \xi_{it} \tag{11}$$

$$\begin{aligned} ei_{it} &= \alpha + \rho \sum_j w_{ij} ei_{it} + \beta_1 fir_{it} + \beta_2 \sec t_{it} \\ &+ \beta_3 thirt_{it} + \theta_1 \sum_j w_{ij} firt_{jt} + \theta_2 \sum_j w_{ij} \sec t_{jt} \\ &+ \theta_3 \sum_j w_{ij} thirt_{jt} + \gamma X_{it} + \psi \sum_j w_{ij} X_{jt} + \lambda \sum_j w_{ij} \varepsilon_{jt} + u_i + \varepsilon_{it} \end{aligned} \tag{12}$$

where, Eq. (10), Eq. (11) and Eq. (12) denote Spatial Autoregressive Model (SAR), Spatial Error Model (SEM) and Spatial Durbin Model (SDM), respectively. In these equations, subscript i, j, t denote province i, province j and year t, respectively. ei_{it} is the energy intensity; $firt_{it}$ represents the scale of the net inflow of agricultural sector in the province as a percentage of local GDP; $sect_{it}$ represents the scale of the net inflow of industrial sector as a percentage of local GDP; $thirt_{it}$ represents the scale of the net inflow of service sector as a percentage of local GDP.

It should be noted that the input-output table includes 42 industries. We classified them into the agricultural, industrial, and service sectors based on the National Economic Classification in 2018. Furthermore, the specific classification standards are shown in Figure 5 in the Appendix.

X_{it} represents the control variables, which include industrial structure (*ins*), level of urbanization (*urb*), GDP per capita (*pergdp*), foreign direct investment (*fdi*), environmental regulation (*regu*), and technological innovation (tec). All control variables have been discussed in the literature review. The definitions and statistic descriptions are shown in Table 1, Table 2, and Table 3 respectively. We get these data from the China Statistical Yearbook, China Energy Statistical Yearbook, China Emission Accounts and Datasets, China Environmental Statistical Yearbook, and China Science and Technology Statistical Yearbook.

μ_i depicts the provincial fixed effects and δ_t depicts the time fixed effect; ε_{it} denotes the error term; w_{ij} represents an element of the spatial weight matrix.

Table 1. Definition and sources of each variable

Indicator	Definition
i	Energy consumption (convert to standard coal) per 10,000 yuan of GDP
firt	The percentage of net inflow of agricultural sector to GDP
sect	The percentage of net inflow of industrial sector to GDP
thirt	The percentage of net inflow of service sector to GDP
ins	Value added of the industrial sector as a percentage of GDP
urb	Urban population as a percentage of the total population
pergdp	GDP per capita
fdi	Foreign direct investment as a percentage of GDP
regu	Investment in pollution control as a percentage of GDP
tec	R&d spending as a percentage of GDP

Table 2. Panel A: Descriptive statistics of variables

Variable	N	Mean	SD	Min	Max
ei	390	1.818	0.911	0.604	5.621
firt	390	2.300	8.276	-15.32	40.15
sect	390	-1.282	47.31	-165.1	115.3
thirt	390	-0.522	21.05	-97.00	97.03
ins	390	46.54	8.476	18.01	64.93
urb	390	54.44	13.85	25.07	89.60
perg	390	2.262	1.335	0.611	7.248
regu	390	1.462	1.267	-0.216	9.920
tec	390	1.472	1.067	0.207	6.110

Table 3. Panel B: The Moran's I index of energy intensity

Year	Moran's I	p-Value*
2006	0.109	0.000
2007	0.121	0.000
2008	0.130	0.000
2009	0.134	0.000
2010	0.132	0.000
2011	0.132	0.000
2012	0.134	0.000
2013	0.131	0.000
2014	0.132	0.000
2015	0.132	0.000
2016	0.126	0.000
2017	0.122	0.000
2018	0.125	0.000

Tobler (1970) noted that the connection between regions is strongly influenced by geographical distance, with closer proximity resulting in stronger correlations between regions. With this in mind, we have constructed a symmetric geographical distance weight matrix (W_1) to reflect the impact of geographical factors between provinces:

$$W_{1,ij} = \begin{cases} \dfrac{1}{d_{ij}^{\ 2}}, i \neq j \\ 0, i = j \end{cases} \tag{13}$$

where d_{ij} denotes the geographic distance between province i and province j.

EMPIRICAL RESULTS

Relocations of Industrial and Service Sectors in China

Based on the method in section 3, we measure the relocation of three sectors during 2006-2018. Considering that the relocation scale and trend of the agricultural sector are not obvious, it will not be analyzed separately. We mainly focus on the relocations of industrial and service sectors, which are shown in Figures 2 and 3, respectively.

