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March 2018

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How persistent are the movements to/from the frontier?

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Please cite:

L. Zhang and P.K. Adom (2018): Energy Efficiency Transitions in China: How Persistent are the Movements To/From the Frontier? The Energy Journal, 39(6), 147-169.

Abstract

This study examines the energy efficiency transitions in China using provincial data covering the period 2003–2015. Sustainable progress in energy efficiency achievements is beneficial to energy insecurity and the achievement of the Paris Agreement. This article combines the stochastic frontier method with the panel Markov-switching regression to model energy efficiency transitions. Estimated energy efficiency scores showed significant regional and provincial heterogeneity. Also, while human capital development, urbanization, and foreign direct investment promote energy efficiency, price and income per capita reduce it. The transition probabilities indicate that the high energy-efficient state is less sustainable, and the movement towards the frontier seems less persistent than movement from the frontier. Thus, it appears that China is not making sustainable progress in energy efficiency. The unsustainable nature of the high energy-efficient state suggests that in China, there are weak energy efficiency efforts and energy efficiency policies lack robustness.

Keywords: Energy efficiency transitions, Panel Markov, Stochastic frontier, China

JEL: D2, Q4, Q5

1. Introduction

China has made significant economic progress since 1950, and this has raised energy consumption and carbon dioxide emissions. For example, in 2014, China's total energy consumption (i.e. 2.97 billion tons) accounted for 23% of the global total (Zhang and Lin, 2018). In 2017, global energy demand increased by 2.1% (caused by weaker energy efficiency efforts, lower fossil fuel prices, and global economic growth of 3.7%), with fossil fuels contributing 72% of the increase (International Energy Agency [IEA], 2018). China and India contributed more than 40% to the global increase in energy demand, and China was the major contributor to the growth in oil demand (IEA, 2018). As a result, China is now a global leader in carbon dioxide emissions (Liu, 2015). Despite the fall in 2015, which was driven mainly by the fall in coal energy consumption, carbon dioxide emissions in China reached 9.1 Gt in 2017, which is 1% higher than the level achieved in 2014. Consequently, global energy-related carbon emissions increased by 1.4% in 2017 (IEA, 2018).

Achieving sustainable improvement in energy efficiency in China is thus critical to reducing national and global carbon dioxide emissions (Duan et al., 2017). Energy efficiency improvements reduce the energy expenditure burden on consumers, reduce energy demand and the associated carbon emissions, improve energy security, and prevent investment in additional generation capacity (Duan et al., 2017). For example, between 2000 and 2015, energy efficiency improvements in IEA countries resulted in energy savings of 450 million tonnes of oil equivalent (Mtoe) and decreased the total energy expenditure by US$540 billion (IEA, 2016). Since 2006, China has taken aggressive measures to enhance energy efficiency. During the 11th Five-Year Plan (FYP)(2006–2010), the government set a binding national energy intensity reduction target of 20%. This was revised downwards by 4 percentage points in the 12th FYP (2011–2015) and was subsequently set at 15% in the 13th FYP (2016–2020). Other complementary programs such as the Ten Key Projects Program, the Ten-Thousand

Enterprises Program, and the Obsolete Capacity Retirement Program have also been rolled out to improve energy efficiency in China. Between 2006 and 2014, the government invested a total of US$370 billion in energy efficiency (IEA, 2016).

The result is that energy efficiency improved at an average annual rate of 4% during the 11th and 12th FYP. Across China's energy-consuming sectors, energy efficiency improved by 19%, which is higher than the efficiency improvements in IEA countries (IEA, 2016). Meng et al. (2016) conducted a review of 46 studies on the evaluation of energy and carbon emission efficiency in China. The survey shows that energy efficiency remained stable during 1996–2000, decreased during 2000–2005 and increased during 2006–2010. The transition towards an energy-efficient state has caused significant reductions in China's energy intensity. Between 2000 and 2015, energy intensity in China improved by 30%. The level achieved in 2015 (i.e. 5.6%) was 2.5 percentage points higher than the average per year for the previous decade. Consequently, global energy intensity improved by 1.8% in 2015 (IEA, 2016). Without energy efficiency in China, the global improvement would have been 1.4% (IEA, 2016).

