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SPECIAL ISSUE PAPER

Energy efficiency in the Chinese provinces: a fixed effects stochastic frontier spatial Durbin error panel analysis

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Abstract Energy efficiency improvement has been a key objective of China's long-term energy policy. In this paper, we derive single-factor technical energy efficiency (abbreviated as energy efficiency) in China from multi-factor efficiency estimated by means of a translog production function and a stochastic frontier model on the basis of panel data on 29 Chinese provinces over the period 2003–2011. We find that average energy efficiency has been increasing over the research period and that the provinces with the highest energy efficiency are at the east coast and the ones with the lowest in the west, with an intermediate corridor in between. In the analysis of the determinants of energy efficiency by means of a spatial Durbin error model both factors in the own province and in first-order neighboring provinces are considered. Per capita income in the own province has a positive effect. Furthermore, foreign direct investment and population density in the own province and in neighboring provinces have positive effects, whereas the share of state-owned enterprises in Gross Provincial Product in the own province and in neighboring provinces has negative effects. From the analysis it follows that inflow of foreign direct investment and reform of state-owned enterprises are important policy handles.

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1 Introduction

China's rapid economic growth has resulted in an unprecedented increase in energy consumption, from 571 million tons standard coal equivalent (SCE) in 1978 to 3480 million tons SCE in 2011, with an average annual growth rate of 5.63 %. In 2009, China overtook the USA as the world's largest energy consumer (IEA 2010). In 2012, China consumed 21.9 % of global primary energy (BP 2013), accounted for 77.25 % of the net increase in global primary energy consumption and, for the first time, for more than half of global coal consumption (BP 2013).

The size of its population and of its economy are the main factors that drive China's huge amount of aggregate energy consumption (York 2007; Yu et al. 2012). China is the world's most populous country and the second largest economy. In 2012, its population of more than 1.3 billion accounted for about one-fifth of the world population and its economy, with a GDP of US$ 11 trillion, for approximately 11.5 % of global GDP (IMF 2013).

Industrialization and urbanization are the main contributors to the increase in energy consumption in China (Liu and Li 2011; Zhang et al. 2011a, b; Fu et al. 2013). Particularly, China's economic growth depends to a large extent on the rapid increase of the secondary sector (Zhang et al. 2011b), which currently accounts for approximately 70 % of total primary energy consumption. What's more, China is accelerating its industrialization (Liu and Li 2011) which will lead to a further increase of energy demand (Cattaneo et al. 2011).

China's industrialization has been made possible by massive urbanization (Liu 2009). Its urbanization rate has risen from 26.4 % in 1990 to 51.3 % in 2011 (Zhang and Lin 2012). The rapid growth of cities has resulted in large infrastructure projects, notably housing and transportation, which need considerable quantities of steel, cement and other energy-intensive products (Jones 1991). Already today, 75 % of energy is consumed in cities (Madlener and Sunak 2011). By 2030, it is projected to have risen to 83 % (IEA 2009) because China's government is speeding up urbanization in a bid to further stimulate the economy and to make it more robust (Davis 2013).

China has been suffering from a rapidly growing energy gap during the past two decades. In 1992, it consumed 1091.70 million tons SCE outpacing its energy production of 1072.56 million tons SCE, leading to a deficit of 19.14 million tons. In 2010, there was a deficit of 300.15 million tons. Hence, the imbalance between China's energy demand and supply has worsened in recent decades (Crompton and Wu 2005), which poses a huge threat to national energy security. As meeting energy demand is of utmost importance to China's economic and social development (Yuan et al. 2008), the state-run monopolistic energy companies have gone abroad for energy supplies, such as oil from the Middle East and natural gas from Central Asia and Russia.

In recent years, China's environment has been worsening due to the use of coal. Particularly, 70 % of fine particulates, 90 % of SO_x, 67 % of NO_x and 70 % of CO_2 emissions resulted from coal combustion (Fang and Zeng 2007). These pollutants have led to several serious environmental issues. Acid rain caused by SO_x has been affecting 298 cities in China (Zhang et al. 2011c). CO_2 is the dominant contributor to climate change which has led to an increase of serious droughts in northwestern China and devastating floods in the southwest (Tang et al. 2013). It is estimated that economic losses caused by pollution account for 2–3 % of China's GDP (Zhang et al. 2010; Song et al. 2011).

China's overall energy efficiency lags behind that of developed countries (Fisher-Vanden et al. 2004), although it has improved significantly, from 5.27 ton SCE per 10,000 Yuan of output in 1990 to 2.33 in 2011. Based on purchasing power parities, China's energy intensity is about 2.5 times higher than that of the world average, 4 times higher than that of the USA and 7.7 times higher than that of Japan (IEA 2011).

Energy efficiency improvement plays a decisive role in addressing both the energy gap and environmental degradation because it directly contributes to reducing energy consumption and emissions (Tanaka 2008). To reduce the pressing energy gap and decrease environmental degradation, China's central government implemented a mandatory national energy efficiency improvement target of 20 % in its 11th Five-Year Plan (2006–2010). This was the first time that a quantitative, binding target was set which signals the government's concern about long-term sustainable economic development via energy efficiency improvement (Zhang et al. 2011a). In the 12th Five-Year Plan, the target has been sharpened by an additional 16 % reduction.

