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Unfolding the spatial spillover effects of urbanization on interregional energy connectivity: Evidence from province-level data

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Acronyms

GDP Gross domestic product

ESI Economic structure index

UR Urbanization rates

URIR Urban-rural income ratio

IER Income-expenditure ratio

LF Labor force

EL Educational level

Symbols

F Embodied energy intensity vector

B Direct energy consumption per unit

A Intermediate coefficient matrix in MRIO table

U Intermediate monetary transaction matrix in MRIO table

q^{rs}_{ij} Embodied energy flows from sector i in region r to sector j in region s

d^{rs} Energy transfers from region rto region s G Embodied energy network v^r

The node of region r

d^r Energy use embodied in the inflows and outflows of province r

e^r The total number of inflows and outflows from province r

D_i The weighted degree of province i

p_{abt}ðkÞ p_{abt}ðkÞ represents for the conditional probability of a region transferring from status a in year t to status b in year t þ 1 with a spatial lag type k R_t The status matrix at year of t w_{ij} The spatial weight between regions i and j

Z_I The significant level for I r The strength of the spatial correlation of dependent variables between a specific region and surrounding regions with geographical proximity

b The coefficient for independent variables g A coefficient depicting the spatial regression effect of independent variables

y_{it} The energy connectivity of region i at time t x_{it} The independently exogenous variables m_i The certain spatial and temporal effects (random or fixed) at region i ε_{it} The error term with the identical distribution

Abstract

China has exhibited an active attitude with regard to abating global climate change. To analyze the effect of economy development and urbanization quality on interregional energy transmissions against a backdrop of new-type urbanization, this study integrated MRIO model, complex network method, and spatial autocorrelation analysis to systematically analyze the spatiality and spillover effects of interregional energy connections. The results show that the interregional energy connectivity was spatially dependent whilst urban-rural income ratios and population structures were statistically significant in the national-level spatial econometric analysis. Specifically, a regional-level spatial regression analysis demonstrated that population structure, education level, the energy connectivity of other regions, and the income-expenditure ratios of other regions were four determinants that were significant in eastern, central, and western areas. Structural optimization is a key direction for future energy reduction nationwide. This study shed light on the current spillover effects of energy connective intensity, which is beneficial for making stratified and fair energy reduction policies at the regional level.

1. Introduction

China currently faces big challenges which have arisen from the high-speed development of its economy, urbanization, and the growth of population [1,2]. Cumulatively, such processes have inevitably boosted the nation's total energy consumption [3]. After the releasing of the reform and opening-up initiative, comparing to the gross domestic product (GDP) of China in 1978 based on constant prices, it has been 34.4 times increase in GDP at a growth rate of 12.5%

annually (China Statistical Yearbook, 2018). Such a remarkable achievement is partially a consequence of rapid urbanization, which has increased more than five times since 1978 with an annual rate of increase of 4.5% (China Statistical Yearbook, 2018). Moreover, the booming population starting from 1956, on the one side, brings demographic dividends for industrial prosperity given the labor-intensive features of traditional manufacturing industry. Such population growth has further accelerated urbanization and productivity growth. In addition, the increasing population has created high pressure on the supply of natural resources. To date, China has exhibited an active attitude with regard to abating global climate change. Under the framework of the Paris Agreement, China has agreed to reduce carbon emissions per capita more than 60% below 2005 levels by 2030. This commitment requires the Chinese government to adopt effective actions on climate change. It follows that it is imperative to understand the complexity and driving mechanism of urbanization on environmental degradation.

Currently, a vast body of work focuses on the relationship that exists between environmental impact and urbanization. These relevant studies put their emphases on the diverse role of urbanization on emission and energy performances [4e6]. The relationship between urbanization and energy consumption remains a controversial issue [7]. On the one hand, urbanization is accompanied by vast infrastructure and housing constructions, which inevitably require large amounts of energy consumption [8,9]. On the other hand, and from the long-term perspective, the increase in energy consumption triggered by urbanization may be overcome Nomenclature by energy efficiency improvements from economy agglomeration and industrial specialization arising from urbanization processes [10,11]. The impact of various factors, including economic growth, income level, trade openness, industrialization, and political stability on the urbanization-energy relationship and its effects in the contexts of newly industrialized countries, new emerging-market countries, developing countries are systematically studied [12,13]. In addition, an increasing number of investigations focusing on the effects of social, economic, and demographic factors on urban growth have been conducted worldwide [14e16].

Given the previous research, a number of research gaps can be identified. First, although the direct effects of urbanization on the environment have been extensively studied from multiple scales, relevant researches have failed to measure the indirect interactions induced by the industrial supply chain. As a result, the concept of embodied energy, which is defined as a kind of virtual energy including onsite direct energy consumption and indirect energy input from the upstream supply chain, should be introduced to enable one to garner an in-depth understanding of overall energy utilization. With economic globalization, environmental burden occurring in the upstream industrial chain is supposed to be dominant in industrial total environmental impacts. For instance, the indirect energy use occupied approximately 85% of the total energy use embodied in the China's construction industry in 2007 [17,18]. Second, previous research has mainly been concerned with energy consumption generated from individual regions rather than focusing on interregional connections. Such an approach has, therefore, failed to address the potential determinants for energy reduction that exist from a trading perspective. The major barrier to such a research approach lies in the systematic configuration of trading connections nationwide. Complex network theory provides a foundation for forming energy interaction patterns from a network perspective. In fact, the accelerating of globalization means that regions are embodied deeper into global and domestic supply chains [19,20]. Consequently, reinforced trading processes play a critical role in environmental impact transferring and carbon leakage [21]. The ignorance or misunderstanding of such trading mechanisms may result in unfair policy making. Third, given the geographical vastness of China, there exists therein a large variation in climatic zones, geographical locations, resource endowments, and economic levels. All of these factors have an indirect impact on interregional energy imports and exports. To address this, a model which measures region-specific characteristics is needed to trace both interregional energy connections and transmissions. Despite of the increasing trading intensity with the global economic integration progress, the spatial autocorrelation and heterogeneity for cross-regional energy interactions is barely mentioned in the literature. This oversight poses a challenge of formulating strategies necessary for achieving sustainable development from a spatial perspective.