In China, the transition towards a clean energy state via energy efficiency has generated sizeable benefits to consumers, the economy, and the environment. The enhancement in energy efficiency over 2000 levels had saved about 1.2 Gt CO_2 annually by 2014. In fact, without energy efficiency improvement, energy-related emissions in China would have been 13% higher in 2014 (IEA, 2016). Energy efficiency in China had two positive financial outcomes: (1) it prevented an additional cost of US$6.9–US$10.9 billion in thermal power generation in the manufacturing sector, representing 48% of total investment in energy conservation during the first four years of the 12th FYP, and (2) it reduced China's spending on imports by US$10 billion in 2015 and decreased energy expenditure for selected large industry sectors by US$18 billion in 2014 (IEA, 2016).

However, the slowdown in global energy efficiency in 2017[1] (IEA, 2018) questions the sustainability or persistent nature of energy efficiency achievements. Achieving persistency in energy efficiency improvements is beneficial in the following ways: (1) it helps to achieve sustainable progress in energy security, (2) it puts China and the global economy on a sustainable pathway towards a decarbonised energy system, and (3) in terms of policy, it shows the extent of the commitment made and the robust/stringent nature of government energy efficiency policies. Nonetheless, in the case of China, there are no empirical studies that seek to ascertain the degree of persistence in energy efficiency achievements.

Motivated by the above, this study models the persistent nature of the movements of provinces in China towards and away from the frontier, where the frontier denotes the most energy-efficient state. To do this, first, we apply the stochastic frontier model to separate persistent energy efficiency from transient energy efficiency and then estimate the overall energy efficiency scores. Second, based on the estimated transient energy efficiency scores, we define different energy efficiency states based on how close a province is to the frontier or how far away from the frontier it is and then apply the panel Markov-switching technique to model the transitions both within and among the different energy efficiency states. The estimated transition probabilities give indications of the degree of persistence of the different states identified and the transition to/from the frontier.

In China, the problem of energy efficiency has been approached in several ways. Some studies apply the decomposition-based technique to decompose energy intensity into different effects (Su and Ang, 2017, *inter alia*), while others apply econometric-based techniques to understand the underlying causes of energy intensity (as a measure of energy efficiency) in China (Pang

[1] Global energy intensity in 2017 slowed down to 1.7%, driven mainly by the weaker improvement in energy efficiency coverage and stringency and lower energy prices, compared with the previous three-year average of 2.3%. The rate is half what is required to remain on track with the Paris Agreement (IEA, 2018).

and Su, 2017; Ma and Yu, 2017, *inter alia*). While the former is criticized as being descriptive in nature and unable to capture cause and effect, the latter is criticized on the grounds of using an inappropriate measure of energy efficiency – energy intensity (Filippini and Hunt, 2011, 2012). While energy intensity is a much broader measure that is affected by economic structure, the environment, and other factors, energy efficiency in an economic sense relates more to the technical characteristics that affect energy intensity (Zhang and Broadstock, 2016).

In evaluating energy efficiency, two methodologies have been proposed: non-parametric (Data Envelopment Analytic – DEA) and parametric (Stochastic Frontier Analysis – SFA) techniques. The approach in this study is based on the latter. The DEA provides a deterministic measurement of energy efficiency performance. Wang et al. (2017) applied the DEA to measure energy efficiency in China during 2006–2010, taking into account sectoral heterogeneity. The results generally showed a consistent improvement in energy efficiency during 2006–2009 but dropped in 2010 with evidence of sectoral heterogeneity. The major driver was technical efficiency improvement. Several other studies such as He et al. (2018), Li and Zheng (2017), and Wu et al. (2017) employed the DEA to measure energy efficiency in China. However, these studies assumed a homogeneous production technology. This problem has been dealt with by other studies that have applied the meta-frontier DEA by taking into account heterogeneity in production technologies (Liu and Lin, 2018; Lin and Zhang, 2017; Fei and Lin, 2016, *inter alia*). For example, Liu and Lin (2018) applied the meta-frontier DEA to estimate energy efficiency in the transportation sector and investigate its drivers, finding that energy efficiency is generally low and ladder-like in distribution with obvious regional differences, and also that price of energy, industry structure, income, and transportation sector output have positive effects on energy efficiency. Apart from the fact that these DEA methods are deterministic in nature and vulnerable to the problems of omission variable bias and measurement errors, none of the above studies emphasised the importance of determining the persistent nature of energy efficiency states.

The parametric-based SFA imposes functional forms and distributional assumptions on the error component. This makes the SFA superior to the DEA in terms of dealing with measurement errors and omission variable bias problems, which could affect energy efficiency estimates.

