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Understanding drivers of energy efficiency changes in China

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HIGHLIGHTS

- DEA incorporating CO_2 as undesirable output is used to evaluate energy efficiency.
- Energy efficiency metrics is incorporated as a dependent variable.
- Combining spatial panel econometric method with DEA is adopted.
- The drivers of energy efficiency improvements are obtained.

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ABSTRACT

Under a total-factor framework, this manuscript constructs a slacks-based measure data envelopment analysis (SBM-DEA) model and an index of total-factor energy efficiency (TFEE) to investigate the energy efficiency of the 29 provincial-administrative regions (PARs) in China during 1997–2011. Applying spatial panel data models to explore the regional clustering and influential factors of energy efficiency in China's 29 provincial-administrative regions during 1997–2011, results show that China experienced a continuing increase in energy efficiency during the sample period. In addition, we find evidence of the diffusion of energy efficiency improvements. Research and development investment, particularly when interacted with increases in energy prices, and when government intervention is low, are a powerful drivers of efficiency improvements. We illustrate heterogeneous impacts across Chinese regions. Income gains in more industrialized provinces and education gains in less industrialized provinces also produce efficiency improvements. In contrast to existing literature, we do not find responsiveness to changes in energy prices, growth rates, or income per capita in less industrialized regions. These results highlight the uniqueness of the Chinese experience and warrant more in-depth exploration of the drivers of energy efficiency in China.

1. Introduction

In the past three decades, China's economy has developed rapidly, and China has become the world's largest energy consumer as well as CO_2 emitter [1,2]. Meanwhile, China has announced its target of achieving peak of CO_2 in 2030 in the U.S.–China Joint Announcement on Climate Change in 2014 [3]. This goal, plus a carbon intensity reduction target of 60–65% by 2030 were proposed in China's Intended Nationally Determined Contribution (INDC) before the Paris climate talks in 2015. To curb CO_2 emissions, Liu et al. [4] proposed that regional targets, reliable carbon emissions monitoring, reporting and verification, improved market mechanisms and advanced green technology would help realize Chinese carbon emissions targets. The Chinese government's attention towards improving energy efficiency may be an effective way to reduce CO_2 emissions while maintaining energy security, economic growth, and social development in China [5]. In the 12th Five Year (2011–2015) Plan, the Chinese government established a series of energy and emission targets including an energy intensity reduction of 16% and a carbon intensity reduction of 17% from 2010 levels. Nevertheless, the factors that can promote or impede energy efficiency improvements in China remain unclear.

A variety of macro-economic factors are related to the international transfer of energy efficiency technology. Foreign direct investment (FDI), trade, and the openness of an economy may help spur technological diffusion and improve energy efficiency [6–9]. In particular, FDI in China has been attributed to be a major driver of energy efficiency improvements [10]. A larger industrial base,

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and in particular, a larger manufacturing base, has been demonstrated to be related to openness and technological diffusion [6,9]. And investment in technology is correlated with increases in productivity and efficiency that tends to resemble the resource scarcities of the firm's home country [11].

Technological transfer can occur through the transfer of engineering knowledge, managerial, operational skills, as well as through the transfer of specific technologies [9]. These transfers can be facilitated through foreign direct investment, multinational enterprise, joint ventures, and clean development mechanisms related to climate change policy [7,12,13]. In contrast, technical inefficiency is correlated to increased government intervention in the form of institutions that reduce economic, political, and civil liberties [14]. A variety of institutional barriers have been demonstrated to reduce energy efficiency in China [10].

At the micro level, numerous studies have pointed to the diffusion of energy efficiency technology through spatial relationships, as well as through a benefit cost framework. For a variety of market and non-market reasons, firms, households, and consumers may fail to adopt what appear to be economically or technologically feasible energy efficiency improvements [15,16]. For example, Dietz [17] demonstrated that underestimated household energy use and potential savings is an important contributor to the energy efficiency gap in U.S. While we include energy price in our analysis, a large body of research explores both the determinants [18–22] of technological diffusion and the market and non-market barriers to efficiency technology diffusion [23–26]. Specifically, the barriers (e.g. awareness and behavioral issues) and drivers (e.g. technical support, cost reductions, threat of rise in energy prices, and energy taxes) for enterprises to adopt energy-efficiency measures have been analyzed [27–29]. Moreover, May et al. provides a 7-step method to develop production-tailored and energy-related key performance indicators, which were used to support companies in their operative decision-making process [30]. These micro-level and policy processes, while beyond the scope of this analysis, underlie many of the macro-level trends that we test in this manuscript. The drivers and barriers of energy efficiency are summarized in Table 1 for comparison.

We employ a two-stage analysis where we assess the relative efficiency of each Chinese Provincial Administrative Region (PAR) over the 1997–2011 time frame and test the determinants of changes in energy efficiency. First, we use Data Envelopment Analysis (DEA), which has been applied to solve efficiency problems in energy or environmental modeling [31,32]. DEA is a well-established non-parametric frontier approach that evaluates the relative efficiencies of a set of comparable decision making units (DMUs) with multiple inputs and outputs [33–35]. Under a total-factor framework, energy efficiency with both energy input and non-energy inputs (e.g. labor force and capital stock) by DEA, can be called total-factor energy efficiency (TFEE). In contrast, energy intensity and energy productivity are two well-known energy-efficiency indicators in macro-level policy analysis. Energy intensity is defined as a ratio of energy consumption to economic output, while energy productivity is the reciprocal of energy intensity. However, these measurements are partial-factor energy-efficiency indicators and only consider a single input or output, ignoring the potential substitution between energy consumption and other factors [36–38].

Table 1
Drivers and barriers of energy efficiency.

Factor scale levels	Factor classifications	Factors	References
Macro-scale	Drivers	Foreign direct investment Trade The openness of an economy Investment in technology	[6–11]
	Barriers	Government intervention like institutional barriers	[10], [14]
Micro-scale	Drivers	Technical support Technology cost reductions Threat of rise in energy prices Energy taxes	[27–29]
	Barriers	Awareness Behavioral issues	[17,27–29]

2. Literature review

A variety of studies have employed TFEE using DEA to evaluate energy efficiency (see [35] for a review). Hu and Wang [36] proposed TFEE to evaluate regional energy use in China; this method has subsequently been applied by a variety of researchers [39–42]. In addition, studies employing the industrial level have received attention. Wang et al. adopted the total factor energy efficiency to determine the discrepancy of energy efficiency in the Chinese industrial sector [43]. Similarly, Honma and Liu evaluated industry-level total-factor energy efficiency of 14 developed countries and compared Japan's energy efficiency with that of other countries [44]. Other variations include a Malmquist-Luenberger productivity index, which calculates total-factor energy productivity [45–49].