Moreover, within existent literature the process of urbanization has been predominantly depicted by the urbanization rate, which is defined as the proportion of urban residents to total residents. This is mainly because population aggregation is a distinct characteristic that exists at the earlier stages of urbanization. After rapid urbanization at the price of resource depletion and environmental degradation, the Chinese central government determines to transform the traditional quantity-led and resource-extensive urbanization mode into quality-oriented inclusive development mode [22e24]. To achieve this, Chinese government adopted a strategy termed as New-Type Urbanization, which covers a board range of fields, including people-centered development, residential environment upgradation, energy conservation and etc. The main idea of the strategy is to steer away from irrational physical construction towards a people-centered urbanization in which there is an enhanced emphasis on improving capacity, opportunity, and the dignity of those who live in urban centers [25,26]. Such peoplecentered urbanization is intended to give people have a sense of gain. It follows that mitigating inequality and improving population quality are of importance if the process of urbanization is going to achieve high-quality growth. In fact, enhanced labor quality and education levels can overcome the barrier of rural-urban transition, and thereby stimulate population aggregation and urban growth [27]. Therefore, in addition to the urbanization rate, this study pays more attention to the issue of urbanization quality, and uses the urban-rural income ratio and income-expenditure ratio to reflect income inequality and people's sense of gain, whilst labor capacity and education levels are used as indicators for measuring population quality. Identifying the most influencial determinants under the background of new-type urbanization for climate-change mitigation is of importance for instructing policy initiation.

Hence, it is vital for investigating the impact of economy development and urbanization quality on interregional energy connectivity against a backdrop of new-type urbanization. To achieve this, this study integrated MRIO model with complex network method to systematically analyze energy strength of interregional connections. Subsequently, a number of influential factors to depict urbanization from the aspects of economic structure, income inequality, people's sense of gain, and population quality were collected, including the economic structure index (ESI), urbanization rates (UR), the urban-rural income ratio (URIR), income-expenditure ratio (IER), labor force (LF), and educational level (EL), were analyzed using a spatial econometrics model to identify key determinants for regional energy connections. The detailed objectives include:

(1) To provide a holistic understanding of interregional energy connectivity by considering indirect energy interactions induced by the upstream supply chain;
(2) To uncover spatial autocorrelation and heterogeneity between urbanization quality and energy connectivity against a backdrop of new-type urbanization;

(3) To provide an additional insight into energy saving determinants through the interregional trading process under multi-scales.

Understanding the determinants of China's energy connectivity is crucial for making stratified reduction targets at the regional level as the provincial government is the direct executive body responsible for energy conservation and emission reduction. An indepth investigation of spatial spillover effects of energy consumption embodied in interregional connections is imperative to develop a fair responsibility system for energy conservation, which is beneficial for allocating environmental burden among different regions.

In the following sections, Section 2 presents the major methods and data consolidation process, whilst Section 3 summarizes the results of the spatial regression analysis. Thereafter, Section 4 presents a discussion and the policy implications that emanate from the research noted herein. Section 5 draws the conclusions of this study.

2. Methodology

2.1. Energy flow analysis

The embodied energy intensity vector F can be obtained from the input-output analysis according to Ref. [17]:

$$F = B(I - A)^{-1} \quad (1)$$

where B is the vector representing the direct energy consumption per unit, which can be collected from the provincial statistical yearbooks. A is the intermediate coefficient matrix obtained from the MRIO table. The inter-sectoral energy fluxes among different regions are calculated as follows:

Q ¼ FUb (2)

Consequently, the interregional energy flows, which are obtained by merging sectoral energy transfers, can be expressed as follows:

n n

drs ¼ X X qrs_{ij} (3)

i¼1 j¼1

where q^{rs}_{ij} donates embodied energy flows from sector i in region r to sector j in region s.

To explore the intensity of regional energy connections induced by the trading process, this study employed a weighted degree, which is equal to the total weight of a node divided by the number of edges connecting to it, as the independent variable for investigating regional energy connectivity. Consequently, the nodes in the network are the regions responsible for producing or consuming energy; the edges are the trading connections that exist among nodes; the node's weight is defined as the amount of energy use embodied in all flows connecting to it. As a result, the developed network can be expressed as:

G¼ðV;EÞ; (4)

where G represents the embodied energy network. The node set is

Ve ¼ fvrg, where vr is the province r. The edge set is E^r ¼ fto $_v e^k$rk. Ifg, whered^{rk} > 0, ^{rk} is the weighted directed edge connecting node v

then e^{rk} ¼ 1 and its weight is equal to d^{rk}; otherwise, e^{rk} ¼ 0. Consequently, the weighted degree can be expressed as Equation (5), which is regarded as the key variable that determines the spatial association in the embodied energy flow system.

Dr ¼d_err ¼ ^{P}Ꝑdeinin þ$_{þ}$ Ꝑ^{P}-deoutout ¼ ^{P}Ꝑrrderkrk þ$_{þ}$ Ꝑ^{P}kkedrkrk; (5)

where D^r is the weighted degree of province r, representing the embodied energy connectivity of node v^r, d^r denotes the energy use embodied in the inflows and outflows of province; and e^r denotes the total number of inflows and outflows from province r, including in-degree and out-degree. This study employed the weighted degree as the dependent variable to detail regional energy connectivity. In practice, the weighted degree exhibits the energy strength of connections in the multilateral trading process, which both contain information on consumption and production sides. The results are beneficial to understanding the current energy consumption status of a region in the national trading process.

2.2. A Markov-chains based analysis method

A process satisfies the Markov property if one can make predictions for the future of the process based solely on its present state. In other words, conditional on the present state of the system, its future and past states are independent. To test the Markov aP¼1 bP¼1

^{ab}b m m

property, the statistics Z ¼ 2 f_{ab} ln $^{p}{}_{p}$is constructed to

satisfy c^2 distribution with the degree of freedom ðm 1Þ^2, where m is the possible states and m ¼m5 in our case. f_{ab} is the frequency

mP$^{a\ 1}$mfab m^{ab}

from status a to status b, p_b ^{¼} Ꝑ1¼Ꝑb 1 fab and p_{ab} ^{¼} Ꝑb ^{f} fab. For the sig-

a¼ ¼ ¼1

isnificant level a, if the statistics Z >c^{2a}ððm fi cant level1^{þ2}Þ, the process sat-$_a$, and the fi es the

Markov property at the signi

prediction can be made based on Markov-chain analysis.

Markov-chains analysis aims to reflect environmental status transfer at the province or city level through a discrete computational process. More specifically, the province-level energy strength data can be initially grouped into five states, namely 20% below national average level (L1), between 20% and 40% of national average level (L2), between 40% and 60% of national average level (L3), between 60% and 100% of national average level (L4), and above national average level (L5). On this basis, the current probability and future transition probability of each status can be calculated as Equation (6).