Energy efficiency is commonly defined as the ratio of energy consumption to GDP (Hang and Tu 2007; Chai et al. 2009; Mulder and Groot 2012). However, this is a crude and inaccurate indicator (Ang 2006; Filippini and Hunt 2011; Stern 2012) because it only considers energy as input and ignores other key inputs, notably capital and labor (Hu and Wang 2006; Lin and Du 2013). An adequate measure of energy efficiency can be obtained by means of data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (Filippini and Hunt 2012). The former is a nonparametric, linear programming method and the latter a parametric econometric method. SFA has the advantage that it can take into account statistical noise (Tsekouras et al. 2004) which is important in the Chinese case because official data suffer from various measurement errors due to inter alia inaccuracies in data collection and compilation methods and skills of statisticians at lower administrative levels (Wang and Meng 2001; Holz 2004; Lin and Du 2013).

Since its introduction by Aigner et al. (1977) and Meeusen and Broeck (1977), SFA has been increasingly applied to analyze energy efficiency. For example, Buck and Young (2007) analyzed energy efficiency of Canadian commercial buildings, while Boyd (2007) estimated energy efficiency for a sample of wet corn milling plants. SFA has also been used to evaluate regional energy efficiency for 85 industrialized and developing countries over a 37-year period (Stern 2012), for 21 OECD countries in 2001 (Zhou et al. 2012) and for 4 OPEC countries over the period 1972–2010 (Adetutu 2014).

Few studies have been conducted to estimate energy efficiency of Chinese provinces by means of SFA. One exception is Zou et al. (2013) who applied stochastic frontier analysis based on a Cobb–Douglas production function to estimate energy efficiency of 30 Chinese provinces over the period 1998–2009. However, the author did not distinguish between individual heterogeneity and inefficiency. Failure to control for individual heterogeneity will bias the estimator when the efficiency measure is confounded with individual heterogeneity (Wang and Ho 2010).

The objective of this paper is to estimate energy efficiency of 29 Chinese provinces over the period 2003–2011 by means of a spatial fixed effects panel stochastic frontier model followed by a fixed effects spatial Durbin error model.[1] The findings may help policy makers to further understand the spatio-temporal development of energy efficiency and its main determinants and to develop energy policies.

The paper is organized as follows. Section 2 presents the theoretical technical inefficiency models which are used to derive technical energy efficiency measures. Section 3 describes the variables applied in the analysis of technical energy efficiency and their data sources, while Sect. 4 presents the empirical results. Section 5 concludes.

2 The technical efficiency models

2.1 The multi-factor inefficiency model

The measure of energy efficiency analyzed in this paper is derived from the general stochastic production function and the multi-factor inefficiency framework for panel data, as presented by Wang and Ho (2010). It reads:

$$Y_{it} = F(X_{it}; \beta) \exp(\alpha_i + \nu_{it} - \mu_{it}) \tag{1}$$

$$\mu_{it} = f(Z_{it}\delta) * \varepsilon_{it}, \quad i = 1, \ldots, N; \; t = 1, \ldots T \tag{2}$$

where the subscript i denotes the i_{th} province ($i = 1, 2, \ldots 29$), and t denotes time ($t = 1, 2, \ldots 9$). The production function $F(X_{it}; \beta)$ describes output Y_{it} as a function of a vector of inputs X_{it} with β the vector of unknown parameters to be estimated. The error term consists of three components: α_i which represents province-specific unobserved heterogeneity, ν_{it} the standard error term and μ_{it} which is a nonnegative error term that follows a truncated normal distribution. It reflects the shortfall of a province's output from the efficient frontier. In other words, it captures technical inefficiency.

Equation (2) describes μ_{it} as a function of inefficiency determinants Z_{it} with error term $\varepsilon \sim \mathrm{N}^{+}(\mu, \sigma_{\mu}^{2})$ which is independent of Z_{it}. Note that in model (1)–(2) as well as in model (9) we account for unobserved heterogeneity by means of fixed effects because in China province-specific heterogeneity cannot be assumed to be random. The reason is that there are substantial differences in terms of notably natural and environmental conditions, resource reserves, economic growth, industrial structure, level of technology, population size and population density.

The first step in our energy efficiency analysis is the estimation of Eqs. (1) and (2). For that purpose, we apply Wang and Ho's (2010) consistent maximum likelihood

[1] We analyze panel data of 29 Chinese provinces over the period 2003–2011. Tibet, Hong Kong, Macau and Taiwan are excluded because of lack of data. Guizhou is not included in the analysis because of incomplete data.

approach that removes the fixed effects mentioned above by first differencing or within transformation.

To estimate the Eqs. (1) and (2), the functional form of the production function needs to be specified. We apply the translog stochastic frontier production function because it is a flexible functional form (Tsekouras et al. 2004). Moreover, the translog function does not place a priori restrictions on the production technology (Christensen et al. 1973; Segal 2003; Pavelescu 2011). The translog stochastic frontier production function with the 3 inputs capital, labor and energy reads:

$$\begin{aligned} LnGPP_{it} = {} & \beta_0 + \beta_1 LnCapital_{it} + \beta_2 LnLabor_{it} + \beta_3 LnEnergy_{it} \\ & + \frac{1}{2}\beta_4 (LnCapital_{it})^2 + \frac{1}{2}\beta_5 (LnLabor_{it})^2 + \frac{1}{2}\beta_6 (LnEnergy_{it})^2 \\ & + \beta_7 (LnCapital_{it})(LnLabor_{it}) + \beta_8 (LnCapital_{it})(LnEnergy_{it}) \\ & + \beta_9 (LnLabor_{it})(LnEnergy_{it}) + \alpha_i + \nu_{it} - \mu_{it} \end{aligned} \tag{3}$$

where Ln denotes the natural logarithm. GPP_{it} denotes output or Gross Provincial Product (GPP), and $Capital_{it}$, $Labor_{it}$ and $Energy_{it}$ are the inputs capital, labor and energy of the i_{th} province at time t, respectively.

