Front. Earth Sci. 2015, 9(2): 355–368
DOI 10.1007/s11707-014-0469-0

RESEARCH ARTICLE

Characterizing China's energy consumption with selective economic factors and energy-resource endowment: a spatial econometric approach

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Abstract Coupled with intricate regional interactions, the provincial disparity of energy-resource endowment and other economic conditions in China have created spatially complex energy consumption patterns that require analyses beyond the traditional ones. To distill the spatial effect out of the resource and economic factors on China's energy consumption, this study recast the traditional econometric model in a spatial context. Several analytic steps were taken to reveal different aspects of the issue. Per capita energy consumption (AVEC) at the provincial level was first mapped to reveal spatial clusters of high energy consumption being located in either well developed or energy resourceful regions. This visual spatial autocorrelation pattern of AVEC was quantitatively tested to confirm its existence among Chinese provinces. A Moran scatterplot was employed to further display a relatively centralized trend occurring in those provinces that had parallel AVEC, revealing a spatial structure with attraction among high-high or low-low regions and repellency among high-low or low-high regions. By a comparison between the ordinary least square (OLS) model and its spatial econometric counterparts, a spatial error model (SEM) was selected to analyze the impact of major economic determinants on AVEC. While the analytic results revealed a significant positive correlation between AVEC and economic development, other determinants showed some intricate influential patterns. The provinces endowed with rich energy reserves were inclined to consume much more energy than those otherwise, whereas changing the economic structure by increasing the proportion of secondary and tertiary industries also tended to consume more energy. Both situations seem to underpin the fact that these provinces were largely trapped in the economies that were supported by technologies of low energy efficiency during the period, while other parts of the country were rapidly modernized by adopting advanced technologies and more efficient industries. On the other hand, institutional change (i.e., marketization) and innovation (i.e., technological progress) exerted positive impacts on AVEC improvement, as always expected in this and other studies. Finally, the model comparison indicated that SEM was capable of separating spatial effect from the error term of OLS, so as to improve goodness-of-fit and the significance level of individual determinants.

Keywords per capita energy consumption, economic growth, energy endowment, spatial autocorrelation, spatial econometric model

1 Introduction

The world has witnessed the awesome growth of China's economy since 1978, when the country started its nationwide economic reform and opening-up to the global economy. This spectacular growth is, however, underscored by an equally unprecedented consumption of energy. In 2001 for the first time China's demand for primary energy outpaced its energy production. In 2010, China's energy consumption finally took over the top position from the United States, with a record of 22.52 billion toe (tons of oil equivalent) slightly surpassing the amount (21.70 billion toe) consumed by the US (Pao et al., 2012). Although China has rather abundant energy resources, its per capita energy resources and consumption have been far less than the world average due to its largest population in the world. As one of the biggest economies in the world, China apparently needs to reconsider its energy policy and adopt new energy management

Received September 3, 2013; accepted April 28, 2014

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strategies to sustain its future development. To achieve these goals, plausible contributing factors for energy consumption must be evaluated, and major determinants need to be identified.

It is a generic consensus that energy consumption is directly related to economic growth as well as energy-resource endowment. This relationship in China has been a major concern in both the policy sector and the academic society (Yuan et al., 2008). Most studies on this issue were conducted from the perspective of co-integrating relationships between energy consumption and economic explanatory variables (Cheng, 1999; Yang, 2000; Hondroyiannis et al., 2002; Soytas and Sari, 2003; Jumbe, 2004). Although the conclusions drawn from the above and many other studies not cited here provide some insight into the complex interaction between energy consumption and economic growth, they are unanimously based on total energy consumption rather than per capita energy consumption, which is a more appropriate indicator of the true demand for primary energy in a given region. Furthermore, the multiplicity of influencing factors and their regional disparities as well regional interactions complicate the energy issue in China. Among these important factors is energy resources endowment, which has long been neglected in the equation, and thus needs to be considered in further studies.

In this paper, we intend to examine the issue under the situation of asymmetrical distribution between energy endowment and per capita energy consumption in China. By geo-visualizing the 2008 energy consumption, reserves, and GDP in a per capita sense (Figs. 1–3), we found out that high per capita energy consumption was clustered in both the east coastal region and northwestern China, with the former being the most developed areas having a high energy demand to sustain their economic growth, and the latter being rich in energy resources. In contrast, low per-capita energy consumption is seen to be concentrated in the middle and southwest provinces, which typically are neither well developed nor energy rich. On the other hand, there is an obvious division line separating the “high-consumption north” from the “low-consumption south” (Fig. 1). Results from the above visualization analysis seem to lead to a plausible hypothesis: the distribution of per capita energy consumption in China is significantly correlated with two primary factors, economic development level and energy resource. To confirm this intuitive observation, the Pearson correlation coefficients of both per capita energy consumption and per capita GDP