$R_{tþ}1¼P \ Rt$ (6)

where R_t and are the status matrices at year of t and t þ 1, which accords with the transfer matrix.

Since the status in one region will be influenced by the status in neighboring regions, the traditional Markov-chain can be further developed into the spatial Markov-chain by integrating spatial lag effects. This improvement can benefit to observe the transferring probability of a spatial unit under different geographical conditions. The transfer matrix of P is decomposed into K matrices of noted as P_{abt}ðkÞ, where k2½1;k. represents for the conditional probability of a region transferring from status a in year t to status b in year tþ 1 with a spatial lag type k. The type for the spatial lag condition is calculated from Equation (7)

lagi ¼ X Diwij (7)

where D_i is the weighted degree of province i. w_{ij} is the spatial weight between regions i and j; w_{ij} ¼ 1 when regions i and j is neighboring, otherwise w_{ij} ¼ 0; and the value of $lag_i$is divided into

5 status accordingly. The comparison of spatial and non-spatial matrices can explore the relationship between the transferring probability and neighboring spatial units, which is beneficial for understanding the spatial spillover effects among spatial units with different geographical conditions.

2.3. Spatial autocorrelation analysis

To capture the spatiality and spillover effects of regional energy connectivity, this study employed the spatial econometrics models. The process for the selection of models and diagnosis was as Fig. 1.

At first, for the panel dataset, the hybrid OLS model and the spatial panel models were employed to differentiate the nonspatial and spatial effects, while in the spatial hypothesis the space-fixed effects, time-fixed effects, and space-and-time-fixed effects were all examined by likelihood ratio (LR) and R square to identify the most appropriate fixed effects. To distinguish the fixed or random effects, the Hausman test was used.

The existence of spatial autocorrelation for D_i was tested by Global Moran's I. Here, $D_i$denotes the weighted degree of province i induced by the complex network G (i2½1; n). $D^i$is the variable of interest to comprehensively reflect the strength and breadth of the connections in each province. Consequently, a holistic map of the spatial correlations was produced. Global Moran's I can be calculated based on the following equation:

I ¼nPⁿin¼1Pⁿjn¼1wijðDin DÞDj 2D; (8)

Pi¼1Pj¼1w$_{ij}$Pi¼1ðD$_i$ DÞ

where I is the result of global Moran's I; D$_i$denotes the total

–

weighted degree of the nodes in region r; Dis an average value of the weighted degree of a region; w$_{ij}$ represents the weight between region i and region j from a spatial perspective; w$_{ij}$ ¼ 1 when region i and region j share edges geographically, and w$_{ij}$ ¼ 0 otherwise.

To examine the significance of Global Moran I, Z-test is utilized, which can be calculated by the following equations

I EðIÞ

Z$_I$ ¼ ~~p ð Þffi~~;   (9)

V I

where EðIÞ ¼ n$^1_1$ and VðIÞ ¼ EðI^{2}Þ EðIÞ^2, Z$_I$ suggests significant level for I.

Consequently, with a statistically significant Z$_I$, a positive value of Moran's I index manifests the observed dataset are inclined to cluster, whereas a negative value suggests to be discretely distributed. According to Elhorst (2012), spatial autocorrelation effect includes spatial lag effect as well as spatial error effect, which is diagnosed by Lagrange Multiplier (LM) tests and their robustness, and accordingly the spatial effects can be analyzed by different econometrics models. More specifically, spatial Durbin panel model (SDM) is the most generic model in spatial regression analysis and hypothesizes that the dependent variable at a specific place is both correlated with neighboring dependent variables and the unknown variables from the domestic and the surrounding regions. As a result, the energy connectivity of a region is determined partially by the energy strength of neighboring regions due to the spillover effects and partially by unknown factors from the local and neighboring regions. Accordingly, the standard equation of SDM model is:

$$y_{it} = r \sum_{j=1}^{n} w_{ij} y_{jt} + x_{it} b_i + \sum_{j=1}^{n} w_{ij} x_{jt} g + m_i + \varepsilon_{it} \qquad (12)$$

where y_{it} denotes the energy connectivity of region i at time t, r denotes the spatial regression coefficient, representing the strength of the spatial correlation of dependent variables between a specific region and surrounding regions with geographical proximity. $\sum_{j=1}^{n} w_{ij} y_{jt}$ denotes the total spillover effect of y_{jt} from the surrounding regions. x_{it} denotes the independently exogenous variables. In this study, x_{it} includes the ESI, URIR, UR, LF, IER, and EL. b is the coefficient for independent variables. $\sum_{j=1}^{n} w_{ij} x_{jt}$ denotes the spatial impact of independent variables from surrounding regions. g is a coefficient depicting the spatial regression effect of independent variables. m_i represents for the certain spatial and temporal effects (random or fixed) at region i. ε_{it} is the error term with the identical distribution. w_{ij} is a matrix of spatial weight. In this study, the 0e1 matrix is used to describe spatial weight, in which the weight is equal to 1 when two regions are neighboring.

The SDM can be further simplified into the spatial lag panel model (SLM) by the assumption that the dependent variable of a specific region is partially affected by neighboring dependent variables. The SDM can be specified as

n

yit ¼r X wijyjt þ xitbþmi þεit; (13)

j¼1

Similarly, the SDM can be also simplified into the spatial error panel model (SEM) by hypothesizing that the dependent variable of a specific region is partially determined by omitted variables from both the local and neighboring regions.

yit ¼xitbþmi þ uit (14)