However, only a handful of studies (see [35] for an overview as well as more recent studies such as Rao et al. [42], Färe et al. [50], Ho et al. [51], Burnett and Hansen [52] and Yang and Pollitt [53]) consider pollution as an undesirable output, and of those, only Welch and Barnum [54] and Wang et al. [55] consider carbon emissions as an undesirable output. Energy efficiency evaluation results are biased by not including undesirable outputs like CO_2 emissions [56].

This paper expands upon existing literature through several innovations. The vast majority of studies of productive efficiency, technological transfer, and the role of macro-economic drivers of efficiency and growth occur at the international level, while studies that incorporate undesirable outputs in production are frequently performed at the plant level, and few of these consider carbon dioxide. We fuse these two disparate bodies of research by calculating TFEE while including carbon dioxide as an undesirable output across 29 provincial-administrative regions (PARs). Second, using second stage spatial econometric panel data techniques, we explore the drivers of efficiency improvements over time, while allowing for the spatial diffusion of energy efficiency improvements. This methodological approach allows us to explore the interaction of a wide array of political and socio-economic impacts on energy efficiency using a methodology that allows for spatial contagion while controlling for static heterogeneity across observations and ambient technological progress.

3. Models and data

To evaluate energy efficiency, we consider carbon dioxide an undesirable output, and we apply a slacks-based measure (SBM) which is a non-radial method and is suitable for measuring efficiencies when inputs and outputs may change non-proportionally [57]. It allows for both radial adjustments through improvements in energy efficiency technology, and slacks (or the excess of input or output) adjustments through allocation or structural improvements.

3.1. Total-factor energy efficiency with SBM-DEA

A variety of optimization models exist in the DEA literature that employ different assumptions relating to returns to scale. The Ch arnes–Cooper–Rhodes optimization model is based on constant return to scale [58] while Banker et al. [59] adopted this model to include variable returns to scale. A large number of extensions to these two basic DEA models have appeared in the literature [60]. As discussed by Guo et al. [61], carbon emissions can be reduced by using either energy conservation technology improvements or structural energy adjustments, measured by radial adjustments and slacks adjustments, respectively. Traditional DEA models measure radial efficiencies, in which the adjustment of inputs and outputs are proportional. However, these models do not consider excess inputs and outputs.

Tone [62] suggests a slacks-based measure data envelopment analysis (SBM-DEA) model that incorporates both ratio efficiency and slacks into a scalar measure. SBM is a non-radial efficiency measure constructed from excess inputs and outputs, and can identify economic inefficiencies [35]. This SBM can also incorporate undesirable outputs into consideration [57], which is described as follows. Suppose there are N decision making units (DMUs). Each DMU has input, desirable output, and undesirable output vectors $\mathbf{x} \in \mathbf{R}^M$, $\mathbf{y} \in \mathbf{R}^K$ and $\mathbf{u} \in \mathbf{R}^L$, respectively. Correspondingly, the input, desirable output, and undesirable output matrices for N DMUs are denoted by $\mathbf{X} = (x_{mn}) \in \mathbf{R}^{M\times N}$, $\mathbf{Y} = (\mathbf{y}_{kn}) \in \mathbf{R}^{K\times N}$, $\mathbf{U} = (u_{ln}) \in \mathbf{R}^{L\times N}$, respectively. We assume that the data set is positive, i.e. $\mathbf{X} > 0$, $\mathbf{Y} > 0$, and $\mathbf{U} > 0$.

The production possibility set P is defined as:

$$P = \{(\mathbf{x}, \mathbf{y}, \mathbf{u}) | \mathbf{x} \geqslant \mathbf{X}\lambda, \mathbf{y} \leqslant \mathbf{Y}\lambda, \mathrm{u} \geqslant \mathbf{U}\lambda, \lambda \geqslant \mathbf{0}\} \quad (1)$$

where λ is an $N \times 1$ vector of constants.

To measure the efficiency of DMU_0 $(\mathbf{x}_0, \mathbf{y}_0, \mathbf{u}_0)$ under the hypotheses of constant returns to scale and strongly (freely) disposable outputs, we apply the following SBM-DEA model:

$$\begin{aligned}
\min \quad & \rho = \frac{1 - \frac{1}{M}\sum_{m=1}^{M}\frac{s_m^-}{x_{m0}}}{1 + \frac{1}{K+L}\left(\sum_{k=1}^{K}\frac{s_{gk}^+}{y_{k0}} + \sum_{l=1}^{L}\frac{s_{bl}^-}{u_{l0}}\right)} \\
\text{s.t.} \quad & \mathbf{x}_0 = \mathbf{X}\lambda + \mathbf{s}^- \\
& \mathbf{y}_0 = \mathbf{Y}\lambda - \mathbf{s}_g^+ \\
& \mathbf{u}_0 = \mathbf{U}\lambda + \mathbf{s}_b^- \\
& \mathbf{s}^- \geqslant \mathbf{0}, \mathbf{s}_g^+ \geqslant \mathbf{0}, \mathbf{s}_b^- \geqslant \mathbf{0}, \lambda \geqslant \mathbf{0}
\end{aligned} \quad (2)$$

where $\mathbf{x}_0 \in \mathbf{R}^M, \mathbf{y}_0 \in \mathbf{R}^K, \mathbf{u}_0 \in \mathbf{R}^L$ are the vectors of inputs, desirable outputs and undesirable outputs of the DMU_0, respectively; and $\lambda \geqslant \mathbf{0}$, $\mathbf{s}^- \geqslant \mathbf{0}$, $\mathbf{s}_g^+ \geqslant \mathbf{0}$, $\mathbf{s}_b^- \geqslant \mathbf{0}$. The vectors $\mathbf{s}^- \in \mathbf{R}^M$, $\mathbf{s}_g^+ \in \mathbf{R}^K$, $\mathbf{s}_b^- \in \mathbf{R}^L$ are called slacks, representing excess input, shortage of desirable output, and excess undesirable output, respectively. The objective function strictly decreases with respect to $s_m^-(\forall m)$, $s_{gk}^+(\forall k)$ and $s_{bl}^-(\forall l)$, and the object value satisfies $0 < \rho^* \leqslant 1$. Let the optimal solution of model (2) be $(\lambda^*, \mathbf{s}^{-*}, \mathbf{s}_g^{+*}, \mathbf{s}_b^{-*})$. Then, we can obtain that the DMU_0 is efficient in the presence of undesirable outputs if and only if $\rho^* = 1$, i.e., $\mathbf{s}^{-*} = \mathbf{0}$, $\mathbf{s}_g^{+*} = \mathbf{0}$ and $\mathbf{s}_b^{-*} = \mathbf{0}$. If the DMU_0 is inefficient, i.e., $\rho^* < 1$, it can become more efficient by reducing the excesses in inputs and bad outputs and reducing the shortage in good outputs via the following SBM-projection: $\mathbf{x}_0 \leftarrow \mathbf{x}_0 - \mathbf{s}^{-*}$, $\mathbf{y}_0^g \leftarrow \mathbf{y}_0^g + \mathbf{s}_g^{+*}$, $\mathbf{y}_0^b \leftarrow \mathbf{y}_0^b - \mathbf{s}_b^{-*}$.