Multi-factor technical efficiency (*TE*) is defined as (Battese and Coelli 1992):

$$TE_{it} = E[\exp(-\mu_{it})|(\upsilon_{it} - \mu_{it})] \tag{4}$$

2.2 The single-factor energy efficiency model

We follow Tang et al. (2013) and the references therein, notably Reinhard et al. (1999) and Karagiannis et al. (2003), Ma et al. (2014), Kouser and Qaim (2015) and define single-factor technical (energy) efficiency (EE) as the ratio of the minimum feasible use of energy to observed use of energy, conditional upon given production technology, level of output and levels of the other inputs. Hence:

$$EE_{it} = \min\{\lambda : F(K_{it}, L_{it}, \lambda E_{it}) \geq GDP_{it}\} \rightarrow (0, 1) \tag{5}$$

where λ denotes *EE*. E_{it} represents the actual amount of energy used and λE_{it} the best practice quantity of energy use. Following Reinhard et al. (1999) EE_{it} can be written as:

$$EE_{it} = \frac{E_{it}^F}{E_{it}} \tag{6}$$

where E_{it}^F is the minimum feasible use of energy and E_{it} the actual amount of energy used. Energy efficiency for the i_{th} province at time t can be obtained as (Reinhard et al. 1999):

$$EE_{it} = \exp\left(\frac{-\xi_{it} \pm \sqrt{\xi_{it}^2 - 2\beta_6\mu_{it}}}{\beta_6}\right) \tag{7}$$

with

$$\xi_{it} = \beta_3 + \beta_8 LnK_{it} + \beta_9 LnL_{it} + \beta_6 LnE_{it} \tag{8}$$

derived from (3). To get insight into the energy efficiency determinants, we perform a second-stage analysis with EE_{it} in (7) as dependent variable.

We assume that the determinants not only have effects in the own region, but that they can also impact energy efficiency in neighboring regions, i.e., we take spatial spillovers into account. For example, technology can diffuse across provinces. We apply a spatial Durbin error model to analyze the determinants of energy efficiency. For a cross section of N observations at time t this model reads (Elhorst 2014):

$$\begin{aligned} EE_t &= \alpha\iota + \delta EE_{t-1} + Z_t\beta_1 + WZ_t\beta_2 + \mu_i + \gamma_t + \varepsilon_t \\ \varepsilon_t &= \lambda W\varepsilon_t + \nu_t \end{aligned} \tag{9}$$

where EE_t is the N vector of the dependent variable defined in (7), $\alpha\iota$is the constant term with parameter α and ι the N vector of ones, EE_{t-1} is the one-period lagged dependent variable with parameter δ, Z_t is an $N \times K$ matrix of determinants with unknown $K \times 1$ parameter vector β_1. The fourth term on the right-hand side contains the spatially lagged determinants with unknown parameter vector β_2. The spatial weights matrix W with elements w_{ij} captures the spillovers among the Chinese provinces. Ideally, a weights matrix is based on economic characteristics, for instance input–output relationships, as represented by an interregional input–output table. The construction of such a W matrix is beyond the scope of the present paper, however. Therefore, we opt for an alternative approach and consider spatially lagged variables of various orders of contiguity. That is, we estimate the model without spatial dependence, test the residuals for spatial dependence of various orders of contiguity and add spatially lagged controls accordingly. We apply a binary first-order rook-contiguity matrix whose elements are 1 if two provinces share a common border, and 0 otherwise. We row-standardize W so that the sum of the row elements equals 1.[2] The terms μ_i and γ_t in Eq. (9) represent the provincial specific effects and the time-period specific effects, respectively. The error term, ε_{it}, depends on the error terms of the neighboring provinces and an idiosyncratic component υ. λ is the spatial autocorrelation coefficient (Elhorst 2014).

3 The variables and their data sources

In this section, we discuss the dependent and explanatory variables in (1)–(2) and (9) as well as their data sources.

Regarding Eq. (1), output is real gross provincial product (GPP) in 1997 constant prices. Output data are obtained from the China Statistical Yearbooks. Labor is the

[2] We similarly consider spatially lagged controls in model (2).

total number of workers employed (data source: the Statistical Yearbooks of the 29 provinces). Energy use is energy consumption in million tons SCE (data source: the China Energy Statistical Yearbooks).

For capital stock no yearly data are available. We approximate it as follows (Goldsmith 1951; Shan 2008; Wei et al. 2009; Song and Zheng 2012):

$$K_{it} = K_{it-1}(1 - \delta_{it}) + I_{it} \tag{10}$$

where K is the capital stock, δ its depreciation rate, and I deflated gross fixed capital formation. Since the depreciation rates for the 29 provinces are not available, they are set at 10.96 % for all provinces as proposed by Shan (2008). The base year capital stock is calculated as:

$$K_{iT-1} = \frac{I_{iT-1}}{\delta_i + \theta_i} \tag{11}$$

where $K_{i,T-1}$ and $I_{i,T-1}$ are the base year capital stock and gross fixed capital formation of province i, respectively. θ_i is the average growth rate of real fixed capital formation of province i. The data for capital stock calculation are obtained from the Comprehensive Statistical Data and Material Yearbooks, the Statistics on Investment in Fixed Assets Yearbooks and the China Statistical Yearbooks.