Figure 2. Relocation of the industrial sector in 2007, 2012, and 2017

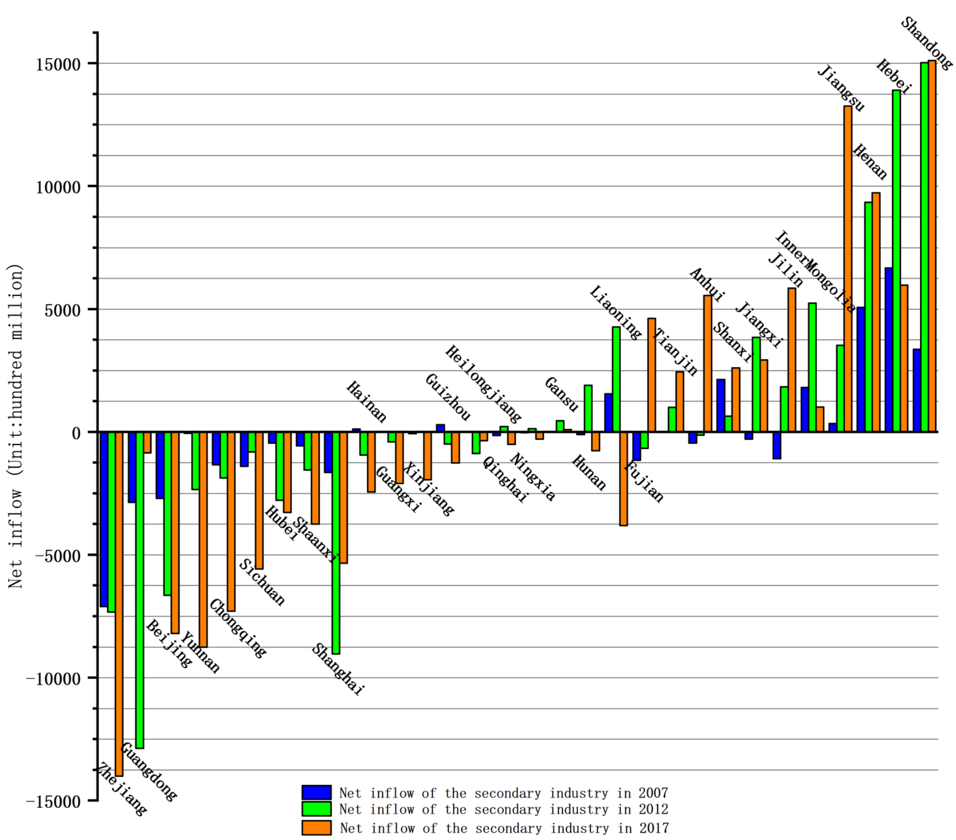


Figure 3. Relocation of the service sector

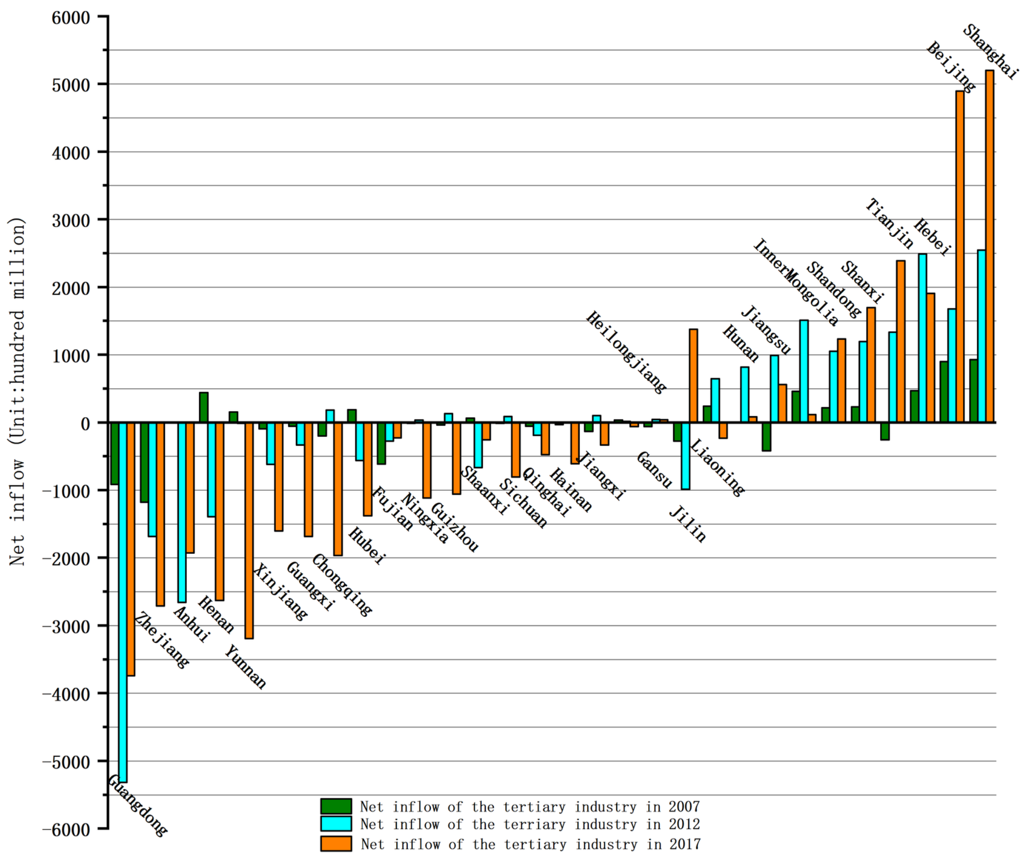


Figure 2 illustrates the relocation of China's industrial sector among its 30 provinces in 2007, 2012, and 2017. The vertical axis represents net inflow, where a positive value indicates a net inflow area of the industrial sector while a negative value indicates a net outflow area. The industrial sector has the most significant relocation scale, with some provinces exceeding one trillion yuan in certain years. On average, the industrial sector's relocation scale is 2-3 times that of the service sector and 8-10 times that of the agricultural sector. Regarding the relocation trend, the relocation of China's industrial sector displays an obvious trend of "westward" and "northward." The two main outflow areas are the eastern and southwestern regions, such as Guangdong, Zhejiang, Beijing, Shanghai, Yunnan, Chongqing, and Sichuan. The two main inflow areas are the northern coastal and central regions, such as Shandong Hebei, Henan, Inner Mongolia, Anhui, Shanxi, and Jiangxi.

Multiple factors drive the large-scale outflow of the industrial sector in the eastern provinces. First, the prices of production factors in these provinces have experienced significant increases in recent years due to the rapid growth of the local economy (Xi, Zhang, Zhu, Zhang, & Yuan, 2022). This price increase makes the production costs of the local industrial sector higher than that of other regions. Furthermore, as living standards continue to improve, residents and governments have become increasingly environmentally conscious, leading to the implementation of stricter environmental regulations in these areas (Xinze Li, Du, Ouyang, & Liu, 2022). This raising of regulations has raised the environmental cost of the local industrial sector and further squeezed their profit margins.

Moreover, the successful industrial upgrading in eastern China is also an important driver for its large-scale industrial outflow. The eastern provinces, such as Guangdong, Zhejiang, and Shanghai, have been actively promoting the transformation of their industries towards service and technology-intensive sectors. These efforts have made the service sector in these provinces replace the industrial sector as the key driving force behind their economic growth (Wang, Zhang, Springer, & Yang, 2021). Besides, many industrial sectors in these provinces have also completed the transformation towards technology-intensive industries (Lin & Shi, 2022), which further accelerates the outflow of the low-end industrial sector from the region.