Slacks of energy inputs are potential energy savings, representing the maximum potential energy reductions to "optimal practice". The target energy input of a DMU is the value of projection on the production frontier, or a combination of one or more efficient DMUs. Following Hu and Wang [36], we define TFEE for the ith DMU at time t as:

$$\mathrm{TFEE}_{(i,t)} = \frac{\text{Target Energy Inputs}_{(i,t)}}{\text{Actual Energy Inputs}_{(i,t)}}, \quad (3)$$

where $\mathrm{TFEE}_{(i,t)}$ represents the ith DMU's relative energy efficiency at time t to the "optimal practice", and $0 \leqslant \mathrm{TFEE}_{(i,t)} \leqslant 1$. The greater the $\mathrm{TFEE}_{(i,t)}$, the more efficiently energy is consumed. When $\mathrm{TFEE}_{(i,t)} = 1$, the actual energy input is equal to minimum energy input, among the measured units.

3.2. Dynamic evaluation by integrating window analysis with SBM-DEA

The DEA approach was originally used to measure cross-sectional data, in which comparisons can be made between DMUs at one time period. To compare the performance of DMUs over time, this paper adopts a variation of the SBM-DEA approach, called DEA window analysis [63]. DEA window (DEA-W) analysis employs moving averages to choose the number of time periods as "windows" [64,65]. DEA-W offers advantages of avoiding problems related to robustness [66], analyzing trends over a specified time period, and examining stability and other properties of the efficiency evaluation across or within windows [67]. A formalization of DEA-W analysis is presented below.

Suppose there are N observed DMUs for T periods. If the window expressed by W_t starts at period t and covers w $(1 \leqslant w \leqslant T - t + 1)$ adjacent periods, it will include $N \times w$ observations, where w is the width of the window. The matrices of inputs, desirable outputs and undesirable outputs of the window W_t are given as follows:

$$\mathbf{X}_{W_t} = (\mathbf{x}_t^1, \mathbf{x}_t^2, \ldots, \mathbf{x}_t^N, \mathbf{x}_{t+1}^1, \mathbf{x}_{t+1}^2, \ldots, \mathbf{x}_{t+1}^N, \ldots, \mathbf{x}_{t+w-1}^1, \mathbf{x}_{t+w-1}^2, \ldots, \mathbf{x}_{t+w-1}^N) \quad (4)$$

$$\mathbf{Y}_{W_t} = (\mathbf{y}_t^1, \mathbf{y}_t^2, \ldots, \mathbf{y}_t^N, \mathbf{y}_{t+1}^1, \mathbf{y}_{t+1}^2, \ldots, \mathbf{y}_{t+1}^N, \ldots, \mathbf{y}_{t+w-1}^1, \mathbf{y}_{t+w-1}^2, \ldots, \mathbf{y}_{t+w-1}^N) \quad (5)$$

$$\mathbf{U}_{W_t} = (\mathbf{u}_t^1, \mathbf{u}_t^2, \ldots, \mathbf{u}_t^N, \mathbf{u}_{t+1}^1, \mathbf{u}_{t+1}^2, \ldots, \mathbf{u}_{t+1}^N, \ldots, \mathbf{u}_{t+w-1}^1, \mathbf{u}_{t+w-1}^2, \ldots, \mathbf{u}_{t+w-1}^N) \quad (6)$$

In this paper, 29 provincial administrative regions (PARs) in China (N = 29) are taken into consideration during 1997–2009 (T = 13). Following Charnes et al. [64], Halkos and Tzeremes [66], Charnes et al. [68], Asmild et al. [69] and Zhang et al. [41], we choose window width of three (w = 3), to satisfy the assumption that there are no technical changes for all DMUs within each window. For example, the first window covers the years of 1997, 1998 and 1999. Thus, for each window, there are 87 ($N \times w$ = 29 × 3 = 87) DMUs. The window moves one year at time (thus, the next three years 1998, 1999 and 2000 construct the second window). The process continues until the last window is constructed, containing years of 2009, 2010 and 2011.

3.3. Data

We take capital stock, labor employment, and energy consumption as inputs, gross domestic product (GDP) as a desirable output, and CO_2 emission as an undesirable output. Detailed data sources and processing are shown in Table 2.

4. Regional TFEEs in China

During the sample period, China's energy consumption grew rapidly and the total energy consumption of the 29 PARs increased to 4.22 billion tce in 2011 from 1.38 billion tce in 1997. China's energy intensity declined from 0.179 Mtce per billion RMB in 1997 to 0.116 Mtce per billion RMB in 2011. Under a total-factor framework, according to Eqs. (1)–(6), we calculate the slacks'

Table 2
Data sources and processing [a].

Indicator	Unit	Data sources	Data processing
Capital stock	Billion Yuan (fixed at 1997price)	Shan [70]	Data from1997to 2006 are directly obtained from Shan [70]; data from 2007 to 2011are estimated by using a perpetual inventory method.
Labor employment	Million workers	China Statistical Yearbook (1998–2012)	–
Energy consumption	Million tons of coal equivalent (Mtce)	China Energy Statistical Yearbook(2000, 2003, 2005, 2010–2012)	Includes consumption of coal, crude oil and their products, natural gas, and electricity. It does not include the consumption of low calorific value fuel, bio-energy and solar energy.
GDP	Billion 1997 Yuan	China Statistical Yearbook (1998–2012)	–
CO_2 emission	Million tons	$C = \sum_{i=1}^{n} c_i f_i E_i$	In the equation, C represents regional CO_2emissions; c_i, f_i, E_i are net calorific value, CO_2 emission factor, and quantity of the ith energy consumption, respectively. Here, c_i and E_i are both collected from the China Energy Statistical Yearbook, and f_i from IPCC [71].

[a] This paper covers 29 PARs in the Chinese mainland, excluding Tibet due to lack of data. Chongqing is regarded as a part of Sichuan in this paper.

adjustments of energy inputs and obtain TFEE scores of 29 PARs during 1997–2011 in Fig. 1.

To show the difference and changes of energy efficiencies of the 29 PARs, we calculate the average TFEE of each PAR and the shares of 29PARs' total amount of adjustable energy use, as shown in Fig. 2.