We now turn to a discussion of the controls in Eqs. (2) and (9), viz. the time-lagged dependent variable, state-owned enterprise (*SOE*), trade openness (*Trade*), foreign direct investment (*FDI*), GPP per capita (*GPPc*) and population density (*Density*). Because of the close relationship between multi-factor technical efficiency and single-factor technical energy efficiency, we hypothesize the same set of controls for both. The magnitudes of their impacts are not constrained to be the same.

Time-lagged dependent variable. This term captures lagged effects of the exogenous variables (geometric lag model). It also captures the fact that efficiency improvement is a gradual process because it takes time for new technologies to be adopted in production processes (Metcalf 2008).

SOE. China's SOEs operate less efficiently than non-SOEs in terms of profits, productivity and growth (Zhang 2004; Dougherty et al. 2007), which is attributed to the separation of ownership and control (Lin and Tan 1999). The share of the secondary sector in GDP has been recognized as one of the driving forces behind the persistence of China's low energy efficiency (Chai et al. 2009). SOEs still play an important role in China's industrial sector. In 2011 they accounted for approximately 26 % of the gross industrial output value. In China, SOEs dominate the sectors of mining and exploitation of natural resources, notably energy resources. For example, in 2011 SOEs accounted for 76 % of the total industrial output value in five energy-related industrial sectors (viz. mining and washing of coal, extraction of petroleum and natural gas, processing of petroleum, coking, processing of nuclear fuel, production and supply of gas and production and supply of electric power and heat power). Hence, the variable *SOE* is also a proxy for energy reserves. Fisher-Vanden et al. (2004) showed that China's SOEs are overrepresented in the energy-intensive raw materials and heavy industrial sectors.

Fisher-Vanden et al. (2004) also found that foreign-invested firms and Hong Kong, Macao, Taiwan firms were more energy efficient than their state-owned mainland China counterparts. Fisher-Vanden (2013) drew similar conclusions. Hence, we hypothesize that the larger the proportion of SOEs in a province, the lower its efficiency. We define SOE as the ratio of the value of industrial output of state-owned and state-holding industrial enterprises to the value of total output. Data are obtained from the China Industry Economy Statistical Yearbooks.

Trade. Trade increases efficiency by way of import or stimulation of improved technology (Wei et al. 2001; Keller 2002, 2004; Alcalá and Ciccone 2004; Zhou et al. 2011). Imports of a large variety of technologically advanced physical capital, such as machinery and equipment, immediately contribute to efficiency improvement (Coe et al. 1997; Henry et al. 2009). Besides, competition in export markets encourages the adoption and implementation of efficient production techniques and inputs (Miller and Upadhyay 2000). Hence, we hypothesize that trade has a positive effect on efficiency. In this study, import and export are combined as total trade, as in Zhou et al. (2011). We use the ratio of total trade to GPP as an indicator of trade openness (Harrison 1996; Shahbaz et al. 2013; Ren et al. 2014). Data are obtained from the China Statistical Yearbooks.

FDI. FDI is an effective channel to transfer new technologies from developed to developing countries (Herrerias et al. 2013). Through new inputs, labor training, skills acquisition and the introduction of technological knowledge and managerial expertise, FDI contributes to efficiency of production processes of, notably, developing countries (Rodriguez-Clare 1996; Kugler 2006; Blalock and Gertler 2008; Alguacil et al. 2011). There is also a growing literature on the role of FDI in improving energy efficiency [see among others, Fisher-Vanden et al. (2006); Hang and Tu (2007); Peterson (2008); Hübler and Keller (2010)]. Hence, we hypothesize that FDI contributes to energy efficiency improvement. In this study, we use the ratio of FDI to GPP as an explanatory variable. FDI data are obtained from the CEIC Database.

Gross Per Capita Product (GPPc). Income (per capita) is closely related to environmental quality including energy efficiency (Fouquau et al. 2009; Song and Zheng 2012). The relationship has been analyzed in the form of the environmental Kuznets curve which postulates that environmental degradation increases when income rises but turns into a negative relationship when income has passed a threshold (Stern 2006; Song and Zheng 2012; López and Yoon 2013). One of the main drivers of the Kuznets curve is the secondary sector whose role tends to decrease when *GPPc* increases (Zhang et al. 2011b; Yuan et al. 2014). Since this driver has been discussed above, the following discussion is restricted to the other drivers of the Kuznets curve and their relationship to energy efficiency.

A second driver of the Kuznets curve is consumption. On the one hand, higher per capita income leads to more consumption of energy-intensive products like cars, refrigerators and air conditioners. On the other hand, given one's consumption bundle, a higher income makes it possible to buy more energy-efficient products like fuel efficient and electric cars. The net outcome is ambiguous. Higher incomes also have an impact on people's environmental awareness which in its turn leads to an increased demand for environmental protection (Suri and Chapman 1998; Dinda 2004). Furthermore, countries and regions at higher income levels tend to spend more on environmental research and the adoption of clean technology (Panayotou 1993; Komen et al. 1997; Stern 2004). Wu (2012) showed that China's energy efficiency generally improved as its income increased. Hence, we hypothesize that *GPPc* has a positive impact on energy efficiency.