However, different from the eastern region, the large-scale outflow of the industrial sector in southwestern provinces is more due to objective factors. China's southwestern region is mainly mountainous, significantly increasing the local transportation costs. Moreover, as a landlocked area, the southwestern region faces challenges in importing foreign industrial raw materials. This limitation restricts the production scale of industries, such as the petrochemical and steel sectors. Consequently, southwest China has a notable outflow of the industrial sector.

In contrast to the above two regions, the northern coastal and central regions can provide better conditions for developing the industrial sector. First, the land is flat in most parts of these two regions, which provides rich land resources and convenient transportation. Second, China's two regions have the highest population density, supplying sufficient and cheap labor for local industrial enterprises. Besides, environmental regulation in the two regions is also looser than in developed eastern regions. With these comparative advantages, the northern and central regions have undertaken a large inflow of industrial sectors in recent years. On the one hand, this has greatly spurred local economic development; however, it has also placed pressure on local environmental protection and emission reduction efforts.

Figure 3 illustrates China's service sector's relocation scale and trend in 2007, 2012, and 2017. Compared to the industrial sector, the service sector's relocation scale is smaller, with an average annual relocation of less than 500 billion yuan in most provinces. Regarding relocation trends, the eastern coastal areas, such as Beijing, Shanghai, Tianjin, and Jiangsu, have attracted a large inflow of the service sector due to their highly concentrated financial industries and booming real estate sectors. The southern coastal, central, and western provinces, such as Guangdong, Zhejiang, Anhui, Henan, Xinjiang, and Chongqing, are the main outflow areas of the service sector. These regions have a great demand for service products, but their local service sector is not developed enough, thus resulting in a significant outflow of the service sector.