Fig. 1 demonstrates that China's energy efficiency improved during the 1997 to 2011 time period. This improvement is consistent with other studies in different periods from 1995 to 2005. Seven countries, such as Argentina, Bolivia, Botswana experienced slightly fluctuating energy efficiencies over time and eleven countries, such as Iran and Syria experienced a downward trend [41]. In terms of average TFEEs, 6 out of top 10 PARs are located in the coastal areas, in which Fujian, Guangdong and Shanghai had the highest energy efficiencies with average TFEEs over 0.95, followed by Jiangsu, Hainan and Zhejiang. These six PARs are highly developed coastal areas, whose GDP accounted for 34.6% of 29 PAR's GDP, but energy consumption only for 23.2% of 29 PAR's energy consumption. In contrast, of the 10 PARs with the lowest efficiencies, 4 PARs are located in west China, and 4 PARs are located in central China, among which Ningxia, Shanxi, Guizhou and Qinghai performed worst in energy use with average TFEEs mostly lower than 0.3. Hebei and Shanxi are provinces of considerably low energy efficiencies, but have huge adjustments of energy inputs, which accounts for 7.2% and 4.7% of 29 PARs' total potential energy conversation.

TFEEs of Heilongjiang, Jiangsu, Beijing, Tianjin, Jilin, Sichuan, Anhui and Liaoning increased by more than 0.13 during 2002–2006, while TFEEs of Inner Mongolia and Jiangxi decreased by 0.212 and 0.130, respectively. Heilongjiang was the most energy-efficiency-improved province, with an average TFEE that increased from 0.401 during 1997–2001 to 0.931 during 2002–2006. During 2007–2011, TFEEs in most PARs improved, especially in Anhui, Jiangxi, Jilin, Beijing and Zhejiang.

Similarly, other studies also indicated that the energy efficiency in China has geographic characteristics. For example, Ref. [72], notes that the provinces in eastern area such as Beijing, Tianjin and Liaoning experienced significant energy consumption savings and CO_2 reductions, while provinces in western region such as Gansu did not exhibit these trends.

5. Factors influencing TFEE in China

While China's energy efficiency improved by 43.1% from 1997 to 2011, changes in regional disparities of energy efficiency in China can help demonstrate the impacts of development and other macro-economic trends on energy efficiency [73].

Interactions between regions, such as trade, technology diffusion, knowledge spillovers, and factor (e.g. capital, labor and energy) flows, may lead to greater geographically interdependent regions. The role of spatial relationships in convergence processes has been examined in a large body of literature [74–78]. Spatial relationships may also drive the adoption of energy efficiency improvements [20]. In this manuscript, we investigate the drivers of energy efficiency in China and understand the drivers behind the improvements in energy efficiency by using spatial econometric analysis.

In addition to examining China as a whole, we divide China's 29 PARs into two groups: Group 1 (G1) and Group 2 (G2). G1 covers 14 PARs, such as Shanghai, Beijing, Tianjin, Guangdong, Zhejiang, Jiangsu, Jiangxi, Hainan, Anhui, Hunan, Shandong, Hubei, Guangxi, and Fujian. These more industrialized provinces generated 63.7% of the total GDP with 59.7% of the total population and 49.1% of total energy consumption in 29 PARs during 1997–2011. G2 includes 11 less developed western PARs (Xinjing, Shanxi, Henan, Yunnan, Qinghai, Gansu, Shaanxi, Sichuan, Ningxia, Inner Mongolia, and Guizhou) and 3 northeastern PARs (Heilongjiang, Jilin, and Liaoning) and the Hebei province. These 15 PARs are more resource abundant and may have greater potential in energy efficiency gains and emissions reduction. Existing studies confirm that both internal and external factors relative to the Chinese economy have contributed to lower energy efficiency rates [79]. The determinants of energy efficiency focus primarily on energy price, technical progress, economic structural changes, changes in the share of output by ownership type, changes in the structure of energy consumption, energy policies, and the degree of openness in the economy. Consistent with existing literature, we consider several main factors as well as other control variables: energy prices, technological progress, the degree of openness, industrial structure, government intervention, income gains, educational gains, population density, and the growth rate of the economy.

5.1. Spatial econometric models

Traditional linear regression models do not take correlation due to geospatial relationships into account. If TFEE is spatially correlated, the traditional linear regression model will produce heteroskedastic standard errors and hypothesis tests will be inaccurate. Anselin et al. [80] suggests two methods to correct for spatial autocorrelation: one is to introduce weighted endogenous variables to the original model, such as done in the spatial lag model (SLM) or spatial autoregressive model (SAR); the second is to allow for the error term to have an additional spatial component that is correlated across observations, such as done in the spatial error model (SEM).