Several studies have used SFA to evaluate energy efficiency. Lin and Wang (2014) applied the SFA to evaluate the energy efficiency of the Chinese iron and steel industry. They found that generally, energy efficiency performance increased during 2005–2011, with an average energy efficiency score of 0.699. Lin and Long (2015) evaluated the energy efficiency performance of the Chinese chemical industry in China during 2005–2011 and estimated average energy efficiency to be 0.6897 for the period, with the Eastern Region emerging as the best performer. They determined that the price of energy and enterprise scale enhanced energy efficiency, and the effect of ownership structure was negative. Shen and Lin (2017) extended their analysis to include all Chinese industries in the 30 administrative regions using input-output data for the period 2002–2014. Energy efficiency in the industrial sector was found to grow at an annual average rate of 3.63%. Also, while technical change, technical efficiency, and input mix contributed positively to energy efficiency, the effect of scale efficiency was negative. Zou et al. (2013) compared DEA and SFA in an evaluation of energy efficiency in the 30 administrative regions during 1998–2009. Though the estimated efficiency values differed between the methods, they provided a similar ranking. The Eastern Region of China emerged as the best performer.

Other studies have separated transient (i.e. short-run) efficiency from persistent (i.e. long-run efficiency). This distinction is considered important as short-run and long-run efficiency have different policy implications (Alberini and Filippini, 2018; Adom et al., 2018). Filippini and Zhang (2016) applied the SFA to separate persistent efficiency from transient efficiency using provincial data from China. Average persistent and transient energy efficiency was found to be 0.81 and 0.97, respectively, with the average overall energy efficiency at 0.78. They revealed that by increasing energy efficiency to the 100% level in the long-run, China will save a total of 1000 Mtoe in energy consumption, representing 25% of the total in 2012. Zhang (2017) also applied the SFA to separate persistent efficiency from transient efficiency in Chinese provinces. Based on the estimated efficiency values, the study proposed an energy efficiency-based allocation principle, in contrast to the energy intensity-based allocation principle. The author concluded that an efficiency-based allocation provides a smooth distribution reduction burden among regions compared to the intensity-based allocation.

The above SFA studies assume that provinces have similar production technologies. Lin and Du (2014) applied the latent class SFA to Chinese data to deal with the problems of unobserved heterogeneity in production technologies and found that estimated energy efficiency was not high, with an average of 0.632 during 1997–2010. Further, the estimated average energy efficiency scores changed with different production technologies, which emphasises the importance of unobserved heterogeneity in production technologies across regions. Elsewhere, Llorca et al. (2017) also applied the latent SFA to estimate energy efficiency in the transportation sector of Latin America and the Caribbean.

The foregoing studies provide information about the energy efficiency status of provinces or firms for each time period but do not determine the persistent nature of energy efficiency achievements or the persistent nature of the movements to/from the frontier, albeit it is considered an important policy issue (Adom and Adams, 2018; IEA, 2018; Adom, 2016). The main contribution of the current article is that it provides the first empirical evidence on the persistent nature of the energy efficiency state using the case of China, which is a global leader in energy consumption and carbon dioxide emissions. This study is different to the time-series approach adopted in Adom and Adams (2018) and Adom (2016). The use of the panel-based Markov-switching model in this study provides several advantages: (1) it has larger degrees of freedom to improve the efficiency of the estimates, (2) it captures much more complex human behaviour, (3) It provides information on intertemporal dynamics and individuality of entities, which helps to control for the effects of missing or unobserved variables, (4) it provides information on the inter-individual differences that help reduce any possible collinearity that may exist between a variable and its lag, (5) it provides a micro foundation for macro data analysis, and (6) it provides better prediction of individual outcomes based on observed behaviour of others, especially in the case of a homogeneous sample. Further, this study uses the frontier-based definition of efficiency in contrast to the time-based approach adopted in Adom (2016) and Adom and Adams (2018).

The study is organised as follows. Section 2 describes the method and data, Section 3 and 4 discuss the results from SFA and the Markov-switching model, and Section 5 concludes the paper with policy recommendations.