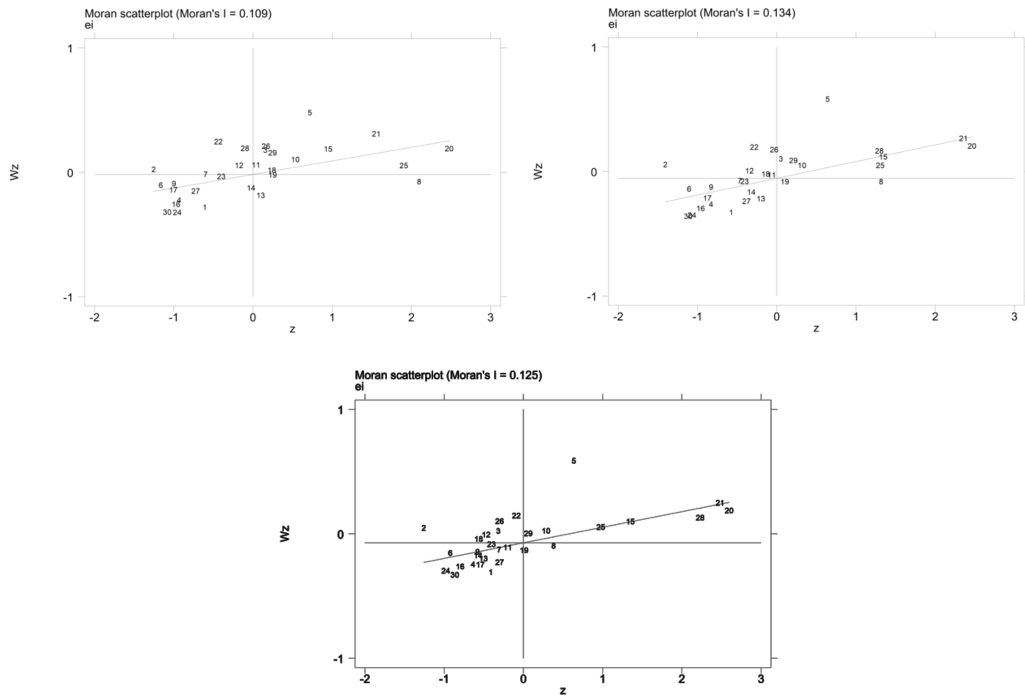
In general, several eastern provinces, such as Beijing, Tianjin, and Shanghai, have successfully attracted a substantial influx of the service sector, benefiting from their favorable policies and strategic locations. The significant inflow of these high-value-added industries has played an important role in energy intensity reduction within these provinces.

Spatial Autocorrelation Test

To identify whether global spatial autocorrelation exists between variables, we measure the annual global Moran's energy intensity index. As shown in Table 3, Moran's I indices are all significant at a 1% level, implying that energy intensities display significant characteristics of spatial autocorrelation and spatial clustering.

Besides, the scatter plots of the local Moran's indices in 2006, 2012, and 2018 are drawn to verify whether there exist local spatial correlations. These plots are shown in Figure 4. The vertical axis represents the spatial lag value, and the horizontal axis represents the standardized provincial energy intensity. The numbers 1 to 30 represent each of China's 30 provinces, in order with Anhui, Beijing, Chongqing, and Zhejiang (in alphabetical order). Most provinces' energy intensities are in the first and third quadrants, indicating positive spatial correlations between provinces. As a result, spatial econometrics models are needed to explore the impact of industrial relocation on energy intensity.

Figure 4. Moran's I scatter plot of energy intensity



Estimation of Non-Spatial Models and Lagrange Multiplier Tests

We use LM and robust LM tests to determine whether the model should include spatial lag or error term (Elhorst & Fréret, 2009). The results in Table 4 show that both the LM spatial error and lag tests rejected the null hypothesis at the 1% significance level, indicating that spatial lag and error terms should be included in the model. Therefore, we adopt the SDM model with both spatial lag and error terms as the main analysis tool for this study.

Benchmark Regression Results

To examine the impact of industrial relocation on energy intensity, we adopt two types of SDM models, namely spatial fixed effect and two-way fixed effect. We present the estimation results in columns (3)-(4) of Table 5, respectively. To ensure the robustness of our results, we also report the regression outcomes of SAR and SEM in columns (1)-(2). And the results of the Hausman, Likelihood Ratio (LR), and Wald tests are presented in Table 6.