n

(15)j¼1

uit ¼l X wijuit þεit

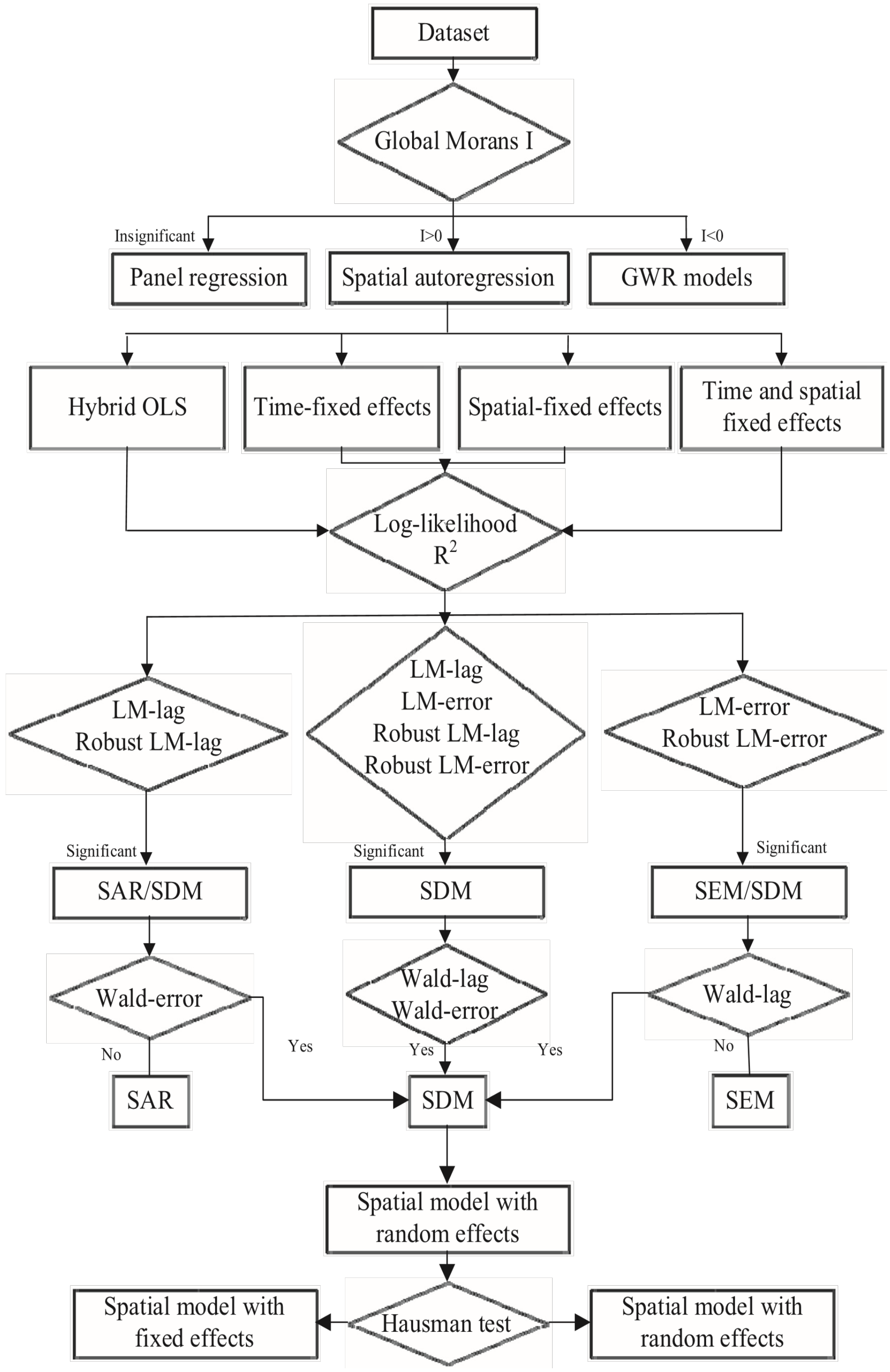


Fig. 1. Computational process of spatial autocorrelation analysis.

Wald/LR tests can decide the selection among SDM, SLM and SEM. To accurately depict the marginal effect, this study also presented spatial direct and indirect effects of dependent and independent variables according to LeSage and Pace (2009).

2.4. Data processing and consolidation

To calculate the weighted degree of each region in the national energy network, the time series MRIO tables, namely Table 2007, Table 2010, and Table 2012, published by the Chinese Academy of Science are used to establish the network framework.

The MRIO Tables 2007 and 2010 contain monetary flow information of 30 regions in China except Tibet. In each region, the MRIO table provides the monetary information of 30 sectors. In contrast, the MRIO table of 2012 adds the sectoral information of Tibet and changes the sectoral scale from 30 sectors to 42 sectors in each region. Therefore, some integrations are conducted to make MRIO tables consistent with each other. To obtain the sectoral statistical data, provincial statistical yearbooks and the energy balance tables in China Energy Statistical Yearbook are used.

In this study, we select the economy structure index (ESI) instead of using GDP to pay more attention on the function of economy structure in alleviating energy strength in the trading process. The variable of ESI can be presented as follows:

$$ESI = \frac{E_1}{E_2} + \frac{E_2}{E_2} + \frac{E_3}{E_2} \, 100; \qquad (16)$$

where E_1, E_2, and E_3 are the total economic output of the agriculture industry, the secondary industry, and the tertiary industry, respectively.

To depict urbanization level, as opposed to urbanization rate which has normally been used in previous research, we selected income-expenditure ratio (IER) to illustrate people's sense of gain and urban-rural income ratio (URIR) to specify the inequality in the urban-rural coordinated development. With respect to the population, we included people aged between 15 and 64 and the proportion of people with college degrees or above, which represented the labor capacity and educational level of the population, respectively. All these dependent variables are all obtained from the National Statistical Yearbook.

3. Results analysis

3.1. Results of complex network analysis

To determine the energy connectivity of each region, the results of degree analysis and strength analysis have been shown in Tables S4 and S5 in the supplementary file. Obviously, the degree size was almost evenly distributed among different years. From a temporal perspective, the degree network in 2012 represented a more complicated and intensive interregional connection, revealing a boarder multilateral trading linkage over time. In comparison to spatial interaction pattern in the degree analysis, only part of regions represented high values of in-strength and outstrength, including both developed regions in the coastal area (e.g., Beijing, Shanghai, Jiangsu, and Zhejiang) and developing regions in the inland area (e.g., Hebei, Liaoning, and Henan). Furthermore, the network pattern is highly consistent with the current distribution of economy agglomerations in China, where the linkages among Jing-Jin-Ji (Beijing-Tianjin-Hebei), Yangtze River Delta (Shanghai, Jiangsu and Zhejiang), and Pearl River Delta (Guangdong) represented highest value of strength.

3.2. Markov-chain based spatial analysis

The results of Markov property test has been shown in Table S6 in the supplementary file. The possible states for weighted degree from the year of 2007e2010 and the year of 2010e2012 are divided into 5 states. On the basis of one-step transitional frequency matrix, both Z_{2007}2010 and Z_{2010}2012 are larger than $c^2_{0:05}$ðð5 1Þ^{2}Þ ¼ 26:2960. The results have proved that both transitional processes of weighted degree from the year of 2007e2010 and from the year

Table 1

Markov-chain transitional matrix for regional energy strength from 2007 to 2012.