2. Methodology

2.1 Stochastic frontier model (SFA)

The methodology is based on the energy demand frontier by Filippini and Hunt (2011).

$$ED_{it} = f(P_{it}, Y_{it}, X_{it}; \beta) e^{v_{it}} e^{u_{it}} \qquad (1)$$

Equation 1 is the energy demand frontier, where ED is minimum energy use to produce an energy service, $f(P_{it}, Y_{it}, X_{it}; \beta)$ denotes the deterministic part of the energy demand frontier, *P* is the real price of energy index, *Y* is the real GDP, *X* is a vector of other explanatory variables that might explain energy consumption, '*i*' denotes province, '*t*' is the time period, β is a vector of parameters that is associated with the deterministic part of the production function, $e^{V_{it}}$ denotes the stochastic component of the energy demand frontier, and $f(P_{it}, Y_{it}, X_{it}; \beta)e^{V_{it}}$ is the optimal minimum amount of energy required to produce the energy service output. Deviations from this optimal minimum denote production inefficiency due to inefficiency in energy input; which is captured in Equation 1 by $e^{U_{it}}$. The noise term is two-sided non-negative with a normal distribution while the inefficiency term is one-sided non-negative with a half-normal distribution. This study follows the linear functional specification (see Equation 2) and includes similar controls with some modifications as used in Filippini and Zhang (2016) and Zhang (2017). We control for population, industry, service sector output, and average household size as in Filippini and Zhang (2016) and Zhang (2017). Household density is excluded in this study as it captures size and correlates with household size. This paper includes the total number of passenger vehicles, which is the sum of commercial and public, to capture the effects of transportation. This is in contrast to Filippini and Zhang (2016) and Zhang (2017), who all used the number of cars and the number of buses.

$$\ln ED_{it} = \ln f(P_{it}, Y_{it}, X_{it}; \beta) + V_{it} + U_{it} \qquad (2)$$

This article follows the approach of Jondraw et al. (1982) to estimate energy efficiency. Equation 3 shows the estimate of energy efficiency, where E_{it}^{F} is the minimum energy demand of the *i*th province at time *t* and E_{it} is the observed energy consumption. Overall energy efficiency is the product of persistent and transient energy efficiency.

$$EF_{it} = \frac{E_{it}^{F}}{E_{it}} = \exp(-\widehat{U_{it}}) \qquad (3)$$

It is crucial to take into account the presence of time-invariant inefficiency, time-invariant unobserved heterogeneity variables, and time-varying energy efficiency when estimating the energy demand frontier (Filippini and Zhang, 2016; Zhang, 2017). As noted by Filippini and

Zhang (2016), in the case of China, these issues are prevalent due to the relatively large size and heterogeneity of the morphology and socioeconomic organizations of provinces. There are presently no well-proven techniques that, for example, estimate persistent and transient energy inefficiency simultaneously[2]. In this study, we estimate the fixed effect versions of the SFA.[3] First, the fixed effect model (hereafter FEM) by Cornwell et al. (1990) is used to estimate persistent energy efficiency. Second, the true fixed effect model (hereafter TFEM) by Greene (2005a) is used to estimate transient energy efficiency. In this paper, the issue of endogeneity is treated with the instrumental variables approach following Filippini and Zhang (2016), even though there is still no approved way to effectively handle endogeneity within the SFA.

FEM is distribution free and assumes linearity as the only assumption. However, it assumes that the efficiency term is time-invariant and varies across cross-section only, which rules out the possibility of learning-by-doing. Therefore, the persistent efficiency may be under-estimated in this model. TFEM separates unobserved province-specific heterogeneity from time-varying efficiency. In the presence of persistent efficiency, TFEM estimates only transient efficiency. Chen et al. (2014) and Belloti and IIardi (2018) reveal that Greene's maximum likelihood dummy variable estimator suffers from the incidental parameters problem, which leads to an inconsistent estimate of the variance parameter. This article also estimates the consistent true fixed effect model by Chen et al. (2014), but the high correlation (0.9482) between the efficiency estimates from Chen and Greene's TFEM seems to downplay this

[2] Recently developed approaches are either complex (Colombi et al., 2014; Kumbhakar et al., 2014; Tsionas and Kumbhakar, 2014) or yet to be proven (Filippini and Greene, 2016).

[3] As there is no statistical test for choosing the variations of SFA models, we estimate a regular fixed and random effects model and use the Hausman test to decide the model choices. The Hausman test favours the fixed effect model. Though the current study uses a somewhat similar data to that used in Filippini and Zhang (2016), there are differences in terms of the model set-up (see the method section for further clarification) and the sample size used. The current study has a larger sample size (covering 30 provinces over the period 2003–2015) than that used in Filippini and Zhang (which covered 29 provinces over the period 2003–2012). As revealed by Clark and Linzer (2015), in the very small datasets, the random-effects estimator outperforms the fixed effect estimator even when there are extreme violations of the assumption of zero correlation. However, there is less support for the random-effect estimator as the size of the dataset increases. This could possibly explain the results in this paper.

problem. Although TFEM separates unobserved province-specific heterogeneity from time-varying efficiency, it does not capture persistent efficiency. Therefore, our estimate of transient efficiency is likely to suffer from being over-estimated.