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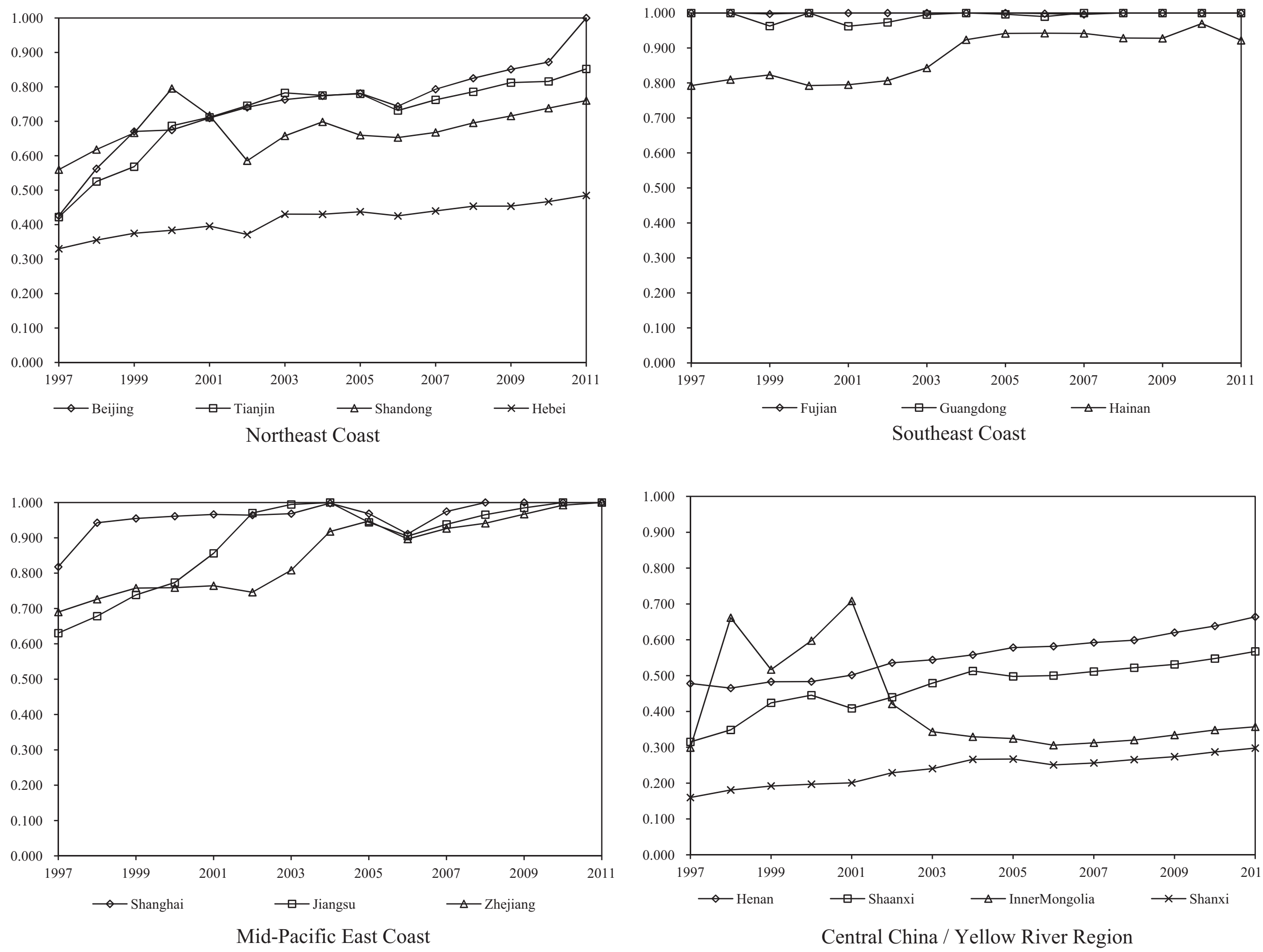

Fig. 1. TFEE by PARs by region: 1997–2011.

We first construct a basic econometric model as following:

$$\mathrm{EF}_{it} = \alpha + \Sigma\beta X_{it} + \varepsilon_{it} \tag{7}$$

where EF_{it} as a dependent variable represents the total-factor energy efficiency of PAR i in year t ($i = 1, 2, \ldots, n$; $t = 1, 2, \ldots, T$); X_{it} are a vector of independent variables representing energy prices, degree of openness, research and development expenditures, percent of the economy involved in heavy industry, growth rate, the percentage of the economy driven by government expenditures, population density, income per capita, and post-primary education rates respectively and ε_{it} is a stochastic random error and $\varepsilon_{it} \sim N(0, \sigma^2)$.

To evaluate the spatial interaction effect on TFEE, we incorporate spatial dependence by adding a spatially lagged term of the dependent variable. Therefore, Eq. (7) can be rewritten as a spatial autoregressive model (SAR)

$$\begin{aligned} &\mathrm{EF}_{it} = \alpha + \rho\mathbf{W}\mathrm{EF}_{it} + \sum\beta X_{it} + \varepsilon_{it} \\ &\varepsilon_{it} \sim N(0, \sigma^2) \end{aligned} \tag{8}$$

where $\mathbf{W}$ is a known $n \times n$ spatial weights matrix (described below); ρ is a scalar spatial autoregressive coefficient. $\mathbf{W}\mathrm{EF}_{it}$ is a spatial lagged dependent variable.

Spatial parameter results are highly susceptible to assumptions regarding the appropriate spatial weights matrix [81]. While we employ and interpret an inverse distance spatial weight matrix, we estimate specifications that include alternative spatial weights matrices as well. The inverse spatial weights matrix can be expressed by the conventionally row-standardized form as follows:

$$\mathrm{W} = \begin{bmatrix} \frac{1}{\mathrm{d}_{11}} & \frac{1}{\mathrm{d}_{12}} & \cdots & \frac{1}{\mathrm{d}_{1j}} \\ \frac{1}{\mathrm{d}_{21}} & \frac{1}{\mathrm{d}_{22}} & \cdots & \frac{1}{\mathrm{d}_{2j}} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{1}{\mathrm{d}_{i1}} & \frac{1}{\mathrm{d}_{i2}} & \cdots & \frac{1}{\mathrm{d}_{ij}} \end{bmatrix} \quad (i, j = 1, 2, \ldots, 29) \tag{9}$$

In which d_{ij} is the distance between the capitals of PAR i and j and can be written as

$$\begin{aligned} \mathrm{d}_{ij} = \mathrm{R}(\cos^{-1}(&\cos(lat_i) \times \cos(lat_j) \times \cos(log_i - log_j) \\ &+ \sin(lat_i) \times \sin(lat_j))) \end{aligned} \tag{10}$$

We use (log_i, lat_i) and (log_j, lat_j) to express the longitude and latitude of the capitals of PAR i and j, respectively. R is the radius of the earth (6371 km). Results from alternative weights specifications, included in the supplemental material, include an inverse-distance squared weights matrix, and a contiguity matrix.

A spatial error model (SEM) can be considered alternatively to the SAR [82]; we present results of this model in the supplemental material.

Pooled data, estimated with an SAR or SEM model, is likely to produce autocorrelation and biased parameter estimates. Efficiency in a province i in year t is likely to be highly correlated with efficiency in province i in year $t - 1$. In addition, any characteristics that co-vary spatially across provinces will be exhibited in the spatial parameter, and produce findings of spatial dependence when in reality, no spatial dependence exists. Employing panel