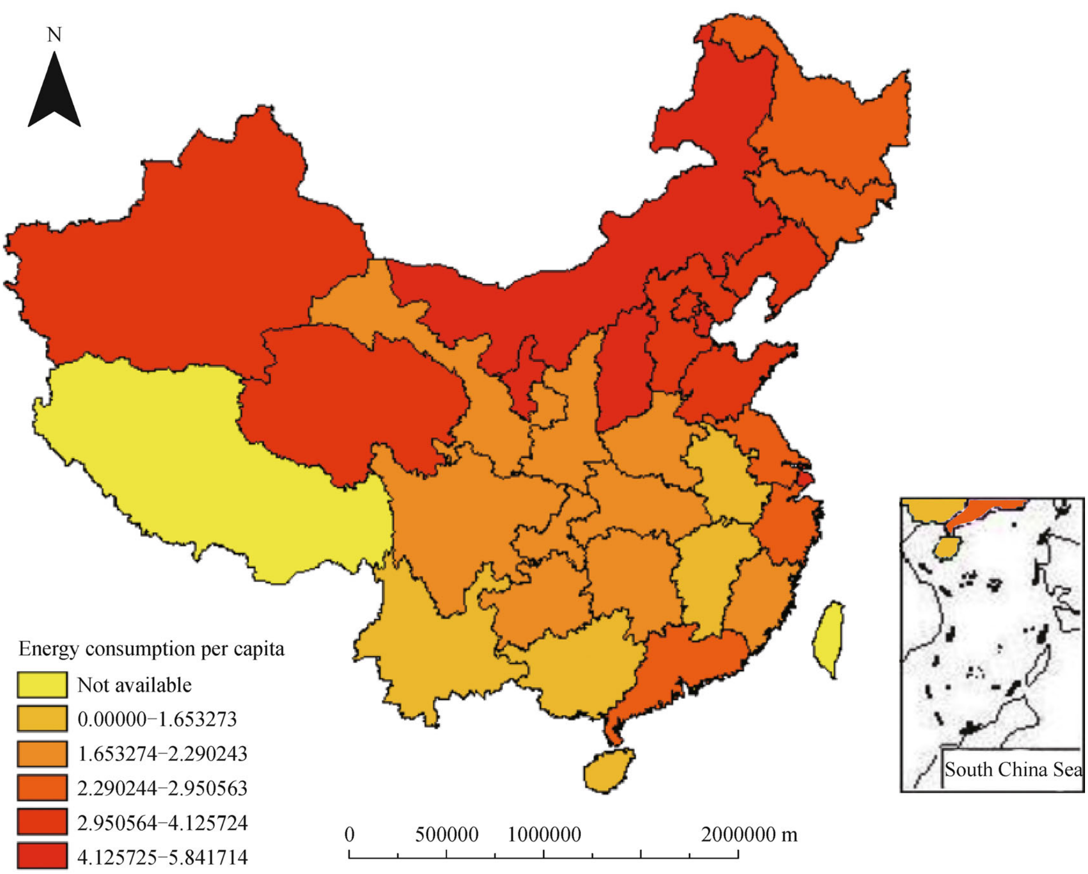

Fig. 1 Spatial distribution of per capita energy consumption (ton/per person) by province (2008)

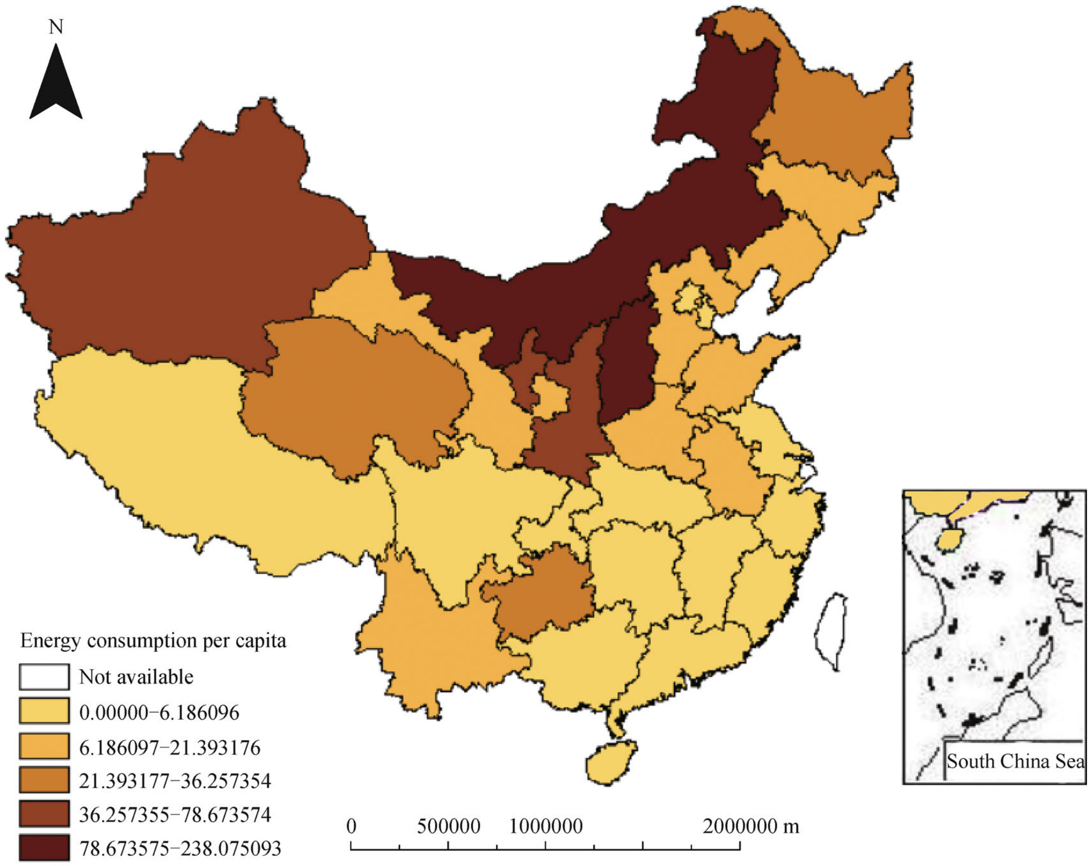

Fig. 2 Spatial distribution of per capita energy reserves (ton/per person) by province (2008)

as well as per capita energy resource reserves were produced, resulting in an R^2 of 0.6302 for the former and 0.3531 for the latter, both at a 0.05 significance level.

Although the above spatial data visualization and simple Pearson correlation analysis are useful for establishing the research hypothesis, this hypothesis is still subject to formal confirmatory analysis. In the rest of this paper, we establish spatially-aware econometric models to test the aforementioned relationships and, more importantly, to explore the spatial effect of economic factors and energy-resource endowment on the distribution pattern of per capita energy consumption in China. The research goal is to answer two specific questions: to what degree the consumption is caused by these factors after their spatial interaction is accounted for, and whether spatial neighborhood exercises significant impacts on contiguous regions. The procedure of achieving this goal will be arranged as follows. The variables and data for empirical analyses are introduced in Section 2, which is followed by an exploratory spatial data analysis to estimate the degree of spatial autocorrelation for per capita energy consumption at a provincial level. A comparative analysis to select a spatial econometric model for testing the listed determinants of per capita energy consumption is provided in Section 3. The section that follows presents the analytic results and their discussion. The last section concludes by summarizing some theoretical evidence and proposing suggestions for differential policy making about energy use and development in China.