	L1	L2	L3	L4	L5
2007e2010					
L1	1.000	e	e	e	e
L2	e	1.000	e	e	e
L3	e	0.125	0.500	0.375	e
L4	e	e	0.125	0.750	0.125
L5	e	e	e	0.111	0.889
2010e2012					
L1	1.000	e	e	e	e
L2	e	0.500	0.500	e	e
L3	e	e	0.800	0.200	e
L4	e	e	0.200	0.700	0.100
L5	e	e	e	0.111	0.889

Note: All values equal to zero are represented as "-" to highlight the probability of values higher than zero.

of 2010e2012 satisfy the Markov property at the significant level 0.05. The probability of status changes during two time intervals has been summarized in Table 1. Obviously, the value of diagonal elements was higher than the non-diagonal counterparts, indicating that the status of regional energy connectivity was mostly unchanged during these two time intervals. Moreover, it can be found that for regions belonging to L4 and L5, there was a downward transfer from high energy connectivity areas to medium-tohigh or medium energy connectivity areas. In contrast, regions in the L2 and L3 categories exhibited an increasing trend of energy connectivity, in which the increasing probability of L3 was 37.5% during 2007e2010 and the increasing probability of L2 was 50% during 2010e2012.

Table 2 exhibited the results of Markov-chain based spatial analysis. In comparison to Table 1, Table 2 revealed that the transfer probability with a downward trend was high in regions neighboring to low level areas. For instance, the probability of a downward movement of regions located in L3 was 0.125 in Table 1, but it has increased to 0.667 when the regions in L3 were neighboring to a relatively low-level category (e.g., L2). Similarly, the probability of a downward transfer of regions located in L5 was 0.111 in Table 1, but had increased to 0.5, 0.375, 0.375 when the regions in L5 are neighboring to L1, L3, and L4, respectively, and decreased to 0.111 when these high level regions were located adjacent to each other. These facts further highlighted the spillover effects among current provinces regarding their energy interactions.

3.3. Moran's I analysis

Table 3 summarized the results of the global Moran's I analysis. The positive value of the global Moran's I index demonstrated that there existed evident spatial clustering among all regions. Obviously, the spatial correlations of regional energy connectivity were statistically significant in 2007, 2010, and 2012, which indicated that regions with high energy connectivity inclined to cluster while those with relatively low energy connectivity crowded together.

To further detect the spatial dependence in local areas, this study conducted a Moran's I scatter plot analysis. According to Fig. 2, more than half of regions (20 regions in 2007, 18 regions in 2010, and 19 region in 2012) concentrated on HH and LL quadrants, indicating that most of the provinces exhibited a highly spatial agglomeration of regional energy connectivity.

3.4. National spatial econometric regression

This study employed spatial and non-spatial models with LM lag and LM error tests to determine the feasibility of space or time fixed

Table 2

Spatial Markov-chain transitional matrix for regional energy connectivity from 2007 to 2012.

		2007e2010					2010e2012				
		L1	L2	L3	L4	L5	L1	L2	L3	L4	L5
L1	L1	e	e	e	e	e	e	e	e	e	e
	L2	e	e	e	e	e	e	e	e	e	e
	L3	e	e	e	e	e	e	e	e	e	e
	L4	0.500	e	e	e	e	0.500	e	e	e	e
	L5	0.500	e	e	e	e	0.500	e	e	e	e
L2	L1	e	e	e	e	e	e	e	e	e	e
	L2	e	0.333	e	e	e	e	e	0.250	e	e
	L3	e	0.667	e	e	e	e	0.250	e	e	e
	L4	e	e	e	e	e	e	0.250	0.250	e	e
	L5	e	e	e	e	e	e	e	e	e	e
L3	L1	e	e	e	e	e	e	e	e	e	e
	L2	e	e	e	e	e	e	e	e	e	e
	L3	e	e	e	e	e	e	e	e	e	e
	L4	e	0.125	0.250	0.250	e	e	e	0.400	e	e
	L5	e	e	0.250	0.125	e	e	e	0.400	0.200	e

L4	L1	e	e	e	e	e	e	e	e	e	e
	L2	e	e	e	e	e	e	e	e	e	e
	L3	e	e	e	e	e	e	e	e	e	e
	L4	e	e	0.125	0.375	e	e	e	e	0.500	e
	L5	e	e	e	0.375	0.125	e	e	0.200	0.200	0.100
L5	L1	e	e	e	e	e	e	e	e	e	e
	L2	e	e	e	e	0.111	e	e	e	e	0.111
	L3	e	e	e	e	0.111	e	e	e	e	0.111
	L4	e	e	e	e	e	e	e	e	e	e
	L5	e	e	e	0.111	0.667	e	e	e	0.111	0.667

Note: All values equal to zero are represented as “-” to highlight the probability of values higher than zero.

Table 3

Results of Moran’s I analysis.

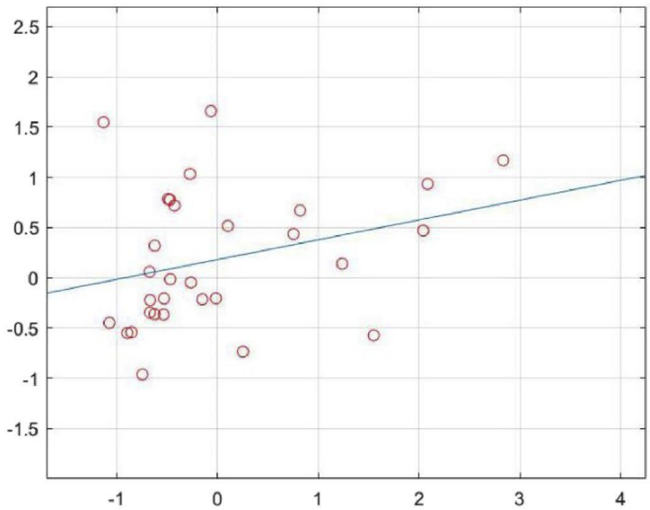
Year	Moran’s I index
2007	0.2413***
2010	0.1983***
2012	0.2873***

effects of selected data and the applicability of the selected model (see Table 4). The LR test was significantly rejected, indicating that both space and time fixed effects were significant. Moreover, the R square and log likelihood were 0.9693 and 303.3414 in the last column, which were largest in all model specifications. Therefore, the datasets exhibited spatial dependence with both space and time fixed effects. The LM test was employed to examine the spatial interaction effects of datasets. The values of LM spatial lag and its robustness tests were 12.7127 and 8.7583, respectively, which were significant at a 1% level, whilst the values of robust LM spatial error was 2.3850, which was statistically insignificant.