Our findings show that the P-values of the Wald and LR tests were all below 0.01, indicating that the SDM model is more suitable for this study than SAR and SEM. Additionally, the P-values of the Hausman test are 0.042 and 0.000, which strongly reject the null hypothesis that the random effect is more appropriate than the fixed effect. Furthermore, the loglikelihood results in column 4 of Table 5 were higher than in column 3, indicating that the two-way fixed effect is better than the spatial fixed effect. Therefore, we regard the results of the SDM with two-way fixed effects in column 4 as the benchmark regression results.

As presented in Table 5, the spatial autoregressive coefficients (ρ) and the spatial error correlation coefficient lambda (λ) are significantly positive at a 1% level, confirming that the energy intensities have significant spatial spillover effects. As for the relocation variables, the *sect*'s estimated coefficient (0.013) is significantly positive at a 5% level, implying that a 1% rise in the percentage of the industrial

Table 4. The results of non-spatial panel models and LM (robust) test

	Pooled OLS	Spatial Fixed Effects	Time-Period Fixed Effects	Two-Way Fixed Effects
firt	-0.001	0.003	-0.001	0.003
	(0.005)	(0.005)	(0.005)	(0.005)
sect	0.041***	0.052***	0.040***	0.052***
	(0.011)	(0.011)	(0.011)	(0.011)
thirt	-0.016***	-0.020***	-0.016***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
ins	0.038***	0.045***	0.038***	0.045***
	(0.008)	(0.008)	(0.008)	(0.008)
urb	0.020***	0.016***	0.019***	0.017***
	(0.005)	(0.005)	(0.006)	(0.005)
pergdp	-0.559***	-0.520***	-0.559***	-0.531***
	(0.064)	(0.062)	(0.064)	(0.062)
fdi	-0.103***	-0.105***	-0.100***	-0.107***
	(0.021)	(0.020)	(0.021)	(0.020)
regu	0.275***	0.245***	0.275***	0.245***
	(0.030)	(0.029)	(0.030)	(0.029)
tec	-0.008**	-0.009***	-0.007**	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
R2	0.508	0.535	0.509	0.536
Adj-R2	0.496	0.522	0.495	0.521
LM Lag	71.052***	63.217***	68.255***	63.829***
	(0.000)	(0.000)	(0.000)	(0.000)
Robust LM-lag	11.155***	7.669***	10.145***	7.607**
	(0.001)	(0.006)	(0.001)	(0.006)
LM error	63.787***	62.977***	62.300***	63.742***
	(0.000)	(0.000)	(0.000)	(0.000)
Robust LM error	3.890**	7.430***	4.190**	7.520**
	(0.049)	(0.006)	(0.041)	(0.006)
N	390	390	390	390

Standard errors in estimated coefficients' parentheses, p-values in four tests' parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

sector's net inflow of local GDP will increase the energy consumption per unit (10000 yuan) of GDP by 0.013 tons of standard coal. The *thirt*'s estimated coefficient (-0.010) is significantly negative at the 1% level, suggesting that a 1% rise in the percentage of the service sector's net inflow of local GDP will decrease the energy consumption per unit (10000 yuan) GDP by 0.010 tons of standard coal. Furthermore, it should be noted that the *W*sect*'s is significantly negative at the 10% level while the *W*thirt*'s is significantly positive at a 5% level, which preliminarily confirms that a larger net

Table 5. Benchmark regression results

	SAR Two-Way Fixed Effects	SEM Two-Way Fixed Effects	SDM Spatial Fixed Effects	SDM Two-Way Fixed Effects
	(1)	(2)	(3)	(4)
firt	0.005	0.005*	0.005	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
sect	0.015***	0.015***	0.013**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
thirt	-0.009***	-0.009***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
ins	0.022***	0.021***	0.028***	0.028***
	(0.006)	(0.006)	(0.007)	(0.007)
urb	0.020**	0.019**	0.030***	0.030***
	(0.010)	(0.010)	(0.010)	(0.011)
pergdp	-0.172**	-0.169*	-0.270***	-0.275***
	(0.084)	(0.088)	(0.088)	(0.092)
fdi	-0.010	-0.012	0.002	0.003
	(0.014)	(0.014)	(0.015)	(0.015)
regu	0.030*	0.029*	0.020	0.022
	(0.017)	(0.017)	(0.016)	(0.017)
tec	-0.010***	-0.010***	-0.009**	-0.011***
	(0.003)	(0.003)	(0.003)	(0.004)
W*firt			0.013	0.011
			(0.008)	(0.010)
W*sect			-0.031*	-0.032*
			(0.019)	(0.019)
W*thirt			0.018***	0.017**
			(0.006)	(0.007)
W*ins			-0.014*	-0.019
			(0.009)	(0.016)
W*urb			0.004	-0.004
			(0.016)	(0.033)
W*pergdp			0.632***	0.743***
			(0.194)	(0.275)
W*fdi			0.093	0.096
			(0.062)	(0.064)
W*regu			-0.023	0.003
			(0.028)	(0.047)