2 Variables and data

2.1 Selection of variables

In this study, per capita energy consumption (AVEC) at the province level was chosen as the dependent variable. It is formally defined as

$$\mathrm{AVEC} = \frac{\text{The aggregated amount of energy consumption of province}}{\text{Population of province}}. \tag{1}$$

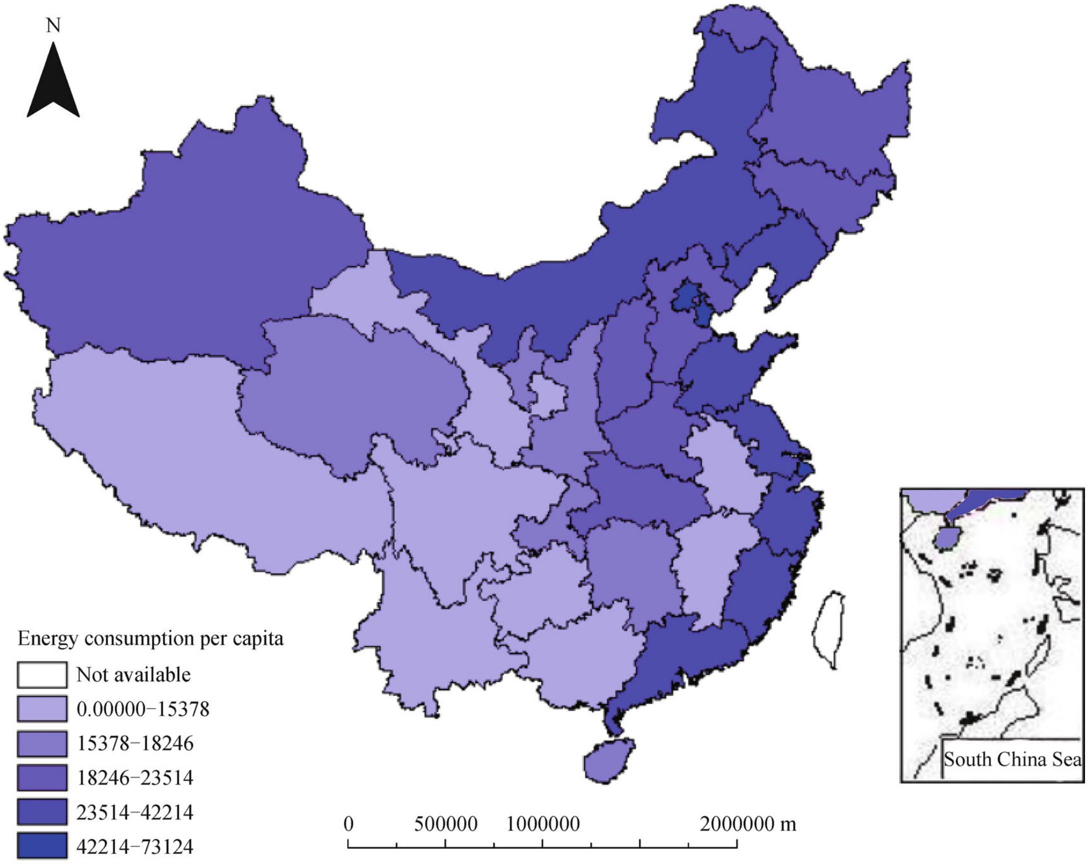

Fig. 3 Spatial distribution of per capita GDP (CNY/per person) by province (2008).

There are five explanatory variables to be used in the study: i.e., per capita GDP, per capita energy resource reserves, industrial structure, marketization, and technological progress.

2.1.1 Per capita GDP (AVGDP)

AVGDP is a common indicator of economic growth and indicates the wealth of the people in a region. Due to the economic growth and increasing urbanization in the past decades, more and more energy resources in China are being consumed (Zhang et al., 2012). A rough observation can be made that areas with higher income demand more energy to sustain their economic growth, and less developed regions tend to consume fewer energy resources. In China, it is fairly plausible to hypothesize that this explanatory variable is positively correlated with per capita energy consumption.

2.1.2 Per capita energy resource reserves (AVES)

Aggregated energy reserves are usually used to reflect energy resources endowment in a region. AVES were defined as energy endowment for the purposes of this study. To measure the energy endowment of each province on the same scale, different kinds of energy must be standardized in the aggregation. Different energy reserves were converted into the form of a standard coal equivalent by adopting the conversion factors (Table 1) from the *China Energy Statistical Yearbook 2010*. Data for hydraulic electricity is not available and not included in the analysis.

Per capita energy reserve is defined as the ratio of standardized energy reserves to population in each province. A visual inspection of the charted statistics (Fig. 2 vs. Fig. 1) reveals that energy-rich provinces (e.g., Inner Mongolia and Shanxi) seem to exhibit high AVEC,

Table 1 Conversion factors from the physical unit of other energy forms to its coal equivalent

Energy	Average low calorie value	Conversion factor/(kgce/kg)
Raw coal	20,908 kJ /(5,000 kcal)/kg	0.7143
Crude oil	41,816 kJ /(10,000 kcal)/ kg	1.4286
Natural gas	38,931 kJ /(9,310 kcal)/ kg	1.3300

Data source: “China Energy Statistical Yearbook 2010”, 1 kgce = 7,000 kcal = 29,307 kJ suggesting the existence of a functional relationship between the abundance of energy resources and the level of AVEC in China. This will be verified with the model.

2.1.3 Industrial structure (secondary industry, SI; and tertiary industry, TI)

The concept of industrial structure to be used here is defined as the relative contribution of secondary and tertiary industries to the total industrial output. The secondary sector weighs significantly in the increase of energy consumption. In China's case, the hypothesis that secondary industry is positively related to AVEC needs to be verified. In recent years, the industrial structure at the provincial level has experienced uneven changes, all with development of the tertiary industries. The tertiary share grew gradually year by year, which was attributed to the higher added values of goods and services as well as the retreat of the secondary industries. As the tertiary share goes up, the industry has to rely on much more energy to support the development. This is the reason why Shanghai, Beijing, etc., with extremely high proportions of tertiary industries, have been reported to consume enormous amounts of per capita energy. It is thus reasonably hypothesized that increasing the share of tertiary industries may contribute to an increase of per capita energy consumption.

2.1.4 Marketization (MKT)

The Chinese economies have been undergoing the process of marketization, and the energy economy is no exception. Energy price undoubtedly has a direct and important impact on energy use, and most literatures attributed China's inefficient use of energy to its energy pricing system (e.g., Fisher-Vanden et al., 2006). The price of energy was fully state-controlled in China until the beginning of economic reform in late 1978. After the initiation of the two-tiered pricing system in 1982[1], prices set by central planning were gradually replaced with market-mediated prices. In the early 1990s, for almost all goods, the market replaced the planned economy as the primary means of allocation. However, price reform in energy sectors (e.g., coal and crude oil), which had long been heavily subsidized by the central government, lagged behind. In 1990, approximately 46% of coal and 80% of crude oil was still plan-allocated (Garbaccio, 1995). Therefore, using energy price as an indicator to reflect the market mechanism is probably inappropriate, as it sometimes cannot lead to believable conclusions. Besides, marketization is a complicated process that can hardly be measured by one or two single variables. A comprehensive description of this process would require too many variables and an extremely complex model beyond management. With all relevant variables being included in the model, on the other hand, high collinearity is likely to become a serious issue. It is therefore necessary to adopt a well-established comprehensive index that can reasonably reflect the moderating mechanism of the market. Due to the lack of existing research in the methodology of measuring marketization in China, the present study adopted the indicator of marketization published in the "NERI INDEX of MKT of China's Provinces 2009 Report", an authoritative work compiled by a group of Chinese economists (Fan et al., 2009).