Population density (Density). Chinese citizens have become increasingly aware of air pollution and its health risks (Song and Zheng 2012). Several provincial governments have taken steps to improve energy efficiency in a bid to reduce energy consumption and air pollution. We hypothesize that the pressure to reduce air pollution via improving energy efficiency is strongest in densely populated provinces. Hence, we include population density in the model and hypothesize that its impact on energy efficiency is positive. Data are obtained from the China Statistical Yearbooks.

Spatial spillovers (W). Several of the above variables are likely to have spatial spillover effects. For example, SOEs in one province may have subsidiaries in neighboring provinces. There may also be spatial spillover effects through interprovincial input–output linkages. FDI may also create technological externalities or knowledge spillovers among provinces in various ways (Cheung and Lin 2004). First, there is a demonstration effect (Li et al. 2001; Hu and Jefferson 2002). Foreign firms are generally considered "model firms" that stimulate local firms to adopt similar new technologies, inter alia, to boost competitiveness in the local market. A second effect is labor turnover. Local firms may obtain advanced technologies from foreign firms by hiring their skilled workers and experts. The last FDI effect materializes via vertical linkages from foreign firms in one province to their local suppliers in neighboring provinces.

Since air pollution spreads across provinces, high population density in neighboring provinces may also impact on a province's energy efficiency. On the one hand, neighboring provinces may follow suit if a province strengthens its environmental policy. On the other hand, pollution spillovers from a given province may induce neighboring provinces to improve their environmental conditions.

Spatial spillover effects are notated *W * Variable*. Spatial spillover effects are measured in the same units as the own variables, and they are expected to have the same signs.

The variables and their definitions are presented in Table 1.

4 Empirical results

4.1 Multi-factor inefficiency model

Equations (1) and (2) were estimated using the maximum likelihood procedure developed by Wang and Ho (2010) which is available in the Stata software package. The results are presented in Table 2.

We followed Battese and Coelli (1992) and performed a likelihood ratio test of the hypothesis that technical inefficiency is absent. That is, we tested the null: $\mu_{it} = \delta = 0$. The null hypothesis was rejected at 1 % (Chi-square value 26.52, 4 degrees of freedom) indicating the presence of multi-factor technical inefficiency in the provincial production system.

Table 1 Definitions, measurement units and descriptive statistics Sources: China Energy Statistical Yearbook (2004–2012), China Statistical Yearbook (2004–2012), China Industry Economy Statistical Yearbook (2004–2012) and China Economic Database (CEIC)

Variable	Definition	Unit	Mean	SD	Min	Max
GPP	Real gross provincial product	100 million Yuan	7959	6901	355	35,827
Capital	Accumulated capital stock	100 million Yuan	16,330	13,357	1010	71,717
Labor	The number of employees	10,000 Person	2380	1601	254	6486
Energy	Energy consumption	10,000 ton SCE	10,520	7127	684	37,132
SOE	The proportion of state-owned enterprises	%	44.48	19.86	6.54	88.41
Trade	The ratio of total trade to GPP	%	54.75	64.18	5.31	259.82
FDI	The ratio of FDI to GPP	%	2.73	2.16	0.09	10.51
GPPc	GPP per capita	10,000 Yuan/capita	1.98	1.29	0.55	6.65
Density	Population density	Person/KM^2	434.13	607.12	7.44	3701

Table 2 The estimated stochastic production function models

Variable	Coefficient	Standard error	*P* value
Dependent variable: *LnGPP*			
(a) The translog stochastic frontier production function			
LnCapital	0.005	0.196	0.982
LnLabor	−0.915	0.377	0.015
LnEnergy	0.774	0.319	0.015
LnCapital * *LnCapital*	−0.074	0.036	0.040
LnLabor * *LnLabor*	0.285	0.063	0.000
LnEnergy * *LnEnergy*	0.050	0.086	0.564
LnCapital * *LnLabor*	0.083	0.028	0.003
LnCapital * *LnEnergy*	0.061	0.048	0.208
LnLabor * *LnEnergy*	−0.198	0.046	0.000
Dependent variable: μ			
(b) Inefficiency model			
SOE	0.001	0.001	0.110
Trade	0.003	0.001	0.040
FDI	−0.015	0.005	0.002
σ_{μ}^2	0.146	0.082	0.076
σ_{υ}^2	0.001	0.0001	0.000
Log likelihood	478.945		
Wald test	13,809.65		0.000

Table 3 Elasticity per input

	Capital	Labor	Energy	Returns to scale
Elasticity	0.4844	0.2091	0.3043	0.9978

The output elasticities with respect to capital, labor and energy are calculated and reported in Table 3. The elasticity of a variable with an interaction term is calculated at the average of the interacting term. The output elasticity of capital is highest, 0.4844, followed by 0.3043 for energy. The elasticity of labor is 0.2091. The returns to scale are calculated as the sum of the elasticities with respect to the three inputs as $0.4844 + 0.2091 + 0.3043 = 0.9978$. This value is virtually equal to 1 indicating constant returns to scale.