continued on following page

Table 5. Continued

	SAR Two-Way Fixed Effects	SEM Two-Way Fixed Effects	SDM Spatial Fixed Effects	SDM Two-Way Fixed Effects
	(1)	(2)	(3)	(4)
W*tec			-0.008	-0.016**
			(0.007)	(0.008)
λ		0.270***		
		(0.140)		
ρ	0.105**		0.118**	0.107***
	(0.128)		(0.121)	(0.123)
Log-Lag	37.487	35.940	40.739	44.487
N	390	390	390	390

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Hausman, Wald, and LR tests

	SDM Spatial Fixed Effects	SDM Two-Way Fixed Effects
Hausman	17.44	32.96
	(0.042)	(0.000)
Wald SAR	29.13	55.88
	(0.000)	(0.000)
Wald SEM	33.32	58.65
	(0.000)	(0.000)
LR-SAR	22.43	39.68
	(0.0076)	(0.0000)
LR-SEM	24.03	42.78
	(0.004)	(0.000)

p-values in four tests' parentheses.

inflow of industrial sector in neighboring provinces related to a lower local energy intensity, while a larger net inflow of service sector in neighboring provinces related to a higher local energy intensity.

As for the control variables, the industrial structure positively affects energy intensity, which is consistent with (Luan, Zou, Chen, & Huang, 2021). An increase in the urbanization rate can enhance regional energy intensity, indicating that the energy-saving effect of China's urbanization has not been realized. The per capita GDP negatively correlates with energy intensity, suggesting that economic growth can reduce energy intensity. This correlation indicates that China has crossed the inflection point of the environmental Kuznets curve (Lin & Zhu, 2021). The estimated coefficient of technological innovation is significant at a 1% level, indicating that a higher technology level can improve local energy efficiency.

We then decompose the spatial effects of the industrial relocation into direct, indirect and total effects. Here, the direct effect is composed of two parts. One part is the effect of explanatory variables on the local explained variable. Another part is the feedback effect, which affects the explanatory variables in neighboring regions, and then affects the local explanatory variables in turn.

Table 7 displays the decomposition results. The three effects of the agricultural sector's net inflow (*firt*) are all insignificant, indicating that the interregional relocation of the agricultural sector has no significant effects on energy intensity. This finding proves hypothesis 1. The agricultural sector's energy consumption and relocation scale are relatively small, so its impact on energy intensity is also limited.

The direct effect of the industrial sector's net inflow (*sect*) is significantly positive (0.013), which means that a 1% increment in the proportion of the net inflow of the industrial sector of local GDP is accompanied by an increase in energy consumption per unit (10000 yuan) of GDP of 0.013 tons standard coal. Since it differs very little from the *sect*'s estimated coefficient in SDM, the main component of the direct effect is the influence of the local net inflow of the industrial sector on local energy intensity, but not the spatial feedback effect. Besides, it should be noted that the indirect effect is significantly negative (-0.032), contrary to the direct effect's sign. This indicates that a higher net inflow of the industrial sector in a region can decrease the energy intensity in other regions. A larger inflow of the industrial sector in a region usually indicates that this region takes on more of the industrial production process than other regions, leading to higher local energy intensity.

On the contrary, the other regions' economies will be correspondingly cleaner due to the "outsourcing" of industrial production. This phenomenon widely exists between developed and less developed areas of China, where the developed areas relocate their high energy-consuming industries to less developed areas. While it may promote the latters' economic growth and alleviate the imbalance issue of the regional economy, it may also create a greater burden on their energy conservation and emission reduction. We also noticed that the total effect of *sect* is insignificant, suggesting that the

Table 7. Direct, indirect, and total effects of variables

Variables	Direct Effects	Indirect Effects	Total Effects
firt	0.006	0.010	0.016
	(0.004)	(0.010)	(0.010)
sect	0.013**	-0.032*	-0.019
	(0.006)	(0.018)	(0.020)
thirt	-0.010***	0.017***	0.007
	(0.002)	(0.007)	(0.007)
ins	0.028***	-0.021	0.008
	(0.006)	(0.015)	(0.015)
urb	0.030***	-0.004	0.026
	(0.011)	(0.031)	(0.031)
pergdp	-0.278***	0.715***	0.437
	(0.092)	(0.266)	(0.277)
fdi	0.002	0.092	0.094
	(0.015)	(0.064)	(0.066)
regu	0.022	0.005	0.027
	(0.016)	(0.046)	(0.050)
tec	-0.011***	-0.014*	-0.025***
	(0.004)	(0.008)	(0.009)

potential energy-saving effect of China's industrial relocation has not yet been fully realized at the national level.