Under market conditions, the equilibrium between supply and demand is presumably controlled by the invisible hand, the market, which leads to the effective allocation of energy resources. A higher degree of market development is assumed to enhance energy efficiency, hence resulting in decreasing per capita energy consumption. Common knowledge tells us that if the mechanism of the market works, excessive energy consumption will be restrained. Although some previous studies found that marketization in China showed no significant effects on energy consumption (e.g., Zhang et al., 2013), it is still worth reexamining.

2.1.5 Technological progress (R&D input, RD; and number of R&D Personnel, PS)

The relation of technological progress with energy consumption has been regarded as a research hotspot in the field of energy economics. Generally speaking, technological progress can benefit technical and procedural improvement in manufacturing, which in turn contributes to less consumption of energy. Some scholars in the field of energy economics hold the opposite viewpoint, however, which is known as the rebound effect of energy consumption. This term was first applied narrowly to the direct increase in demand for an energy service whose supply has increased as a result of improvements in technical efficiency in the use of energy (Khazzoom, 1980; Khazzoom and Miller, 1982). Since then, the rebound effect has been more widely construed. Technological progress could improve energy efficiency but would also simultaneously push the economy to grow further, resulting in new energy demand. As a net result, the saved energy by technological progress may offset the increased amount caused by rapid economic growth. Bosetti et al. (2006) recognized that R&D investment as an important factor played a major role when modeling technical change in climate models. R&D investment was

1) Two-tiered pricing in the 1980's of China refers to a system under which scarce commodities could be obtained by a part of someone or enterprises with rights at a lower level supported by the government and by the rest at a at market level.

the main driver of climate-friendly technical change that eventually affected energy efficiency, which contributed to the decrease of energy consumption. Their subsequent research helped us understand how knowledge spillovers could be produced across regions, how much and at what cost technological improvement could increase energy efficiency via R&D investment, and what energy policies were able to diffuse energy-saving technologies (Bosetti et al., 2007). Fisher-Vanden et al. (2004) maintained that the scale of formal R&D operations could be measured by R&D expenditure and/or R&D personnel. For this study, R&D expenditure was adopted as the primary indicator of technological progress, in order to verify its influence on per capita energy consumption. The size of R&D personnel is also examined in the model. If the estimated coefficients of both indicators point to the same direction, a robust conclusion is deemed to be reached.

2.2 Data sources

Data for the variables described above were acquired from the *China Energy Statistical Yearbook*, *China Statistical Yearbook*, and *China Statistical Yearbook on Science and Technology*, which were compiled by the National Bureau of Statistics of China and published by China Statistics Press. We used the cross-sectional data of year 2008 for 30 mainland Chinese provinces, autonomous regions, and municipalities; Tibet is excluded from our analysis due to data deficiency in this region. Data for all of the variables are logarithmically transformed to avoid possible heteroskedasticity.

3 Spatial dependence and spatial econometric models

3.1 Exploratory spatial data analysis (ESDA)

The increased availability of spatially referenced data and the sophisticated capabilities for data visualization, rapid retrieval, and manipulation in geographic information systems (GIS) have created a demand for new techniques for spatial data analysis of both an exploratory and confirmatory nature (Anselin and Getis, 1992). ESDA is a group of statistical techniques that can be used to interactively visualize and explore data where space matters for discovering interesting spatial patterns (Anselin, 1995). It is also used to produce hypotheses and generate model results and diagnostics. This paper employed ESDA as a preliminary procedure to examine the level of spatial dependence existing among data records and generate spatially-explicit hypotheses for further testing. The Moran statistic is hereby chosen to characterize spatial dependence and heterogeneity of both the dependent variable and the explanatory variables among China's provinces.

3.1.1 Selection of spatial weight matrix

Spatial statistics integrate space and spatial relationships directly into their mathematical models through a spatial weights matrix. A spatial weights matrix quantifies the spatial relationships that exist among the spatial entities (e.g., provinces in this case) under investigation.

The spatial weights matrix adopted in this paper is based on the rook rule, in which only the first-order contiguity sharing a length (not a point) of boundary is considered in the model. Let L_{ij} denote the length of share boundary, between spatial units i and j, then these so-called rook contiguity weights are defined by

$$w_{ij} = \begin{cases} 1, & L_{ij} > 0, \\ 0, & L_{ij} = 0. \end{cases} \tag{2}$$

3.1.2 Spatial autocorrelation

Spatial autocorrelation is an effective measure of how spatial objects of similar values locate with each other in a given region. The provincial data to be used in this study are examined for spatial autocorrelation using Moran's I statistical tests and the geographical visualization of the index. Hereby we are interested in both the global and local autocorrelation patterns of data distribution among provinces. A global test is performed by constructing a Moran scatter plot (Anselin et al., 1996), in which the slope of the regression line directly corresponds to Moran's I. The statistical significance of any finding about spatial autocorrelation is based on a permutation test. Global Moran's I is formally expressed as (Moran, 1950)

$$\text{Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i-\overline{Y}\right)\left(Y_j-\overline{Y}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i}^{n}\left(Y_i-\overline{Y}\right)^2}, \tag{3}$$

where n represents the number of provinces in this study; if provinces i and j share a common border, then $w_{ij}=1$, otherwise $w_{ij}=0$. Y_i and Y_j are the data values in provinces i and j, respectively. In a standardized form, index I has a value range of [−1, 1]. A positive and significant value of Moran's I indicates the existence of spatial autocorrelation, whereas zero represents complete randomness, and negative values denote the tendency of spatial heterogeneity.

The disaggregated nature of spatial autocorrelation can be investigated using the local Moran's I (i.e., I_i) (Anselin, 1995), which provides an indication of the relationship between deviations (z_i) from the mean $\overline{Y}$ (or μ) and a weighted average of values that are neighbors to i. This weighted average is treated as spatial lags of i and expressed as $\sum_{j=1}^{n} w_{ij}z_j$, where w_{ij} is the element in the spatial weights matrix W corresponding to paired province (i, j). The local Moran's I is defined as

$$I_i = z_i \sum_{j=1}^{n} w_{ij} z_j, \tag{4}$$

where w_{ij} is in row-standardized form while $z_i = (Y_i - \mu)/\delta$, and $\delta$is the standard deviation of Y_i. The local spatial autocorrelations can be examined using the Moran scatter plot, which provides four kinds of information about data points according to their quadrant location in the plot: (I) high-high (HH), indicating a high-value province being surrounded by high-value neighbors; (II) low-high (LH), signifying a low-value province being surrounded by high-value neighbors; (III) low-low (LL), denoting a low-value province being surrounded by low-value neighbors; (IV) high-low (HL), representing a high-value province being surrounded by low-value neighbors. Situations (I) and (III) are associated with positive forms of spatial autocorrelation, whereas (II) and (IV) with negative spatial autocorrelation.