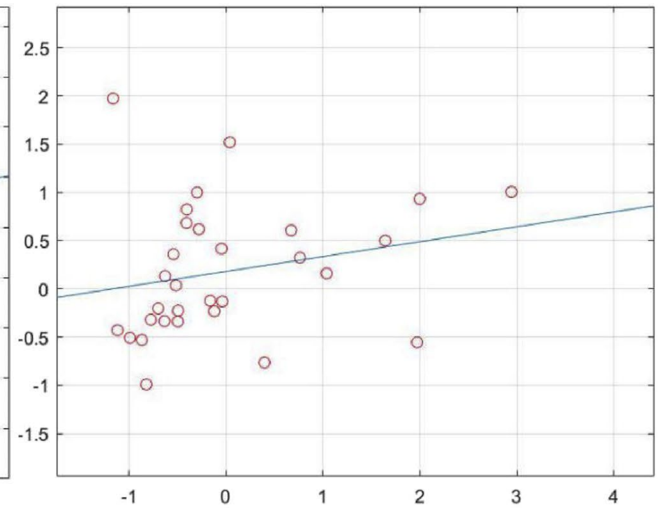
The results (44.8034, P ¼ 0.0000) indicated that only the fixed effect existed. Both the LR test and the Wald test were employed to detect the applicability of Durbin model, spatial lag model, and spatial error model. The results indicated that the spatial lag model was more feasible for spatial regression estimation. Before determining the applicability of the spatial econometric model, a Hausman test (Hausman 1978) was conducted to examine the fixed/random effect of the spatial Durbin model in model specifications.

Table 5 shows the results of the spatial lag analysis. The energy connectivity was spatially dependent with the significance at the 1% level. This fact indicated that a 1% increase of energy connectivity in neighboring regions can cause increments of energy connectivity in the target region by 0.467%. The urban-rural income ratio was significantly positive with the energy strength at the 10% level, indicating that an increase of urban-rural income gap can contribute to higher regional energy connectivity. This is mainly because the developing regions have larger urban-rural income gap due to the significant imbalance between urban and rural areas. These developing regions were characterized by extensive energy consumption behaviors and low economic vibrancy; leading to limited connections with other entities. The economic structure had a negative impact on regional energy connectivity. This fact is consistent with the general perception that the higher proportion of tertiary industry would reduce energy consumption and improve energy efficiency nationwide. Ceteris paribus, the population structure was significantly negative at the 5% level, which means that a higher share of people with labor capacity may lead to the emergence of an agglomeration effect that would improve production efficiency to some extent, thereby mitigating the amount of energy consumption.

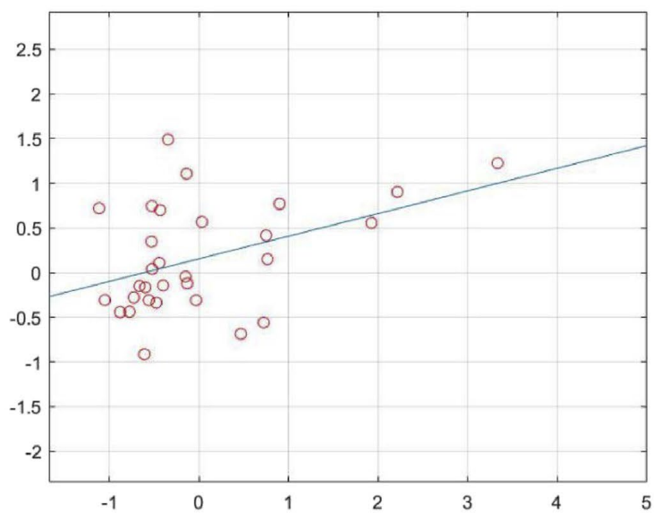
Table 6 has shown the direct, indirect, and total effects of different variables. The direct effect was a consequence of variable changes occurring in a specific region of the local energy connectivity while the indirect effect was induced by an independent variable from the surrounding regions on the local energy performance. Economic structure (ESI) and labor force (LF) were estimated as significant at the 5% level, while urban-rural income ratio was significant at a 10% level in the direct effect. These three variables were also significant in total effects. However, all the variables were insignificant in indirect effect. Furthermore, an additional 1% growth in the sharing of tertiary industry can directly reduce 0.222% of energy connectivity for a specific region and cause an indirect decrease of energy connectivity in surrounding regions by 0.183%, even the indirect impact was insignificant. Similarly, a 1% increase of the sharing of people with labor capacity could directly lead to a 4.296% decrease of regional energy connectivity and indirectly reduce 3.541% of energy connectivity in other regions. Evidently, economic structure, labor force and urban-rural income ratios do have a spillover effects on the energy connectivity of other regions even if they were insignificant.



2007



2010



2012

Fig. 2. Local Moran's I scatter plots of regional energy connectivity.

Table 4

Results of non-spatial test.

	Pooled OLS	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects

ESI	0.284** (2.33)	(0.276***-3.27)	0.280** (2.24)	0.226** (2.74)
URIR	0.101 (1.14)	0.077 (0.799)	0.103 (1.17)	0.269** (2.34)
UR	0.0909 (0.169)	1.94*** (3.31)	0.068 (0.13)	0.549 (0.672)
LF	9.18*** (4.67)	(2.67**-2.00)	9.33*** (4.69)	4.17** (2.57)
IER	2.32*** (7.34)	0.256 (0.991))	2.32*** (6.94)	0.058 (0.213)
EL	0.514 (0.523)	1.06 (1.44))	0.507 (0.506)	0.058 (0.074)
R2	0.5521	0.966	0.5532	0.9693
LogL	423.8986	307.5220	423.7875	303.3414
LM spatial lag	0.0039 [0.950]	15.1149 [0.000]	0.0059 [0.939]	12.7127 [0.000]
LM spatial error	0.0000 [0.914]	15.2087 [0.000]	0.0184 [0.892]	6.3394 [0.012]

Robust LM spatial lag	0.0117 [0.998]	5.4047 [0.020]	0.0000 [0.997]	8.7583 [0.003]
Robust LM spatial error	0.0078 [0.930]	5.4984 [0.019]	0.0125 [0.911]	2.3850 [0.123]

Table 5

Results for the spatial lag model.

	Coefficient	t values
ESI	0.209**	2.31
URIR	0.235*	1.87
UR	0.605	0.676
LF	4.104** 0.209	2.31
IER	0.231	0.702
EL	0.467***	0.267
W* dep		4.359

Table 6

Direct, indirect, and total effects of variables.