Another significant result is the net inflow of the service sector (*thirt*). The direct effect of *thirt* is significant at the 1% level (-0.010), which differs very little from the estimated coefficient in SDM (-0.009). Therefore, the main direct effect is the local *thirt*'s effect on local energy intensity. The estimated indirect effect is significantly positive(0.017), which indicates that the net inflow of the service sector in a region can increase the energy intensity in other regions. The service sector includes many low-energy-intensive industries, such as technology innovation, finance, and information services. Compared with the industrial sector, these industries consume less energy but add more economic output. Therefore, an increase in the net inflow of the service sector can effectively reduce the local energy intensity. For neighboring regions, on the contrary, the outsourcing of their service sector tends to increase their energy intensity. Besides, the direct effect is smaller than the indirect effect. One possible reason is that the indirect effect is equal to the sum of spillovers from all other provinces, and the spillover effect from a particular province may be smaller than the value we reported (Lv, Liu, & Xu, 2022). Finally, the total effect of *thirt* is insignificant, indicating that *thirt* in a province couldn't affect energy intensity at the national level.

The above discussion has proved Hypothesis 1 and 2, and now we focus on the control variables. The direct effect of per capita GDP (*pergdp*) is -0.278, which is significantly negative. This result is consistent with (Lin & Zhu, 2021). Besides, the indirect effect of *pergdp* is significantly positive (0.715), indicating that the economic development in neighboring provinces will increase the local energy intensity. The three effects of technological innovation are all significantly negative, denoting that technological innovation has a significant spatial spillover effect. This may be because technological innovation in a region can decrease the overall energy intensity through technology diffusion (Ilkay, Yilanci, Ulucak, & Jones, 2021).

ROBUSTNESS

Different Econometric Models

In this paper, we also conduct the regression through OLS, fixed effects, SAR, and SEM models to check the robustness of our results. The results are presented in Tables 4 and 5. We observe that the sign and significance level of most coefficients are similar to our main results, which verifies the stability of the results.

Different Spatial Weight Matrix

Different spatial weight matrices may lead to different regression results. Therefore, we conduct a new geography-economy weight matrix ($\boldsymbol{W_2}$) for our robust check:

$$W_{2,ij} = \begin{cases} \dfrac{1}{d_{ij}^{\ 2}\left|GDP_i - GDP_j\right|}, i \neq j \\ 0, i = j \end{cases} \tag{14}$$

where the d_{ij} represents the geographic distance between province i and province j, and GDP_i and GDP_j are, respectively, the gross domestic product in province i and province j. The decomposed results for W_2 are presented in Table 8. As we can see, most coefficients' significance and signs are similar to the benchmark results. Thus, we assess that our regression results are robust.

Table 8. Regression results with a new weight matrix

Variables	Direct Effects	Indirect Effects	Total Effects
firt	0.005	0.011	0.017
	(0.004)	(0.010)	(0.010)
sect	0.010*	-0.035*	-0.025
	(0.006)	(0.021)	(0.023)
thirt	-0.010***	0.022***	0.011
	(0.002)	(0.008)	(0.008)
ins	0.027***	-0.017	0.010
	(0.006)	(0.016)	(0.016)
urb	0.023**	-0.004	0.019
	(0.010)	(0.037)	(0.038)
pergdp	-0.346***	1.000***	0.654*
	(0.103)	(0.324)	(0.336)
fdi	0.009	0.095	0.104
	(0.016)	(0.075)	(0.079)
regu	0.018	0.002	0.021
	(0.017)	(0.048)	(0.053)
tec	0.009**	0.016**	0.025***
	(0.004)	(0.008)	(0.009)

Subsample Regression

China's central government manages the municipalities as a particular provincial administrative unit. Furthermore, the municipalities are quite different from other provinces in population density and economic development model. This may make the effect of industrial relocation on municipalities different from other provinces. Therefore, we exclude the samples of municipalities and conduct the regression again. The decomposed results are shown in Table 9.

As shown in Table 9, the direct and indirect effects of industrial relocation show the same signs as the benchmark results, proving the robustness of the above conclusion again.