3.2 Spatial econometric models

To cope with the spatial effect of the energy consumption data recorded for individual provinces, three different spatial econometric models are tested and compared in this study: the spatial lag model, the spatial error model, and the spatial Durbin model. The spatial lag model is designed to single out the spatial dependence of per capita energy consumption among paired neighboring provinces, whereas the spatial error model is used to examine the significance of errors that are caused by simply being located next to another province. Instead of constraining spatial effects to either the dependent variable or the error term, the spatial Durbin model aims to examine spatial autocorrelation in all variables (Anselin, 2003).

3.2.1 The spatial lag model

Anselin (1988) provided a maximum likelihood method for estimating the parameters of the spatial econometric model, as it combines the standard regression model with a spatially lagged dependent variable, analogous to the lagged dependent variable model of time-series analysis. We will refer to this model as a spatial lag model (SLM), which takes the following form.

$$\begin{aligned} & y = \rho W y + X\beta + \varepsilon \\ & \varepsilon \sim N(0, \sigma^2 I_n) \end{aligned}, \tag{5}$$

where y is an $n \times 1$ vector of dependent variables, X represents the usual data matrix containing explanatory variables, and W is a known spatial weight matrix, hence a first-order rook contiguity matrix. Parameter ρ is the coefficient on the spatially-lagged dependent variable, Wy, and parameters β denote the coefficients of exogenous variables to be estimated.

3.2.2 The spatial error model

Anselin (1988) also provided a maximum likelihood estimation method for a spatial autoregressive error model, where disturbance exhibits spatial dependence. This model is referred to as the spatial error model (SEM) and expressed as

$$\begin{aligned} & y = X\beta + \mu \\ & \mu = \lambda W \mu + \varepsilon, \\ & \varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \tag{6}$$

where y is an $n \times 1$ vector of dependent variables, X represents the usual data matrix containing explanatory variables, and W is a known spatial weight matrix. Parameter λ is the coefficient on the spatially correlated errors analogous to the serial correlation problem in time series models. Parameters β reflect the influence of the explanatory variables on variation in the dependent variable y.

3.2.3 The spatial Durbin model

One shortcoming of the spatial lag model and the spatial error model is that spatial patterns may be explained not only by a spatially lagged dependent variable or spatially correlated error terms, but also by spatially lagged independent variables, at the same time (Manski, 1993). The spatial Durbin model incorporates both spatially lagged variables and is advocated by LeSage and Pace (2009).

The spatial Durbin model is similar to the spatial lag model, except that the spatially weighted vector of explanatory variables is also included. The model reads as follows:

$$\begin{aligned} & y = \rho W y + X\beta + WX\theta + \varepsilon \\ & \varepsilon \sim N(0, \sigma^2 I_n) \end{aligned}, \tag{7}$$

where θ is a spatial parameter vector that needs to be estimated.

The spatial Durbin model for cross-sectional data can be verified via a Bayesian spatial regression method to see if it should be simplified to either a spatial lag model or a spatial error model (LeSage and Pace, 2009). In this analysis, we first conducted a model comparison between spatial lag and spatial error specifications and then used the Bayesian method to further test if the winning model is better than the spatial Durbin model. In addition, LeSage and Pace (2009) state that building one or more spatial regression specifications to test whether or not spatial spillovers exist may lead to erroneous conclusions. Instead, they propose new approaches to measure the direct and indirect spatial spillover impacts in response to changes in the explanatory variables.

4 An empirical study

4.1 Exploring the spatial autocorrelation of empirical datasets

The global Moran's I values of per capita energy consumption, GDP, and energy reserves measured with the first order of the rook-based contiguity rule are reported in Table 2. The Moran's I indices of these three variables were tested to be positive and statistically significant. Specifically, the first-order spatial weight matrix of the three indicators produced considerably high statistic values (between 0.4 and 0.6), and their z-score tests passed a 0.001 significance level. Regions with a similar value level were more spatially clustered than could be expected by pure chance. This suggested that there was a regionalized agglomeration of these three economic conditions in China. This global concentration pattern implied that future efforts for relationship modeling with these indicators must take spatial autocorrelation into account.

To obtain insight into the local spatial pattern of per capita energy consumption, a Moran scatterplot was generated for this index (Fig. 4). A visual inspection of the scatterplot helped uncover a non-random distribution of per capita energy consumption among provinces. The first quadrant (HH) contains 12 provinces and municipalities (Heilongjiang, Jilin, Inner Mongolia, Xinjiang, Beijing, Hebei, Shanxi, Tianjin, Ningxia, Jiangsu, Liaoning and Shanghai), which are either economically developed with high proportion of tertiary industrial sectors or abundant in energy resources and dominated by heavy industries. The second quadrant (LH) only encloses Gansu, Shaanxi, and Henan, which are typical agricultural provinces surrounded by energy-rich and more developed regions. Located in the third quadrant (LL) are mostly the comparatively underdeveloped provinces characterized with lack of energy resources and proximate to the east coast of China (i.e., Anhui, Hubei, Hunan, Jiangxi, Yunnan, Guizhou, Sichuan, Chongqing, Fujian, Guangdong, Guangxi and Hainan). The fourth quadrant (HL) contains only three provinces (i.e., Qinghai, Shandong, and Zhejiang), which are characterized with high per capita energy consumption but bordered with some provinces located in the first quadrant.