We then regress the overall energy efficiency scores on a vector of explanatory variables to identify the drives for the efficiency changes. In the empirical literature, the effects of several factors on energy efficiency have been examined. Since energy efficiency in the economic sense relates to the technical characteristics, we examine the factors that can affect energy efficiency in the technical sense. It should be stated that an improvement in energy efficiency could affect energy consumption (i.e. rebound effect). Therefore, the factors we examine here are expected to have effects on consumption via energy efficiency, but we do not examine this complex channel directly. Specifically, we control for the effects of foreign direct investment (FDI), human capital development (measured here using the years of education), real GDP per capita, the rate of urbanization, size of green parkland to capture the green nature of the province, real price energy index, and regional dummies.

FDI stimulates technological spillover and knowledge transfer, which can enhance the technical processes of production and promote energy efficiency. However, the materialization of technological spillover and knowledge transfer depends on the technological absorptive capacity of the host country. Thus, the effect of FDI can be positive or negative. Urbanization (UR) can worsen the technical processes of production by increasing the demand for energy-intensive goods such as cement and steel. Likewise, the concentration of people in one place can promote economies of scale in the use of energy services. Thus, urbanization can promote or worsen energy efficiency. Following Lv et al. (2017) and Wang et al. (2017), this study includes the effects of FDI and urbanization. The development of human capital (EDU) can promote the environmental awareness of end-users, and this could impact positively on energy efficiency. Following Liu et al. (2017), this study includes the effects of human capital development, and following Liu and Lin (2018), it includes the effects of income per capita (YPC) and price of energy. Higher income could induce investment in energy-efficient equipment or the use of energy-intensive products. Thus, higher income could have positive and negative effects on energy efficiency. Increasing the price of energy can induce investment in energy-efficient equipment in a free market economy, all things being equal, and promote energy efficiency. However, where there is a heavy government presence in the regulation of energy price, the investment-induced effect of price might be distorted and hence compromise energy efficiency in the process. The green nature (GPL) of a province might indicate the importance the province attaches to a clean economy. Hence, in such a province, we expect that energy efficiency should improve. However, this may depend on whether GPL is an initiative of the locals or the government to achieve a political agenda. Equation 4 is the equation we estimate, where RD is the regional dummy that caters for regional specific effects such as policies, institutions, and technical progress. Variables in (4) are stationary in levels (see Appendix A).

$$EF_{it} = \alpha + \beta_{FDI} lFDI_{it} + \beta_{EDU} lEDU_{it} + \beta_{YPC} lYPC_{it} + \beta_{UR} UR_{it} + \beta_{GPL} lGPL_{it} + \beta_{P} P_{it} + \beta_{RD} RD_i + \varepsilon_{it} \qquad (4)$$

This study estimates overall energy efficiency exogenously as the product of persistent and transient energy efficiency and then regresses this variable on a set of factors.[4] A limitation of the two-stage analysis is that we do not consider the trade-offs among the various factors that affect energy efficiency and the potential rebound effects.

2.2 Panel Markov-switching model

[4] This two-stage approach is not satisfactory as mentioned in Wang and Schmidt (2002) and therefore considered as a limitation in this study. However, in the present literature, we are not aware methodologically of how to endogenize overall energy efficiency as calculated in this study within the SFA framework (see Adom et al., 2018).

Figure 1 shows the plot of different energy efficiency states based on transient energy efficiency. For the moment, we assume a two-state model – energy-efficient state (point A) and less energy-efficient state (point B) – for exposition. At any point in time, provinces provide information about their current states (either A or B). We are interested in predicting (in probability terms) the future states, given knowledge of the current state. For example, suppose a province reveals information of energy efficiency at time t1A; we attempt to model what the likely future state would be, given information about the previous state of the province. As revealed in the figure, such future outcomes are uncertain and therefore governed by some probability rule. The province can either remain in the same state or transition into another state at time t2A. The same mechanism applies if a province reveals the initial energy utilization status as energy inefficient.