CONCLUSION AND POLICY IMPLICATIONS

Over the past few decades, China's distinct regional disparities and industrial policies have induced several large waves of industrial relocations, significantly influencing the country's regional economy and energy usage. This study primarily analyzes the magnitude and trend of industrial relocation of China's three major economic sectors from 2006 to 2018. Besides, we also examine the spillover impact of the relocations on regional energy intensity. We can draw the following conclusions:

1. The relocation scales and trends of China's three major sectors differ across regions. The industrial sector has a much greater relocation scale than the agricultural and service sectors.

Table 9. Regression results without municipalities

Variables	Direct Effects	Indirect Effects	Total Effects
firt	0.006	0.011	0.016
	(0.004)	(0.011)	(0.011)
sect	0.010*	-0.038*	-0.028
	(0.006)	(0.021)	(0.023)
thirt	-0.009***	0.022***	0.012
	(0.002)	(0.008)	(0.008)
ins	0.026***	-0.017	0.009
	(0.006)	(0.016)	(0.016)
urb	0.018	-0.004	0.014
	(0.011)	(0.037)	(0.040)
pergdp	-0.304***	0.966***	0.662*
	(0.101)	(0.324)	(0.340)
fdi	0.012	0.110	0.122
	(0.017)	(0.075)	(0.078)
regu	0.020	-0.005	0.015
	(0.017)	(0.048)	(0.052)
tec	-0.009**	-0.016**	-0.025***
	(0.004)	(0.008)	(0.009)

It has demonstrated a discernible trend of relocating towards the west and north, whereas the service sector tends to concentrate within serval developed regions.

2. The net inflow of the industrial sector significantly increases local energy intensity, but the net inflow of the service sector effectively reduces local energy intensity.
3. The relocations of industrial and service sectors influence local energy intensity, and spillover impacts neighboring regions' energy intensity.

Based on these findings, we propose the following policy recommendations:

1. Governments must ensure that the industrial relocation is aligned with environmental targets, especially the goal of regional energy conservation targets. Regions with a large inflow of industrial sectors face significant challenges in balancing industrial expansion and local environmental protection. To address this challenge, the central government should provide additional financial and policy support and develop more flexible energy conservation plans for these regions.
2. The total effect of industrial relocation on energy intensity is insignificant, suggesting that the potential for improving energy efficiency through industrial relocation has not yet been fully realized. To address this, the government should emphasize the role of industrial relocation in integrating resources and optimizing industrial layouts. Industries should be encouraged to relocate to regions with comparative advantages, and the construction of advantageous industry clusters in various regions should be promoted.

3. Industrial relocation presents a good channel for technology transfer. To improve productivity of the lagging areas, the government should encourage the transfer of advanced technologies and management modes through industrial relocation. This is crucial to help the undeveloped regions achieve high-quality and sustainable development.

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APPENDIX

Figure 5.

Name of industry	Category
Agriculture, forestry, animal husbandry and fishery products and services	Agricultural sector
Coal mining products	Industrial sector
Oil and gas extraction products	Industrial sector
Metal mining products	Industrial sector
Mineral and other mineral products	Industrial sector
Food and Tobacco	Industrial sector
Textiles	Industrial sector
Textiles, clothing, shoes, hats, leather, down and their articles	Industrial sector
Wood works and furniture	Industrial sector
Paper printing and cultural and educational sporting goods	Industrial sector
Petroleum, coking products and nuclear fuel processing products	Industrial sector
Chemical products	Industrial sector
Non-metallic mineral products	Industrial sector
Metal smelting and calendering products	Industrial sector
Articles of metal	Industrial sector
General purpose equipment	Industrial sector
Special purpose equipment	Industrial sector
Transportation equipment	Industrial sector
Electrical machinery and equipment	Industrial sector
Communications equipment, computers and other electronic equipment	Industrial sector
Instrument and meter	Industrial sector
Other Manufactured Products	Industrial sector
Metalwork, machinery and equipment repair services	Service sector
The production and supply of electricity and heat	Industrial sector
Gas production and supply	Industrial sector
Water production and supply	Industrial sector
building	Industrial sector
Wholesale and Retail	Service sector
Transportation, warehousing and postal services	Service sector
Accommodation and Catering	Service sector
Information transmission, software and information technology services	Service sector
financial	Service sector
Real estate	Service sector
Leasing and business services	Service sector
Scientific Research	Service sector
Technical Services	Service sector
Water conservancy, environment and public facilities management	Service sector
Resident services, repairs and other services	Service sector
education	Service sector
Health and social work	Service sector

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