Cross-referencing Fig. 1 and Fig. 4 may lead to an important observation: the per capita energy consumption at the provincial level is not randomly distributed, as the high-value provinces tend to cluster in space. In other words, areas with high per capita energy consumption tend to cluster due to abundance in energy resources and lack of advanced technologies, as in the case of northwestern China. For different reasons from the northwest, provinces along the east coast have a similarly high consumption, which is sustained by the high-standard modern lifestyle and strong purchasing power in the region. The mid-western areas surrounding Chongqing consume less per capita energy than the northwest and the east, seemingly resulting from their lack of energy reserves and low development levels. This spatial pattern of per capita energy consumption in China seems to have been locked by and mutually reinforced with the fixed spatial pattern of energy endowment and industrial development. This observation therefore seems to outline two typical cases in China: consumption level related to level of industrialization, and consumption related to lifestyle. In the first case, provinces of similar energy consumption levels tend to produce a similar industrial structure, which has in turn enhanced the consumption in either direction, such as the ever-increasing high consumption level associated with energy-rich, secondary industry based northwest provinces and the sustained low consumption level associated with energy-poor, underdeveloped mid-west provinces. On the other hand, high energy consumption can also be associated with energy-poor but well-developed regions, as in the case of the east coastal provinces, since sustaining high living standards and high economic outputs require even more energy support. In either case, regions are inclined to imitate neighboring economic and energy consumption patterns via spatial spillovers, which we will take into account in the econometric modeling as follows.

4.2 Confirmatory analysis with spatial econometric models

As indicated in many econometric modeling practices, the traditional Ordinary Least Squares (OLS) regression model often has difficulty handling data with significant spatial autocorrelation. This model, however, was widely used as a benchmark to provide meaningful comparisons with the spatial econometric models. Applying the usual OLS regressive estimation to the dataset results in a set of model coefficients associated with individual variables, their tested statistical significance, and model quality evaluation statistics (Table 3).

Table 2 Moran's I statistic tests

Variable	Moran's I	p-value	Mean	Sd
LnAVEC	0.4170	0.0007	– 0.0388	0.1243
LnAVGDP	0.4822	0.0001	– 0.0345	0.1225
LnAVES	0.5913	0.0001	– 0.0349	0.1228

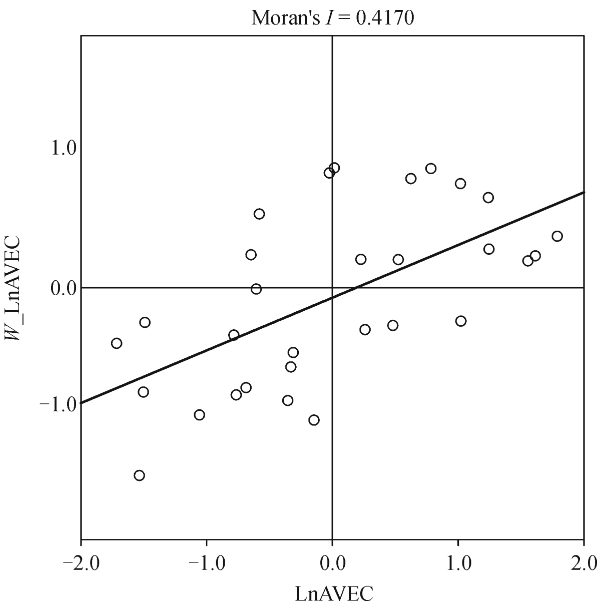

Fig. 4 Moran scatter plot for per capita energy consumption (Log) by province in China for 2008

Several important observations about the OLS regression model can be made from Table 3. First, all estimated coefficients are statistically significant at the level of either 1% or 5%. Second, the goodness-of-fit is high (Adjusted R^2 = 0.8549) and significant ($p < 0.01$), thus the model provides a convincing explanation. Third, collinearity is unlikely to be an issue among the explanatory variables, as their calculated Variation Inflation Factor (VIF) is below 10.

In terms of relationship polarity, all explanatory variables performed as expected. Variables having a positive correlation with per capita energy consumption (LnAVEC) include per capita GDP (LnAVGDP), secondary industry (LnSI), tertiary industry (LnTI), and energy endowment (LnAVES). The magnitude of the GDP effect is somewhat expected, and the high positive elasticity of secondary industry on energy consumption and the even higher value for tertiary industry are also very classical. However, the low contribution of energy endowment as marked in the model is rather unexpected, especially after visually comparing Fig. 1 and Fig. 2. On the other hand, variables having a negative relationship with per capita energy consumption include marketization (LnMKT), research and development (LnRD), and R&D personnel (LnPS). Intensification in those three areas seemed to discourage energy consumption. In terms of absolute influence, all three variables presented elasticity values higher than energy endowment (LnAVES), thus qualifying themselves as important factors in the OLS model.

The OLS regression assumes spatial homogeneity and thus completely neglects possible spatial effects during its data modeling. A spatial regression analysis was employed to build a location-sensitive model with parameter estimates that could fully consider the intricate spatial effects involved in the factors determining the per capita energy consumption pattern in China. The previously calculated Moran's I statistic well indicated the existence of spatial autocorrelation among provincial data values, but it provided no guidance for spatial model selection. Thus, we tested three spatial models (i.e. spatial lag, spatial error, and spatial Durbin) in sequence to determine the optimal model specification for the data.

Following the procedure proposed by Elhorst (2010), the model selection analysis was started by first comparing a spatial lag model (SLM) and a spatial error model (SEM) on the basis of two Lagrange Multiplier tests (regular and robust), which are preferably used in combination. Their

Table 3 Results of OLS regressive estimation

Variable	Coefficient	Std. error	t-statistic	Probability	Tolerance	VIF
Constant	−15.1988	2.1570	−7.0463	0.0000		
LnAVGDP	0.8982	0.1387	6.4761	0.0000	0.2017	4.9583
LnAVES	0.1041	0.0299	3.4768	0.0021	0.2781	3.5952
LnSI	0.8179	0.3529	2.3175	0.0302	0.2273	4.3991
LnTI	1.2129	0.3907	3.1045	0.0052	0.2199	4.5470
LnMKT	−0.6816	0.3230	−2.1102	0.0464	0.1554	6.4330
LnRD	−0.5672	0.2404	−2.3591	0.0276	0.8126	1.2306
LnPS	−0.2051	0.0598	−3.4325	0.0024	0.3832	2.6097
Adjusted R^2	0.8549					
F-statistic	25.4169					
p (F-statistic)	0.0000					
Log LKHD	15.3509					
AIC	−0.4901					
SC	−0.1164					

spatial regressive estimates were derived using the maximum likelihood estimation method and presented in Table 4.

Referring back to Table 3, it is clear that both spatial models performed much better than the OLS model. The goodness-of-fits (R^2) of the spatial models were greatly improved from the OLS estimate, and the one from the spatial error model (i.e., R^2= 0.9113) tops the list. Two other important indicators for model selection, the Akaike Information Criterion (AIC) and the Schiwaz Criterion (SC), were also improved for both spatial models from those of the OLS model, indicating less information loss in the modeling process. Furthermore, the results of model coefficient tests (the two 'Probability' columns in Table 4) via maximum likelihood exhibit that both the spatial lag and spatial error models were superior to the OLS model.