The only significant multi-factor efficiency controls in Table 3 are *SOE*, *Trade* and *FDI* at 11, 5 and 1 %, respectively. Tests of the Moran's I coefficients of the residuals of the base model without spatially lagged controls indicated first-order contiguity for some, but not all, years. However, none of the lagged controls turned out to be significant.

In line with expectations, *SOE* has a negative effect on multi-factor efficiency. *Trade* also has a negative effect, in contrast to expectations. A similar result was obtained by Zhou et al. (2011). A possible explanation for this counterintuitive result is the aggregation of imports and exports. Possible positive effects of imports of high tech products may be overshadowed by the negative effects of exports of primary resources products like tungsten and rare earths and of low tech products like clothing, shoes and toys (Zhan 2006; OECD 2009). China has furthermore been suffering from restricted imports of high tech products from developed countries (López-Casero 2010). Finally, some of the possible positive trade effects may come in the form of FDI, which has the expected significant positive effect indicating that the increase in FDI leads to an increase in multi-factor efficiency.

4.2 Single-factor technical (energy) efficiency model

The yearly energy efficiency scores of the 29 provinces for the period 2003–2011 have been calculated using Eq. (7). The results are presented in "Appendix". The scores of 18 provinces, i.e., Tianjin, Hebei, Shanxi, Inner Mongolia, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Yunnan, Shaanxi, Gansu and Ningxia, have increased continuously. The scores of the rest, i.e., Beijing, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Qinghai and Xinjiang, have fluctuated, though with a clear upward trend. Most of the provinces belonging to the latter category are economically developed coastal provinces. A possible explanation for the slow-downs derives from the fact that they occurred during the years just before the end of the 10th and of the 11th Five-Year Plan. During these years these provincial governments boosted economic growth in their provinces without paying much attention to the environmental impacts—including energy efficiency improvement—to improve their political prestige which depended more on economic than on environmental performance (Song and Zheng 2012).

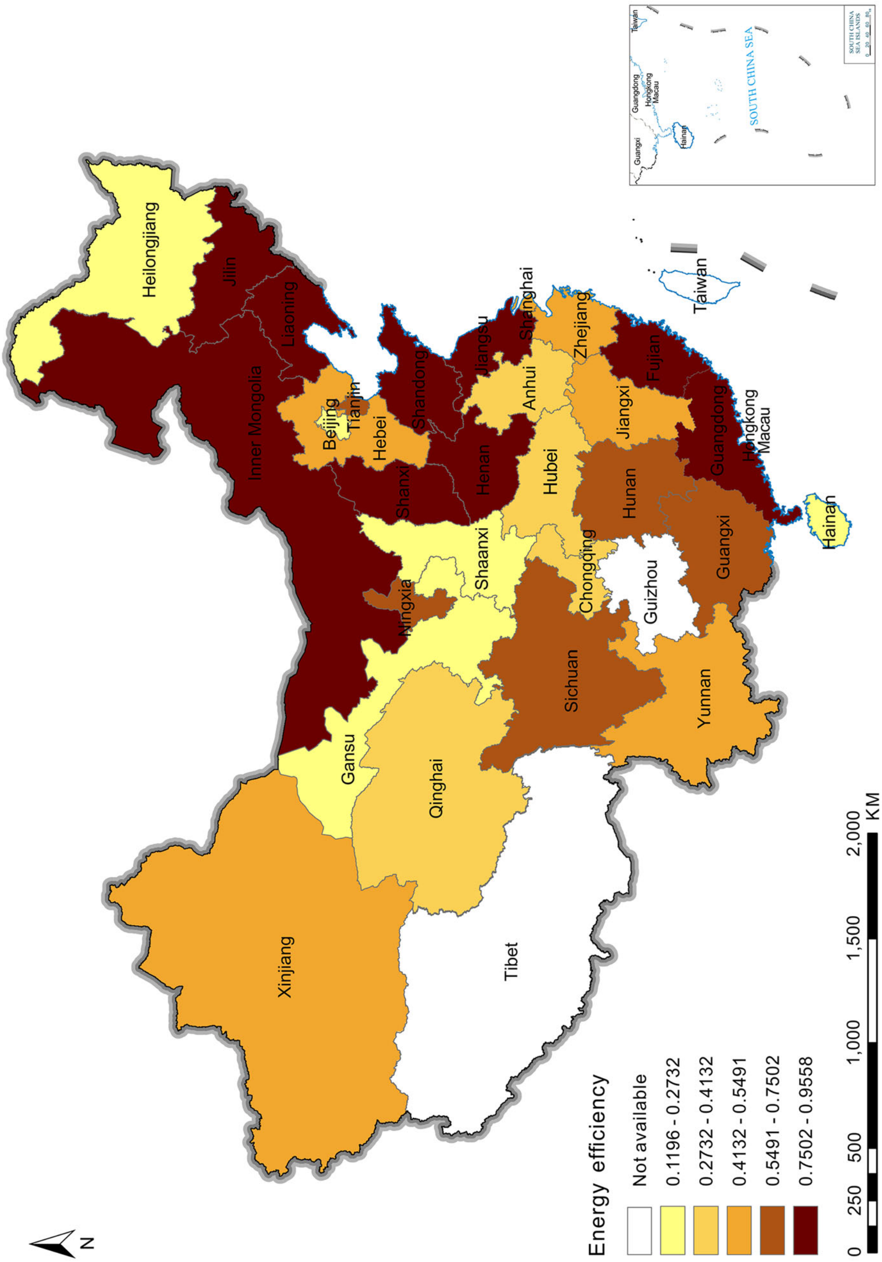

Fig. 1 Distribution of average energy efficiency scores of provinces over the period 2003–2011