In both cases, a probability distribution can be built to describe these various movements between the different states. Such a probability distribution in the Markovian chain distribution is referred to as the transition probabilities. In the absence of any absorbing state, these probability matrices will show how persistent the movements to or from the frontier are.

The idea of applying the Markov-switching model to panel data was first introduced and applied by Kalbfleisch and Lawless (1985) and Kay (1986). In this application, the efficiency scores obtained from the stochastic frontier model are categorised into different states. Therefore, we estimate an n-state Markov model. Denote the process of energy use performance by X_t. It is observed at N discrete time intervals, $t_1,\ldots,t_n$. At each time t_n, a province within the panel records a state $X_{tn} = S_n^{ob}$, where $S_n^{ob} \in S = \{S_1,\ldots,S_n\}$. The random process among/between states is described by a conditional probability expressed in Equation 5, which states that the likelihood of, say, province k to be in state S_n^{ob} at time t_n depends on the previous state S_{n-1}^{ob} at time t_{n-1}.

$$P_{s_{n-1},s_n}(t_{n-1},t_n) = \Pr(X_{t,n} = S_n^{ob} \mid X_{t,n-1} = S_{n-1}^{ob}) \quad (5)$$

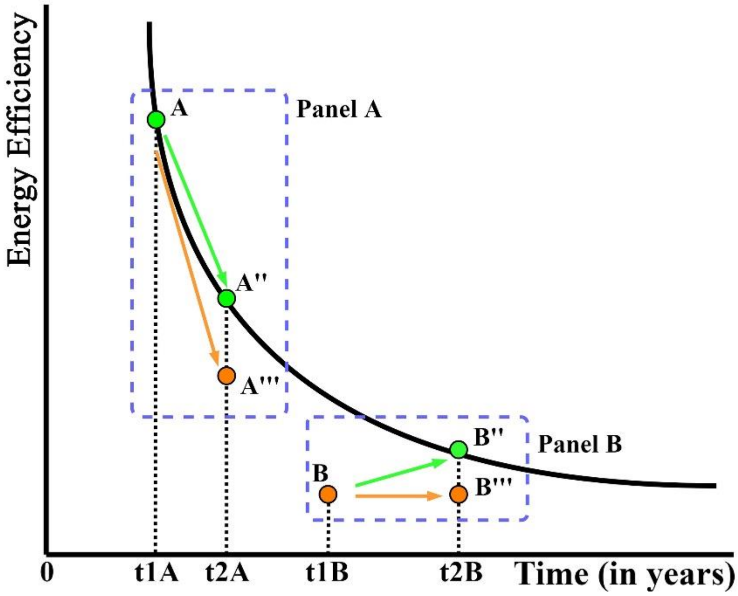

Figure 1: Transition between different energy-efficient states

Further, if we assume a time-homogenous case (i.e. the elements in the transition intensity matrix remain constant) and that all of the provinces within the panel are observed at the same *N* time periods, the likelihood function for the whole sample can be derived as the product of the conditional probabilities (see Equation 6), where $D_{ij,n}$ is the total number of provinces observed in state S_i at time t_{n-1} and state S_j at time t_n. The corresponding log-likelihood is derived as in Equation 7, where *w* denotes a vector of explanatory variables.

$$L(\theta) = \prod_{n=1}^{M} \left\{ \prod_{i,j=1}^{K} P_{ij}\left(t_{n-1}, t_n\right)^{D_{ij,n}} \right\} \quad (6)$$

$$\log L(\theta) = \sum_{N=1}^{M} \sum_{i,j=1}^{K} D_{ij,n} \log P_{ij}(w_n) \quad (7)$$

The assumption of time-homogeneity implies that the differences in time, $T_n = t_n - t_{n-1}$, determine the transition probabilities. The corresponding log-likelihood function can be derived as in Equation 8. Following the quasi-Newton procedure proposed by Kalbfleisch and

Lawless (1985), Equation 8 can be maximized using the maximum likelihood of obtaining the associated parameters.

$$\log L = \sum_{n=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{M} D_{ij,n} \log P_{ij}(T_n) \qquad (8)$$

2.3 Data

This study collects balanced panel data for 30 provinces in mainland China covering the period 2003–2015 on all the selected variables. Other regions are excluded due to missing information for some of the variables used in the study. Macro-level data areobtained from the China National Bureau of Statistics reports "China Statistical Yearbook", energy data are obtained from the "China Energy Statistical Yearbook", and the price index is obtained from the "China Urban Life and Price Yearbook". Table 1 shows the description of the variables and descriptive statistics.