As to the comparison between the two spatial models, both the regular Lagrange Multiplier test and its robust version failed to reject the null hypothesis of being random for the spatial lag model; whereas the robust LM test for the spatial error model rejected the null hypothesis of no spatially autocorrelated error term at a 10% significance level, suggesting spatial error specifications to be a better candidate for this dataset. This outcome is also supported by AIC and SC tests, as their values for the spatial error model are further lower than those for the spatial lag model (Table 4).

Based on the preliminary result from above, we proceeded to compare the spatial error model to the spatial Durbin model for the dataset. The SDM modeling results are reported in Table 5. All explanatory variables except LnAVES are significant at the 0.01 or 0.05 level. Amid the spatially lagged explanatory variables, W*LnAVES, W*LnSI, and W*LnTI are significant at the 0.05 level. Although the goodness-of-fit value (R^2= 0.9384) is greater than that of the SEM result (0.9113), it should be noted that the spatial parameter, ρ, did not pass the significance test, which renders it to be hardly different from zero, indicating that the spatial Durbin model does not provide a good fit to the data. In order to further verify this outcome, the Bayesian spatial regression model test, proposed by LeSage and Pace (2009) for small data samples, was performed with 1200 simulations for both SDM and SEM. The resultant posterior probability was 0.9989 for SDM and 0.0011 for SEM. Therefore, the true model for the dataset in this study is the spatial error model.

Comparing the model estimates of SEM to those from OLS, it is rather interesting to see the effect of spatial errors in the dataset being captured by the spatial error term (λ). With a significance level of 0.0059, the amount of explanatory contribution (−0.6754) that the spatial error effect accounts for is equivalent to that of marketization (−0.6892). Apparently, the improved R^2 is the direct result of the removal of spatial errors in the modeling process. This removal also resulted in a correction in the coefficient estimates for individual explanatory variables. While all seven coefficients retain the same direction as in the OLS model, their values are unanimously adjusted to various

Table 4 Spatial error model and spatial lag model via Maximum Likelihood

Variable	Spatial error model			Spatial lag model		
	Coefficient	Std. error	Probability	Coefficient	Std. error	Probability
Constant	−15.8360	1.5871	0.0000	−14.9938	1.8528	0.0000
LnAVGDP	0.8587	0.0918	0.0000	0.8810	0.1235	0.0000
LnAVES	0.1118	0.0213	0.0000	0.0988	0.0267	0.0002
LnSI	0.9719	0.2572	0.0002	0.7889	0.3023	0.0091
LnTI	1.3437	0.2947	0.0000	1.2116	0.3337	0.0003
LnMKT	−0.6892	0.2251	0.0022	−0.6745	0.2757	0.0144
LnRD	−0.5134	0.1858	0.0057	−0.5854	0.2080	0.0049
LnPS	−0.1626	0.0464	0.0005	−0.2152	0.0529	0.0000
λ	−0.6754	0.2451	0.0059			
ρ				0.0673	0.1208	0.5777
R^2	0.9113			0.8909		
Log likelihood	17.0559			15.4696		
AIC	−18.1117			−12.9393		
SC	−6.9022			−0.3285		
LM-err	1.2031		0.2727			
Robust LM-err	2.7154		0.0994			
LM-lag				0.4817		0.4877
Robust LM-lag				1.9940		0.1579

Table 5 Bayesian spatial Durbin model results

Variable	Coefficient	Std. error	Probability
Constant	– 34.3880	9.8296	0.0015
LnAVGDP	0.7362	0.1597	0.0000
LnAVES	0.0479	0.0392	0.1065
LnSI	1.3590	0.5777	0.0115
LnTI	2.1128	0.7415	0.0040
LnMKT	– 0.8375	0.3877	0.0175
LnRD	– 0.5062	0.2455	0.0215
LnPS	– 0.2672	0.0684	0.0010
W*LnAVGDP	0.2159	0.3986	0.2915
W*LnAVES	0.2068	0.1284	0.0485
W*LnSI	1.8033	0.8863	0.0225
W*LnTI	2.8150	1.4140	0.0225
W*LnMKT	– 0.1568	0.7592	0.4115
W*LnRD	1.6507	1.1632	0.0735
W*LnPS	– 0.1922	0.3008	0.2535
ρ	– 0.2720	0.2978	0.1825
R^2	0.9384		

degrees. When spatial errors are absent, it appears that the contribution from secondary and tertiary industries is more emphasized, whereas the effects of GDP and technological progress are suppressed, and the rest remains about the same. Of particular interest to us was the energy endowment variable (LnAVES). Its contribution gained slight improvement but remained very low. Overall, this might be a more realistic structure of China's energy consumption in relation to the seven factors that were examined in this study.

4.3 Discussion

Further analyses of the modeling results from the aforementioned error-based spatial econometric model (SEM) revealed five primary findings about the effects of economic and energy resource factors on both the structural and the spatial patterns of China's energy consumption.

1) Economic growth is still the most important impetus for the increase in per capita energy consumption. As indicated by its spatial distribution (Fig. 1), eastern China consumed a relatively high share of energy to support its fast economic growth. We can expect that as the reform and opening-up further intensify, per capita energy consumption undoubtedly will keep going up with the increasing living standard. Although the energy consumption level in the middle and southwest areas was comparatively low, with the rise of central China and further implementation of the Great Development of the West program, these areas will catch up with the east region in energy demand and consumption. This combined energy consumption trend will lead to a much greater energy pressure or even a crisis for China in the future.

2) Although energy endowment seemed to visually cluster in a pattern similar to energy consumption in China (Figs. 1 and 2), its estimated elasticity coefficient (0.1118 in Table 4) indicated a rather low weight in the model. This is especially evident when compared to the GDP variable (Figs. 1 and 3) and its model coefficient (0.8587 in Table 4). The downgraded relationship between energy endowment and energy consumption might have been caused by the dual consumption patterns in China. On one hand, areas with abundant energy reserves are inclined to consume more energy resources, as evident in such provinces as Inner Mongolia, Shanxi, and Ningxia. These provinces sought to accelerate their economic growth but were tied up with traditional modes of production with considerably low energy efficiency, leading to a net result of "high endowment and high consumption". On the other hand, many well-developed but energy-poor provinces along the east coast, such as Shandong, Jiangsu, Zhejiang, Shanghai, Fujian, and Guangdong, also scored high in energy consumption, forming a "low endowment and high consumption" cluster. The opposite effects of these two clusters obviously cancelled each other, making the actual leverage of energy endowment very low across all of China. The relationship requires a more complex methodological design than a wholesome regression for analysis.