The spatial distribution of the average provincial energy efficiency scores is given in Fig. 1. The average of the eastern provinces is 0.6406 which is higher than the average of the western provinces which is 0.5106. There is an intermediate corridor with an average of 0.6108. See "Appendix" for further details. In general, the northwestern

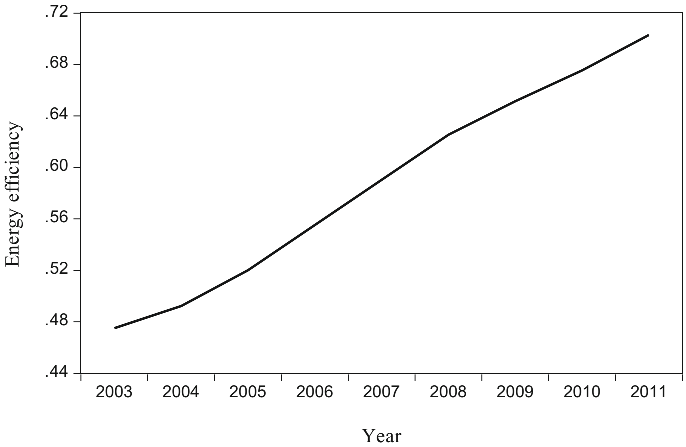

Fig. 2 The average provincial energy efficiency scores from 2003–2011

Table 4 The spatial Durbin error efficiency model

Dependent variable: energy efficiency		
Variable	Initial model	Final model
Time-lagged EE	0.0161 (0.5341)	
LnGPPc	0.1300 (1.7516)	0.0955 (1.5950)*
SOE	−0.0014 (−3.3882)***	−0.0015(−3.7420)***
FDI	0.0360 (11.4037)***	0.0369 (12.1136)***
Density	0.0003 (4.7835)***	0.0003 (4.9335)***
*W * LnGPPc*	0.1348 (0.9874)	
*W * SOE*	−0.0026 (−2.7762)***	−0.0028 (−3.2663)***
*W * FDI*	−0.0047 (−0.6255)	
*W * Density*	0.0010 (5.7039)***	0.0009 (6.3212)***
λ	0.4974 (7.8387)***	0.4926 (7.7189)***
Corrected$-R^2$	0.4480	0.4471
Log$-$likelihood	453.2132	452.2855

t statistics in parenthesis.
* $p < .10$, ** $p < .05$, *** $p < .01$

provinces are energy rich but have low energy efficiency, while the eastern coastal provinces are energy short but are relatively energy efficient.

The yearly average energy efficiency scores of the 29 provinces over the period 2003–2011 are presented in Fig. 2. The figure shows that it has increased continuously and rapidly, from 0.475 in 2003 to 0.703 in 2011.

We now turn to an analysis of the main controls of energy efficiency on the basis of the estimated spatial Durbin error model presented in Table 4.

The second column in Table 4 shows the initial model that contains all the variables and their spatial lags. We applied a stepwise backward elimination procedure to the initial model. Specifically, we deleted insignificant variables one by one, starting with the one with the highest p value. We thus obtained the final model which we discuss below.

LagEE is highly insignificant and hence is deleted from the final model. *LnGPPc* has a positive, though marginally significant effect which is in line with the arguments presented in Sect. 3. *W * LnGPPc*, however, is highly insignificant in the initial model so that it is deleted. As expected, *SOE* has a negative and significant effect indicating that an increase in the share of *SOE* reduces energy efficiency. *W * SOE* is also negative and significant indicating that *SOE* in neighboring provinces also drives down energy efficiency in a province. *FDI* has a significant positive effect on energy efficiency, as expected. *W * FDI* is, however, highly insignificant in the initial model and deleted. *Density* has a positive and significant effect indicating that densely populated provinces may have implemented environmental policies which have improved their energy efficiency. *W * Density* also has a positive and significant effect.

5 Conclusions

In this paper, we have estimated technical energy efficiency (energy efficiency for short) and analyzed its determinants based on a panel data set of 29 Chinese provinces over the period 2003–2011. The measure of energy efficiency is the ratio of minimum feasible energy use to observed energy use, given output and the quantities of other inputs. We derived energy efficiency from the results of the first-stage analysis of multi-factor technical efficiency by the way of a translog production function and a fixed effects, panel data stochastic frontier maximum likelihood estimator, which eliminated the fixed effects through within transformation. The provincial energy efficiency scores showed that the yearly average of the 29 provinces increased rapidly during the period 2003–2011. Furthermore, the eastern provinces had higher scores than the western provinces. Hence, the inefficiency in the western provinces indicates a large potential for saving energy.

In the second-stage analysis, we used a spatial Durbin error model to identify the main determinants of energy efficiency and found that (the natural logarithm of) per capita income, foreign direct investment and population density have positive effects, while the proportion of state-owned enterprises has a negative impact. In addition, for the latter two variables we also found spatial spillover effects with the same signs as the own region impacts. The following conclusions follow from the analysis.