	Direct effects		Indirect effects		Total effects	
	Coefficients	t values	Coefficients	t values	Coefficients	t values

ESI	0.222**	2.291	0.183	1.427	0.405*	1.943
URIR	0.253*	1.889	0.207	1.343	0.460*	1.699
UR	0.687	0.707	0.573	0.610	1.259	0.682
LF	4.296**	2.296	3.541 0.187	1.403	7.838*	1.919
IER	0.223	0.695	0.204	0.604	0.410	0.668
EL	0.245	0.260		0.228	0.449	0.250

3.5. Regional spatial econometric regression

However, it can be observed that urbanization rate, incomeexpenditure ratio, and educational level were not statistically significant. This may have arisen out of the fact that China has a large territorial area with significant imbalances among different areas. The spatial regression that all 30 regions were analyzed simultaneously without due consideration of regional disparities and technical differences may torture the significance and accuracy of parameter estimation. Therefore, this study conducted regional divisions by grouping all 30 regions into eastern, central, and western areas.

The relevant tests to determine the applicability of space or time-period effects occurred in the selected sectional data have been presented in the supplementary file. By using the Hausman test, the LR test, and the Wald test, it can be found that there is no spatial error and spatial error effects existing in the panel data. As a result, the Durbin model was employed to conduct spatial econometric analysis for eastern area, central area, and western area of China.

Table 7 shows the results of econometric analysis in three areas. Evidently, the spatial autocorrelation is more significant in the central and western than the eastern area. There were eight factors

Table 7

Results of econometric analysis in three areas.

	Eastern China	Central China	Western China
ESI	0.522**	0.399***	0.0580
URIR UR	0.343	0.223**	0.421***
	1.116	5.039***	0.394
LF	7.122**	3.201***	5.95***
IER	0.128	0.200	0.251
EL	3.977**	1.540***	2.49*** 0.921***
W* dep	0.276*	0.637***	0,032
W* ESI	0.550	0,767***	0.819*** 1.524
W* UIUR	0.142	0.501***	2.572***
W* UR	2.33 5.71	0.560	0.905**
W* LF	1.88**	1.492	
W*IER		1.227***	
W*EL	3.04	1.039	0.449
R2	0.8212	0.9447	0.7591
Hausman test	24.0978 (0.0302)	82.2008 (0.0000)	27.0182 (0.0124)

in the central area and six factors in the western area which were statistically significant. In contrast, only four factors were significant at a 5% level in the eastern area. Labor force, education level, energy connectivity of other regions, and the income-expenditure ratio of other regions were four determinants significant in all areas.

More specifically, in the eastern area, 1% increase of the sharing of tertiary industry, the sharing of people with labor capability, and the sharing of people with a college degree or above can lead to a decrease of regional energy connectivity at 0.522%, 7.122%, and 3.977%, respectively. It is noteworthy that the value of variables with negative coefficient in the eastern area was higher than the other two counterparts, which exhibited a more obvious reduction effect. In other words, efforts paid on structural improvement of the economy, population, and education were more efficient in energy reduction in the eastern area in comparison to other counterparts. This fact is highly related to economic and technological advantages in the eastern area, where GDP and research and development (R&D) input accounted for 55.6% and 70.1% of the national total amount in 2017 (China Statistical Yearbook, 2018). These regional advantages can accelerate industrial specialization and agglomeration, thereby improving regional efficiency. In addition, 1% increase of energy connectivity and income-expenditure ratio of surrounding regions can increase 0.276% and 1.88% of energy connectivity of a region. In contrast, the coefficient signs of these two factors were opposite in the central and western area, where the energy connectivity of a region was positively correlated to the energy connectivity and income-expenditure ratio of surrounding regions. This is mainly because regional and economic integration is comparatively mature in the eastern area, where economic entities have formed an explicit industrial chain. As a result, any increase of energy occurred in surrounding regions can be delivered through the whole supply chain. The economic development of central and western areas is backward. Regional protectionism and interregional wars for economic resources still exist. As an indicator depicting the importance of a node in the network, increased energy connectivity of the surrounding regions implied that these regions were more vibrant and powerful in the national energy network. Such a strengthened role may weaken the local economy in the whole network; thereby reducing energy connectivity.

In the central area, all factors exerted a significant impact on regional energy connectivity, except income-expenditure ratio. Economic structure and urban-income ratio exhibited negative impacts while urbanization rates and the labor force were positively correlated with regional energy connectivity. It is noteworthy that a 1% increase in the urbanization rate can lead to more than 5% of energy connectivity in this area, which was highest compared to other areas; this indicates that the central area is in fast track of economic development. All these activities can increase regional energy connectivity. Moreover, the energy connectivity is positively correlated with labor in the central area, whereas it played inverse roles in eastern and western China. This is mainly because population structure determines the labor force that is available for the local economy, whilst the growth mode of the local economy is directly affected by the current economic structure. In fact, the economic sharing of the secondary industry in the central area is highest compared to other areas, in which the heavy industry is dominant (Chinese Statistical Yearbook, 2018). Therefore, the central area experienced a typical energy-intensive development mode whereby the increase of people with labor capacity indirectly increased regional energy connectivity. More importantly, the energy connectivity of surrounding regions and the economic structure of surrounding regions were negatively significant, while the urban-rural income ratios of other regions and incomeexpenditure ratios of other regions were positively significant at the 1% level.

Western China exhibited a similar situation to the eastern area, but with several exceptions. For instance, regional energy connectivity would increase 2.49% when educational level has increased 1%. The sign of this coefficient was the same in the middle part but opposite in the eastern China. These facts are highly related to local economic structure, with eastern China being service-oriented and having more efficient production processes. Thus, the labor input could share green structural benefits that decrease energy connectivity. The coefficient of urban-rural income ratio generated the largest positive impact on energy connectivity of the western regions, which implies that the spatial correlated positive impact became stronger in more backward economies. Moreover, the labor forces of the surrounding regions generated a significantly negative effect on the energy connectivity of a region located in the western area. This was mainly because the increasing labor force may enhance their industrial competitiveness of surrounding regions given the labor-intensive features of regions in the western area, thus inevitably weakening the trading vibrancy of the target region.

In summary, the central and western areas exhibited more obvious spatial autocorrelation than the eastern area. This is in line with the fact that the central and western areas, which were the developing and underdeveloped inland areas, have experienced fast urbanization and economic development. As a result, regional energy performance was highly correlated with data that characterized regional economic patterns and development levels. In contrast, as the most developed part of China, the eastern area was superior in technology-intensive development models, where both regional integration and industrial specialization were formed. Therefore, such agglomeration effects can accelerate economic development without compromising extensive energy consumption. As a result, the linear relation between energy strength and urbanization was insignificant.