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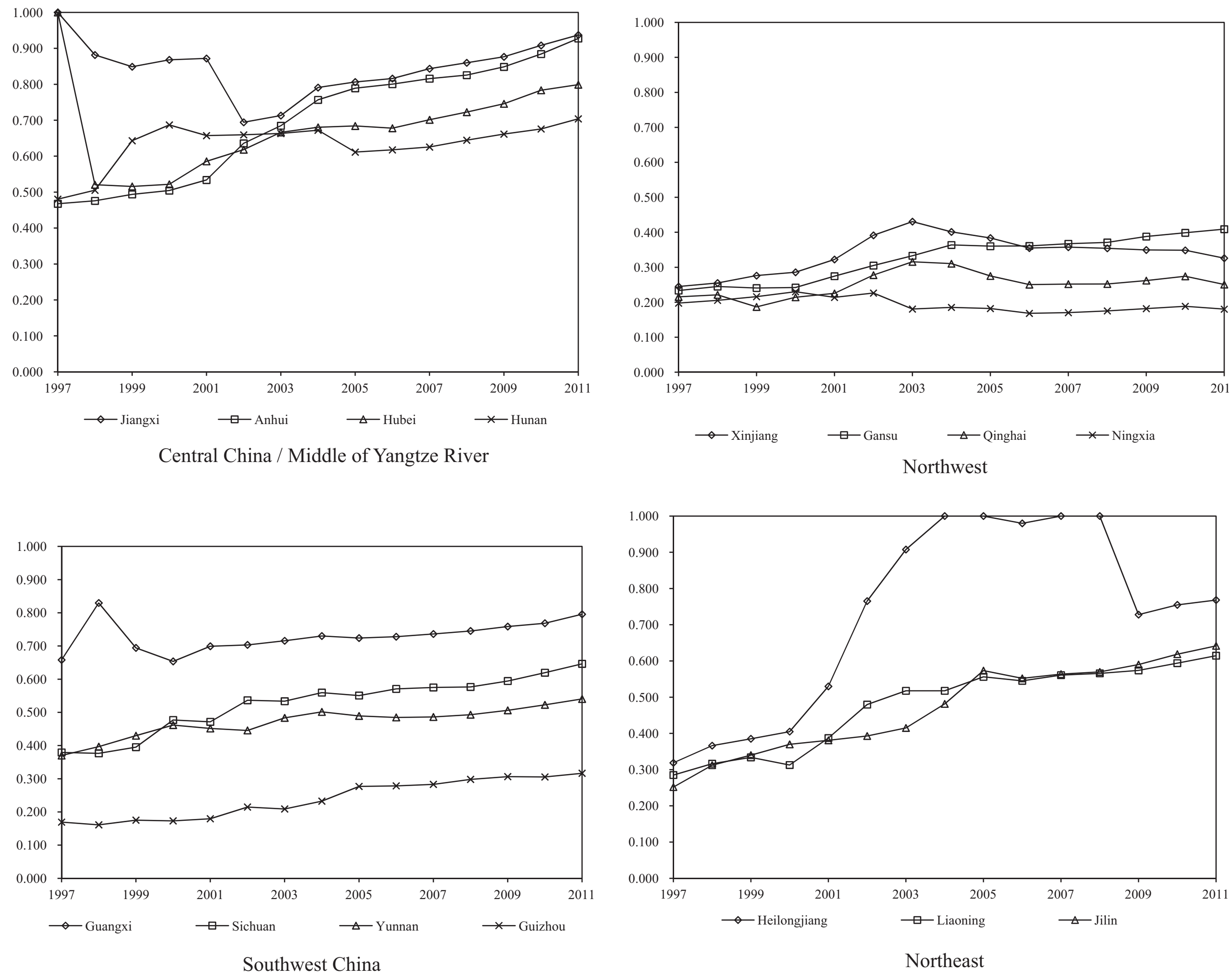

Fig. 1 (*continued*)

data allows us to control for individual level fixed effects, control for static heterogeneity across provinces, and reduce the potential for excluded variable bias. We demean all variables included in the model using a standard fixed-effects transformation $(x_i - \bar{x})$ and include a vector of state level dummies.

Another potential source for bias arises from the temporal nature of spatial dependence. If data are pooled, characteristics of province i in year t can influence outcomes in province i in year $t-1$. A vector of time dummies restricts the spatial dependence of each province to the current year. We include the vector of time dummies only in the spatial regression, because the time dummies are likely to absorb variation in other forms of technological progress, educational gains, income games, etc.

We estimate a spatial autoregressive model with temporal and individual level fixed effects, using MATLAB code provided by Elhorst, which incorporates a correction for biased parameter estimates encountered in spatial fixed effects models [83–85].

We employ both SLM/SAR and SEM. Because SEM results are essentially identical to the SAR results, and we find the inclusion of a spatially lagged dependent variable in the SAR model more theoretically appealing, we discuss the SAR results below and include SEM results in the supplemental material. We present the results of OLS estimation of Eq. (7) and ML estimation of Eq. (8) in Table 3.

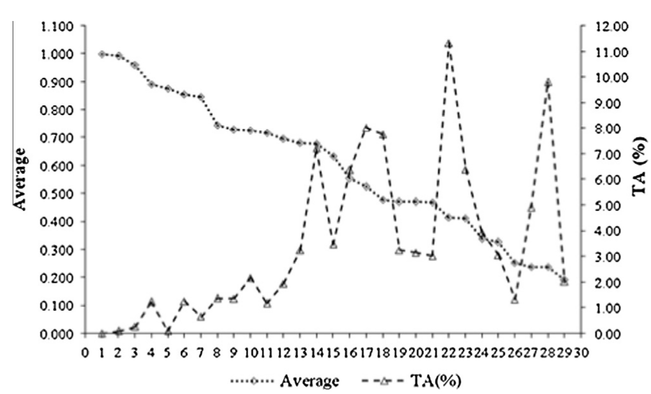

Fig. 2. The average TFEE, TA (%) by PAR. *Note:* number 1–29 stand for Fujian, Guangdong, Shanghai, Jiangsu, Hainan, Zhejiang, Jiangxi, Beijing, Guangxi, Heilongjiang, Tianjin, Anhui, Hubei, Shandong, Hunan, Henan, Sichuan, Liaoning, Yunnan, Jilin, Shaanxi, Hebei, Inner Mongolia, Xinjiang, Gansu, Qinghai, Guizhou, Shanxi, Ningxia. TA: shares of 29 PARs' total amount of adjustable energy use.

5.2. Data description and sources

"Purchasing Price Indices of Raw Material Fuel and Power" are used to measure energy prices. Data are collected from Data and

Table 3
Determinants of energy efficiency in China (entire country).

	China – fixed effects models (includes province dummies)		China – fixed and spatial effects models (includes year and province dummies)	
Energy price	−0.000195	−0.000943***	−0.000763*	−0.001493***
Degree of openness	0.000754**	0.00131***	0.000517	0.001088**
Research & development	0.0703***	−0.0206	0.048188**	−0.035217
Industrial structure	−0.000289	−0.000138	−0.001036	−0.000811
Growth rate	0.00189	0.0142***	−0.003353	0.010347**
Government intervention	0.00309**	0.0125***	0.002138	0.011683***
Population density	−0.0100*	−0.00967*	−0.012297**	−0.011521**
Income per capita	1.01e−06	−1.33e−06	0.000000	−0.000002*
% Post-primary education	0.00306**	0.00256*	−0.003658*	−0.002800
Openness * R&D	–	−0.000480***	–	−0.000426***
Govt intervention * growth rate	–	−0.000690**	–	−0.000699**
Energy price * R&D	–	0.00117***	–	0.001098***
Spatial parameter			0.268968**	0.278985**
Constant	0.324***	0.263***	1.0142	0.8455
Goodness of fit				
n	435	435	435	435
F/LLR	23.88	23.23	519.44097	540.05959
R2	0.351	0.414	0.9191	0.9264

* p values < .10 level.
** p values < .05 level.
*** p values < .01 level.