First, state-owned enterprises who play a crucial role in the Chinese economy, especially in the energy-intensive raw materials and heavy industrial sectors, and their large-scale use of coal, have substantially contributed to China's low energy efficiency. Thus, policy aimed at improving energy efficiency should focus on the state-owned enterprises in the first place. As a first step, command and control measures like process norms and product standards could be taken. A second step would be the introduction of economic policy instruments, particularly charges, taxes and tradable permits. The introduction of the policy handles should be accompanied by strict enforcement measures. Besides, organizational reform of the state-owned enterprises, e.g., conversion into shareholding firms, should be considered.

Secondly, FDI has been an important source of technology import causing inter alia energy efficiency improvement in China which has been the main receptor of FDI among developing countries (Elliott et al. 2013). Since it creates significant technology improvement, FDI supplements and reinforces domestic research and development (R&D). Therefore, the Chinese government should continue stimulating FDI.

Thirdly, heavy dependence on coal has not only resulted in low energy efficiency, but has also led to serious air pollution in China. In virtually all major cities, air pollution has reached unprecedented levels and forms a major threat to public health and causes serious economic damage. To mitigate the situation, the Chinese government has taken various steps. For instance, the share of natural gas has increased from 2.2 % in 2000 to 5 % in 2011 and of hydro, nuclear and wind power, from 6.4 % in 2000 to 8 % in 2011. China aims for renewable energy to account for at least 15 % in 2020 (Zhang et al. 2010). This policy should be continued and increased also for the decades beyond 2020.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 5.

Table 5 Energy efficiency scores by province over the period 2003–2011

Province	2003	2004	2005	2006	2007	2008	2009	2010	2011
Beijing	0.1271	0.1361	0.1314	0.1878	0.1926	0.2591	0.3205	0.3115	0.3419
Tianjin	0.5758	0.6044	0.6395	0.6849	0.7408	0.8147	0.8692	0.9013	0.9211
Hebei	0.3378	0.3916	0.4536	0.4706	0.5159	0.5760	0.5979	0.6170	0.6641
Shanxi	0.8591	0.8613	0.8716	0.8783	0.8965	0.8922	0.8894	0.8952	0.9163
Inner Mongolia	0.9179	0.9283	0.9383	0.9463	0.9518	0.9568	0.9594	0.9627	0.9670
Liaoning	0.9227	0.9216	0.9065	0.9354	0.9619	0.9767	0.9866	0.9941	0.9967
Jilin	0.8953	0.9014	0.9182	0.9236	0.9393	0.9450	0.9315	0.9350	0.9387
Heilongjiang	0.1708	0.1959	0.2118	0.2353	0.2727	0.3183	0.3306	0.3518	0.3715
Shanghai	0.3724	0.3910	0.3858	0.3977	0.4483	0.5813	0.6426	0.6542	0.6963
Jiangsu	0.7919	0.6560	0.7040	0.8386	0.9169	0.9514	0.9576	0.9732	0.9853
Zhejiang	0.2230	0.3242	0.3799	0.4665	0.5273	0.5222	0.5561	0.6114	0.6501
Anhui	0.0870	0.0870	0.0870	0.1895	0.3483	0.4192	0.4723	0.5481	0.6316
Fujian	0.8793	0.8838	0.9045	0.9178	0.9332	0.9521	0.9552	0.9177	0.9234
Jiangxi	0.2929	0.3502	0.4036	0.4662	0.5048	0.5514	0.5948	0.6500	0.6816
Shandong	0.7260	0.7961	0.8165	0.8486	0.8749	0.8206	0.8278	0.8540	0.8830
Henan	0.8573	0.8816	0.9000	0.9218	0.9411	0.9533	0.9614	0.9709	0.9843
Hubei	0.2166	0.2726	0.2893	0.3263	0.3634	0.4001	0.4365	0.4714	0.4797
Hunan	0.5091	0.5244	0.6090	0.6682	0.7156	0.7574	0.7895	0.8156	0.8486

Table 5 continued

Province	2003	2004	2005	2006	2007	2008	2009	2010	2011
Guangdong	0.8849	0.7503	0.8179	0.8651	0.9108	0.9402	0.9498	0.9551	0.9657
Guangxi	0.4844	0.5298	0.5712	0.5964	0.6399	0.6740	0.6977	0.7139	0.7381
Hainan	0.0732	0.0798	0.0802	0.0980	0.1179	0.1314	0.1418	0.1710	0.1827
Chongqing	0.1540	0.1927	0.2410	0.2943	0.3038	0.4779	0.5637	0.6777	0.8139
Sichuan	0.4659	0.5308	0.5905	0.6449	0.6843	0.7649	0.7973	0.8666	0.9244
Yunnan	0.3509	0.3869	0.4182	0.4397	0.4572	0.4909	0.5180	0.5532	0.5972
Shaanxi	0.0844	0.1364	0.1780	0.2106	0.2514	0.2896	0.3324	0.3692	0.4093
Gansu	0.1002	0.1276	0.1430	0.1558	0.1754	0.1940	0.2144	0.2230	0.2262
Qinghai	0.3007	0.2949	0.3373	0.3266	0.3583	0.3450	0.3761	0.3856	0.3921
Ningxia	0.5923	0.6044	0.6169	0.6233	0.6370	0.6477	0.6514	0.6592	0.6717
Xinjiang	0.5223	0.5363	0.5359	0.5415	0.5389	0.5358	0.5700	0.5791	0.5823

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