3) Industrial structure was again proven to be a major factor in the whole picture of China's energy consumption. Both secondary and tertiary industries placed heavy weights on the national energy consumption pattern. The recent internal change of China's industrial structure was characterized by a significant movement of secondary industries to the mid-west region from the east coastal areas, where more tertiary sectors grew to fill the vacancies. The net outcome is, while the share of secondary industries goes down nationally, there is no apparent potential to further lower its absolute number. Spatially speaking, the high energy-consuming and low value-added secondary industrial sectors that were moved to the energy-rich Midwest further pushed up energy demand in these provinces. Since the Midwest is simultaneously a nationally designated storage of energy reserves for the future, the region is surely under an incredible pressure. The increased share of tertiary industries in the east coast, on the other hand, are supposed to be high value-added with low energy input, but the results of this paper revealed the opposite. Namely, the dominance of tertiary sectors in the eastern provinces has led to a higher level of energy consumption, an observation similar to the viewpoint of Yuan and Qu (2009). In spite of great efforts being made to alleviate the continuous energy pressure through industrial restructuring, eastern China seems to still face the challenge of improving energy efficiency in its economic growth.

4) China's marketization since 1978 seems to have generated regulating effects on the use of energy. The reduced use of energy might have resulted from market pricing to control the flow of energy resources in a more rational way. Regions with more advanced modes of production are willing to pay higher prices for energy, as their generated GDP would be more cost-effective than less developed areas. As the model outputs indicated, this institutional change seemed a rather significant measure to reallocate energy resources in China, so that the western regions may grow sustainably by exchanging their rich energy resources for advanced, energy-efficient technologies from the eastern regions. Due to the huge regional disparity of energy endowment and economic development in China, the Chinese central government has over the years implemented different market policies for different provinces, such as strict ones to be applied to the energy-rich yet energy-inefficient regions, aiming to regulate the local use of energy resources and promote the flux of energy into areas with high energy efficiency.

5) As indicated in the model, using advanced technologies to reverse the trend of low efficiency in energy use seemed rather effective in China, making it one of the most promising measures to avoid the possible future energy crisis in China. This compound factor works in two ways. On one hand, improvement of energy efficiency largely relies on technological innovations that improve the energy-power conversion ratio during value-added production. A common practice in China over the last ten years has been to import new equipment and technologies through foreign direct investment or joint ventures for high productivity and energy savings. On the other hand, R&D investment in developing technologies aiming to harvest and use such green or sustainable energies as wind power, solar power, hydropower, and biomass energy has been steadily increased in China, which may significantly bring down the fossil energy use in the years to come. For instance, the increasing expenditure on developing nuclear power technology has proven able to extricate China from the severe restraint of high energy demand in the future. In spite of the recent incident of the earthquake-provoked explosion of Japan's Daiichi nuclear power plant, nuclear power is still undoubtedly accepted as safe and clean energy. The current energy reserve structure is heavily weighted by coal and other types of fossil fuels; this situation may hopefully be rectified by promoting nuclear power as a national policy. Advancement in geological science and technology also contributes to the exploration and exploitation of new fossil energy reserves, which may help to alleviate the nationwide energy pressure. As long as the goal of sustaining a high GDP is maintained in the years to come, the Chinese central government will continue to place great emphasis on technological progress by increasing financial input into R&D sectors and training more R&D personnel. Combined with industrial restructuring, technological progress should be treated as a critical element to tackle China's current and future energy issues.

5 Conclusions

This study has demonstrated the capacity of using spatial econometric modeling in energy issue analysis to deal with inherent spatial errors that are not resolved by traditional statistics. This case study has revealed two drawbacks of the traditional OLS model. First, the spillover effects of spatial neighbors can be too complex for OLS to handle, which may lead to degradation of modeling accuracy. Second, with the presence of spatial autocorrelation, the contribution of each explanatory variable can be biased toward either overestimation, such as in this case study, or underestimation, otherwise. The SEM-based analysis has distilled a significant portion of model contribution as spatial errors due to neighborhood effects and adjusted the elasticity of each contributing factor to improve each model's goodness-of-fit.

Even though the analytic results from the SEM model cannot paint an optimistic picture for the current status of energy consumption in China, this study nevertheless provided a suitable approach to investigating this complex issue from an untraditional perspective, combining energy endowment, economic factors, and spatial interaction among regions with similar or disparate characteristics. The primary findings of this study and their implications are rather profound and thought-provoking, which may help to redirect national and provincial policy making regarding energy consumption and energy conservation in China.

As a whole nation, China presents a great demand in energy for continuous economic growth; but regionally, this situation is complicated by the dichotomy of development stage and energy efficiency. The increasing degree of marketization in China’s economic system seems to have been unlocking the stagnation of energy issues by promoting energy-technology exchanges between the northwest and the east. Recently, the Chinese government has furthered its energy market reform regarding energy pricing, using it as an essential tool to adjust the demand and supply relation for energy in the market. The modeling results in this study suggest that future energy policy making requires greater attention to be paid to both market measures and government taxing in energy-rich regions, as well as increasing investment in energy-efficient equipment and management. Further and more extensive cooperation and exchange between the east and the west should be encouraged or even mandated, so as to speed up the industrial restructuring process for the improvement of energy efficiency.

Industries in China can generally be characterized with a considerably low ratio between economic output and energy input. As suggested by the SEM model output, not only secondary sectors are still dominated by energy devouring machineries, but the newly emerging tertiary industries across the country also suffer from the inadequate use of energy. Therefore, the solution to the energy inefficiency issue is not as simple or straightforward as conventional industrial restructuring for China. It is reasonable to suggest that a more sophisticated plan of coupling nationwide industrial restructuring with technological innovation should be considered. In China’s case, technological progress seems to be a vital catalyst to facilitate the transformation of the old, energy-inefficient industries to the new, energy-efficient, and environmentally friendly ones. Policies towards rapid adoption of renewable energy and energy saving techniques must be made, and R&Ds in both national research institutions and enterprises should be encouraged. Direct transfer of new technologies and management practices from advanced countries and domestic independent innovations should both be emphasized, and only their integration can help China move away from the seemingly doomed trajectory to the foreseen energy crisis in near future. In addition, new energy production and consumption must be seriously subsidized by the local and central governments for the incubation of a different line of energy industry aiming for better natural resource conservation and environmental protection.

Acknowledgements This work was supported by the National Natural Science Foundation of China (Grant No. 40671074) and China Scholarship Council (No. 2011614110).

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