Materials on 60 Years of New China and are fixed at 1997 constant prices. Degree of openness is represented by the proportion of imports and exports to gross domestic production (GDP). Both data are collected from the China Statistical Yearbook. The proportion of heavy industry in gross industrial output value is used to indicate industrial structure. Data of heavy industrial output are from the China Industrial Economic Statistical Yearbook and China Statistical Yearbook for Regional Economy. Data of gross industrial output are from the China Statistical Yearbook and China Economic Census Yearbook. The percentage of governmental expenditure of GDP is used to evaluate the degree of government intervention. Government expenditure data are collected from the China Statistical Yearbook. R&D expenditures, as a percentage of GDP is used to evaluate technical progress. Data of R&D expenditure are collected from China Statistical Yearbook on Science and Technology. The data for education ratio, GDP per capita, population density, and growth rate are all collected from 1998–2012 China Statistical Yearbooks.

5.3. Empirical results

In this section, we test factors influencing TFEE across the sample of all PARs, during 1997–2011, as well as two subsamples to check for robustness or differences between the G1 and G2 regions. Table 3 displays results for all of China. Tables 4 and 5 display results for G1 and G2 groupings of Chinese provinces. Fixed effects models results demonstrate a variety of influences on Chinese energy efficiency at the provincial level. Time fixed effects included in the spatial model, required to appropriately specify a temporal spatial model and improve the efficiency of parameter estimates, may absorb much of the time-variant variation within each province.

Observing results from the individual level fixed effects model, we note the impacts of various factors on improvements in energy efficiency. Increases of energy price, growth rate, industrial intensity, and income alone are not statistically significantly correlated with changes in efficiency. However, when energy price increases,

Table 4
Determinants of energy efficiency in G1 province regions.

	G1 provinces – fixed effects models (includes province dummies)		G1 provinces – fixed & spatial effects models (includes year and province dummies)	
Energy price	−0.000655	−0.00158***	0.000572	−0.001153
Degree of openness	0.000598*	0.00114**	0.000328	0.001073**
Research & development	0.0413*	0.00194	0.032526	−0.001202
Industrial structure	0.00132	0.00243*	0.001564	0.002654
Growth rate	0.00434	0.00775	0.004969	0.008597
Government intervention	0.00732**	0.00881	0.007512*	0.005856
Population density	−0.0160***	−0.0128**	−0.017453***	−0.013443**
Income per capita	3.66e−06***	6.83e−07	0.000004***	0.000001
% Post-primary education	−0.00227	−0.00229	−0.007042***	−0.005740**
Openness * R&D	–	−0.000448**	–	−0.000411**
Govt intervention * growth rate	–	−0.000155	–	−0.000029
Energy price * R&D	–	0.000963***	–	0.000898***
Spatial parameter			0.038984	0.054994
Constant	0.727***	0.694***	1.0286	1.0122
Goodness of fit				
n	210	210	210	210
F/LLR	16.74	14.60	273.02103	279.10511
R2	0.446	0.488	0.8106	0.8213

* p values < .10 level.
** p values < .05 level.
*** p values < .01 level.

Table 5
Determinants of energy efficiency in G2 province regions.

	G2 provinces – fixed effects models (includes province dummies)		G2 provinces – fixed & spatial effects models (includes year and province dummies)	
Energy price	−0.000268	−0.00143***	−0.001341**	−0.001908***
Degree of openness	0.00511***	0.00488**	0.004480**	0.003403
Research & development	0.0967***	−0.107*	0.043089	−0.150996***
Industrial structure	−0.000918	−0.00109	−0.001817**	−0.002012**
Growth rate	−0.00306	0.00734	−0.009790***	0.001280
Government intervention	0.000803	0.00788	−0.003006	0.006992
Population density	−0.149	−0.207	−0.141023	−0.237486*
Income per capita	−4.05e−07	−2.19e−06	−0.000005**	−0.000004**
% Post-primary education	0.00781***	0.00652***	0.001734	0.000084
Openness * R&D	–	−8.22e−05	–	−0.000177
Govt intervention * growth rate	–	−0.000546	–	−0.000598*
Energy price * R&D	–	0.00205***	–	0.002054***
Spatial parameter			0.225991*	0.194972
Constant	0.194	0.354*	1.2199	1.2322
Goodness of fit				
n	225	225	225	225
F/LLR	13.59	13.58	273.34106	287.31936
R2	0.378	0.451	0.8229	0.8433

* p values < .10 level.
** p values < .05 level.
*** p values < .01 level.

provinces with higher R&D expenditures observe improvements in energy efficiency. Provinces that are more open observe improvements in energy efficiency; however, increases in R&D expenditures and increasing openness is negatively correlated with energy efficiency gains. Provinces with greater government expenditures experience increases in energy efficiency, but when government intervention is driving higher growth rates, energy efficiency improvements are diminished. Increases of population density are negatively correlated with energy efficiency gains, and increases in the percentage of the population receiving a post-primary education is positively correlated with increases in energy efficiency.

The spatial model fixed effects results are consistent with the OLS results. In addition, we observe spatial contagion, as energy efficiency improvements in each province spill over to nearby provinces in subsequent years.

Comparing our results with the extant literature, we have found some similarities and differences in the factors driving changes in energy efficiency. As Table 1 demonstrates, the openness of the economy and R&D inputs are thought to have positive impacts on energy efficiency. Somewhat surprisingly, we do not find a positive relationship of energy efficiency and energy prices in G2 regions in this study. In addition, we also find a number of interactive effects. R&D expenditures appears to be a substitute with the openness of the economy, while energy prices and R&D expenditures appear to be complements. We reveal numerous heterogeneous impacts across Chinese regions. More comparison with the extant literature will be discussed below.

6. Discussion and policy implications

Results suggest that political and economic differences at the provincial government level have driven changes in productive efficiency. Below, we detail the differences across provinces and how changes in these factors influences the change of efficiency within each province.