Table 8 shows the direct, indirect, and total effects of the independent variables. It is evident that there are differences between the coefficients in the direct effects analysis and those in the Durbin model. This is mainly because the direct effect takes the feedback effect into account, which is a result of impacts generated by a specific region which then spread into neighboring regions and thence return to the origin. For instance, the direct effect of economic structure was 0.626 and its coefficient was estimated as 0.522. Therefore, its feedback effect was 0.104. In the eastern area, the spillover effect of income-expenditure ratio amounted to 2.468. In other words, an increase of income-expenditure ratio of all neighboring regions increased energy connectivity in the local area. Similarly, the spillover effect of the labor force in the western area was 13.976, indicating that the increasing increase of people with labor capacity in all neighboring regions can lead to an increase of energy connectivity in the local region. More specifically, opposite signs could also be observed between the direct and indirect effects in various areas. For instance, the results for the middle area indicated that the direct effect of income-expenditure ratio was insignificantly negative while the indirect effect had an

Table 8

	Eastern			Central			Western		
	D	I	T	D	I	T	D	I	T
ESI	0.626***	0.901	1.527****	0.1296	0.590	0.719***	0.0776	0.0430	0.121
URIR	0.349	0.0385	0.311	0.589	0.770	0.181	0.252***	0.329	0.582**
UR	1.529	3.444	4.973	7.4227	4.704	2.718***	0.178	0.261	0.0825
LF	8.223***	10.344	18.567**	3.8772	0.848	3.029	1.473	13.976***	15.449***
IER	0.388	2.468*	2.856	0.3756	1.282	0.906***	0.0546	0.613	0.558
EL	4.624***	5.487	10.111*	1.6198	0.0375	1.657*	2.702***	1.564	1.138

Direct, indirect, and total effects of the independent variables by three areas.

inverse impact. This demonstrates that being surrounded by regions with high income-expenditure ratio can increase the energy connectivity of a region. Similarly, the indirect spillover effect of the urbanization rate in the middle area was insignificantly negative and reversed the part of positive direct, together indicated a significant positive total effect (0.906).

4. Discussion and policy implications

From a national perspective, there is no doubt that structural optimization is a breakthrough for future energy reduction nationwide. Both the economy and population structure are beneficial for reducing energy consumption to a certain extent. Therefore, continuous efforts in transferring industrial-based energy-intensive models to service-oriented sustainable development models and the promotion of educational attainment are important for improving trading energy efficiency. More importantly, due to the most significant positive impact of energy connectivity of surrounding regions, it is imperative to amplify the coupling effects in energy reduction by enhancing regional coordination based on geographical proximity. According to Table 7, both urbanization rates and other regions' income-expenditure ratios in eastern, central, and western areas were positively correlated with energy connectivity. Consequently, ceteris paribus, stimulating household consumption and domestic demand by changing consumption structure from fixed-asset investment-led models to service-oriented consumption models is of necessity for energy reduction nationwide.

From a regional perspective, policy actions should be stratified in accordance with the diverse key influencing factors of different regions. For instance, structural optimization and upgrading is the most effective method for mitigating energy connectivity in the eastern area as its economic structure, labor force, and educational levels exerted the largest reduction effects. This adjustment accords with the current economic development status of the eastern area, where the production factors are sufficient and highly concentrated but how effective allocation can be achieved remains a problem. Therefore, concrete efforts should be paid to improving total factor production efficiency through structural reform.

In the central area, minimizing the disparities between urban and rural areas is vital for energy strength abatement. Against this backdrop, it is critical to adopt strategies for achieving urban-rural coordination. In fact, the Chinese government has released a package of regulations to draw the roadmap for rural vitalization; this will be beneficial in alleviating regional energy connectivity. At the same time, given the spatial lag and spatial error effects which occurred in the middle area, top-down administrative instructions for regional integration should be adopted. In previous regional development models, local government preferred regional protectionism and had internal incentives to fragment because crossregional collaboration may scarify local economic interests. However, such administrative fragmentation can cause excessive interregional competition, resulting in unnecessary energy loss during the transmission process. Therefore, it is critical to implement mandatory political interventions to achieve economic agglomeration. In general, regional coordination can stimulate knowledge sharing and industrial specialization, thereby improving energy utilization efficiency.

In the western area, both the labor force of a specific region and surrounding regions are significantly negatively correlated with energy connectivity. This fact emphasizes the importance of increasing the sharing of people with labor capacity. However, China suffers from a scale of labor migration in the millions from west to east. This population-shrinking trend may further exacerbate energy-intensive production process in the western China. Similar to the middle area, to improve regional energy performance, regional coordinated development strategies should be adopted. First, economic unification can cause a boom in the industry, thus being capable of attracting more labor. Second, the free mobility and fast circulation of production essentials from regional coordination processes can improve resource utilization efficiency, thus improving regional energy performance.

5. Conclusion

In the context of accelerated globalization and trading processes, the capturing of spatiality in interregional energy flows is of importance for energy reduction nationwide. This study investigated the spatiality and spillover effects of interregional energy connections by integrating the MRIO model, complex network method, and spatial econometrics model. The findings of this study include:

(1) Markov-chain based spatial analysis highlighted the spillover effects among current provinces regarding their interregional energy interactions.

(2) The national spatial econometric analysis indicated that the energy connectivity was spatially dependent with the significance at the 1% level. Urban-rural income was positively correlated to regional energy connectivity whereas both the economic structure and population structure had a negative impact.

(3) The regional spatial regression analysis demonstrated that population structure, education level, the energy strengths of other regions, and the income-expenditure ratios of other regions were four determinants that were significant in all areas. Structural optimization is a potential direction for future energy reduction in eastern, central, and western areas.

(4) Energy connectivity in China represented an obvious spatial heterogeneity, where the central and western areas exhibited more obvious spatial autocorrelation than the eastern area due to the varied urbanization quality.

The findings of this study revealed spatial autocorrelation and heterogeneity between urbanization quality and interregional energy connectivity by considering indirect energy interactions through the upstream supply chain, which is beneficial for understanding energy saving determinants from both national and regional scales. The investigation of spatiality and spillover effects in regional energy connectivity can facilitate decision makers to make stratified and fair energy conservation strategies at the regional level. To measure the indirect effect of energy interactions, the input-output technique is adopted by using the MRIO data from 2007, 2010, and 2012. Such sectional and fragmental datasets inevitably have weaknesses in achieving temporal representativeness, which have automatically limited the research. Therefore, using the latest time series data to exhibit the trajectory of energy connectivity changes induced by the massive development of China is important in the future research.

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Appendix A. Supplementary data

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