6.1. Growth, income, and education

Economic growth and improvements in income and education are thought to be correlated with energy efficiency gains [20]. Our results show a complex story for these factors in China. In China as a whole, and in G2 provinces, income is uncorrelated with efficiency gains. In China as a whole and in G2 provinces, post-primary education is a driver of efficiency gains. In G1 provinces, income per capita is related to improvements in energy efficiency. Combined with findings that suggest that energy price increases are negatively correlated with efficiency gains (discussed below), we expect that distortions in the G2 region's markets lead to these results. Further, this could be evidence of an efficiency Kuznet's curve [86], where higher income regions have begun to improve efficiency, while in lower income regions, efficiency has not yet improved. While income improvements in G1 provinces are correlated with efficiency gains, education improvements in G1 provinces are uncorrelated with efficiency gains, suggesting that in G1 provinces, income is a lever for change while in G2 provinces, post-primary education improvements is a more effective lever for efficiency improvements. Together these results suggest that policies and programs that support education and economic development can be levers for energy efficiency improvements; however, these results also suggest that economic development may exacerbate energy efficiency problems in the short term.

6.2. Energy prices

Although China has gone a long way to reform its energy price policies, prices in China are low compared with global market prices [87,88]. Perhaps due to government intervention in energy markets, energy prices alone are surprisingly not associated with increases in energy efficiency, our research shows that provinces that increase activity in R&D are more responsive to increases in energy prices. These results are consistent across China as a whole, as well as G1 and G2 regions, though the relative strengths of the interactive relationships vary. While a positive effect of the energy prices has been suggested in other similar studies, our results highlight the uniqueness of the Chinese case [89]. Subsidized energy prices increase energy intensity by increasing of industrial energy consumption [90] and by providing little incentive for technological investments [91]. Energy subsidies are often provided as mechanisms to shielding consumers from volatile energy markets; however, low prices contribute to inefficient consumption and decreased investment. Our results clearly show the potential for higher energy prices to interact with R&D and promote energy efficiency. These results suggest the role for policy-makers to allow for market-driven energy prices and encourage R&D as a way for firms to adapt to higher energy prices.

6.3. Degree of openness

China has moved towards an increase in open markets, particularly in eastern China. We find that areas with a greater degree of openness, as measured by the export and import sector of the economy, enjoy greater resource allocation efficiency and greater energy efficiency. A variety of mechanisms lead to technology transfer from industrialized economies through open markets and lead to greater energy efficiency in provinces with greater international linkages.

These linkages can take a variety of forms. Firms sourcing production in China may require suppliers to adhere to international standards such as ISO certification. Further, FDI flows to China may transfer technology that represents home country resource scarcity [11]. These results help provide support for. Conversations with firm managers suggest that major industrial firms will build an identical factory in China that they would in Germany, regardless of differences in regulatory structures or factor prices. And an increase in access to the international market leads to more access to Clean Development Mechanisms, or other explicit tools designed to promote technology transfer to China [7,12,13]. These results point towards the need for policymakers to engage openness in the G2 regions to help speed improvements in energy efficiency. These results contrast with Li and Shi [92], who argue that though FDI has a positive effect on the whole industry, it reduces efficiency in light and heavy industries.

Strangely, open markets and R&D mitigate each other's effectiveness. While both open markets and R&D alone produce improvements in energy efficiency, when interacted they produce decreased energy efficiency gains. While pursuing open markets and R&D will produce energy efficiency gains, some of the benefits are not additive, and overall gains will be less than the sum of each independent initiative.

6.4. Government intervention

Increase in government involvement in the economy, as measured by the government proportion of economic activity is surprisingly correlated with improvements in energy efficiency. The drivers for this finding are unclear, though it is possible that government involvement with sectors of the economy may be more effective at promoting 5 year plan goals related to efficiency gains. However, this result is influenced by growth rates. When the growth rate increases, government intervention is strongly correlated with decreases in efficiency improvements, suggesting that government-driven growth is harmful for efficiency gains. This result provides a much more nuanced perspective than existing research that suggested a government role for improving thermal generation improvements [93]. Improving institutional quality in the form of governance, economic freedom, ease of doing business and effectiveness of the decision-making process could help improve the productivity of the countries [94], and also contribute to the energy efficiency improvements.

6.5. Technological progress

Changes in technical progress, as measured by R&D expenditures, are highly correlated with changes in energy efficiency; this result is consistent across regions, though other factors, such as energy price has a strong positive interactive effect with R&D while openness has a negative interactive effect. Numerous studies have suggested that technological progress is essential for energy efficiency improvements as well as climate stabilization [95,96]. Similarly, Cui et al. [97] identified that the R&D inputs as the second most important factor to improve energy efficiency, and Wang et al. [98] also has indicated that technical progress was the most important motivation for the increase of China's energy efficiency. During the study period, G2 regions account for just 17.3% of China's patents while G1 regions account for 79%. The shares of R&D expenditures in G1, at an average level, are 1.5 times as that in G2 with an increasing trend towards increased R&D in the G1 regions. That increases in R&D do not seem to benefit energy efficiency in G1 regions, but do in G2 regions, suggests that R&D investments may not translate directly into energy efficiency improvements. Alternatively, because G2 PARs begin from a much lower baseline, there are greater returns to R&D in G2 regions. Further, the extent to which R&D developments diffuse across regions is unclear. Policies to speed deployment of technological innovations and improve energy efficiency adoptions can help China improve its energy footprint and drive efficiency improvements. These results suggest opportunities for the Chinese government to employ incentives for R&D as a mechanism for energy efficiency improvements.

6.6. Diffusion of energy efficiency

Supporting numerous studies that suggest spatial diffusion of energy efficiency and other technological diffusion at the micro-level [15,20,26,99–101], our analysis shows evidence of spatial diffusion of energy efficiency in China. However, we caution that these results may be highly susceptible to the choice of a weights matrix. In alternative specifications, contiguity weights matrices produce findings of spatial differentiation, while inverse squared weights matrices produce similar findings of diffusion. Gibbons and Overman [81] caution that spatial parameter results are highly susceptible to assumptions regarding the appropriate spatial weights matrix, and McMillen [102] similarly cautions that spatial econometric results are highly susceptible to misspecification error. Without a clear mechanism for spatial diffusion, our spatial econometric specification allows us to capture increased efficiency when including time and spatial fixed effects. Statistical significance and point estimates for alternative weights matrices remain similar.

7. Conclusions

Using data envelopment analysis (DEA) and panel data econometric methods, we calculate the relative efficiency of Chinese provinces over time, and determine factors that drive efficiency gains within provinces. Consistent with existing literature, we find that research & development, particularly when interacted with increases in energy prices, is a powerful driver of efficiency improvements. Income gains, in G1 provinces, and education gains, in G2 provinces, also produce efficiency improvements. And open markets produce efficiency gains, though some of these gains are also attained through research & development investments. In contrast to existing literature, we do not find responsiveness to changes in energy prices, growth rates, or income per capita in G2 regions, suggesting that market and policy frictions in China prevent efficient energy use. These results highlight the uniqueness of the Chinese experience and warrant a more in-depth exploration to the drivers of energy efficiency in China.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.05.002.

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