3. Empirical Results

3.1 Frontier determinants

Table 2 provides the frontier estimates based on the FEM and TFEM. The effect of the price of energy is negative, which confirms the claim that increasing the price of energy reduces the scale of energy usage. However, the effect is very small. Filippini and Zhang (2016) obtained a negative price effect but it was statistically insignificant. Income has a positive effect on energy demand, thus economic growth drives the scale of energy use up, which confirms the findings of Liu et al. (2017), Zhang (2017), Wang and Li (2016), and Filippini and Zhang (2016). The negative effect of average household size suggests that a large concentration of people in a small place reduces the scale of energy use due to the benefits of economies of scale. This confirms the results of Zhang (2017) and Filippini and Zhang (2016). Population exerts a positive effect on energy consumption, which suggests that a higher population raises the scale of energy usage, which confirms the findings of Wang and Li (2016) and Filippini and Zhang (2016).

The number of vehicles exerts a positive effect on energy consumption, which confirms the scale effect of the number of vehicles (Filippini and Zhang, 2016). While industry value-added as a share of GDP shows a positive effect, the effect of service sector output as a share of GDP is generally negative but statistically insignificant. Thus, shifts to the more energy-intensive sectors in the economy drive the scale of energy consumption upwards, which confirms Zhang et al. (2017), Zhang (2017), and Filippini and Zhang (2016). The total number of heating and cooling days reveal a positive but insignificant effect on energy consumption. The time trend has a significant concave effect on energy consumption. Thus, technological progress significantly reduces energy consumption in China, which confirms Filippini and Zhang (2016) and Wang and Li (2016).

Table 1: Descriptive statistics

Variables	Description	Observation	Mean	Standard deviation	Minimum	Maximum
LEC	Log of energy consumption in tce	390	9.1320	0.7418	6.5280	10.5687
P	Real energy price index (2003=100)	390	164.4035	28.2678	100	252.1535
LY	Log of real GDP (billion 2003CNY)	390	8.0508	0.85714	5.6298	9.5586
LAHS	Log of average household size per person	390	1.1440	0.1104	0.8459	1.4255
LHCD	Log of heating and cooling degree days	390	5.6945	1.7248	0	7.9394
LPOP	Log of population (10,000 persons)	390	8.1595	0.7538	6.2804	9.2918
LPCV	Log of total vehicles (sum of private and civil)	390	5.5913	1.0802	2.6790	7.9595
ISH	Share of industrial sector in % of GDP	390	47.3390	7.8131	19.7	61.5
SSH	Share of service sector in % of GDP	390	40.7551	8.3937	28.6	79.7
LFDI	Log of foreign direct investment	390	23.3946	1.6802	18.6597	26.1438
LEDU	Log of education	390	2.2453	0.1019	1.9428	2.5190
LYPC	Log of real GDP per capita	390	6.7990	0.4486	5.6430	7.9331
UR	Rate of urbanization	390	49.0602	15.7035	15.58	89.6
LGPL	Log of size of green parkland	390	10.6499	0.9405	7.5547	12.9908

Table 2: Estimation results

Independent variables	FEM	TFEM	TFEM_robust
$price$	-0.0007**	-0.0004	-0.0006**
	(0.00031)	(0.00027)	(0.0003)
$\log(GDP)$	0.2633***	0.2581***	0.2590***
	(0.09256)	(0.08375)	(0.0902)
$\log(Average \cdot household \cdot size)$	-0.30595**	-0.2992***	-0.3058**
	(0.12450)	(0.10557)	(0.1182)
$\log(HDD \& CDD)$	0.0047	0.0072	0.0006
	(0.00527)	(0.00436)	(0.0050)
$\log(Population)$	0.3515***	0.1588	0.2872***
	(0.106244)	(0.11706)	(0.1092)
$\log(Vehicles)$	0.2573***	0.2109***	0.2405***
	(0.042062)	(0.037077)	(0.0404)
$Industrial \cdot share$	0.00296*	0.0038**	0.0036**
	(0.042062)	(0.00146)	(0.0016)
$Service \cdot share$	-0.0015	0.0003	-0.0006
	(0.001798)	(0.00165)	(0.0018)
t	0.07076***	0.0891***	0.0801***
	(0.010625)	(0.0097)	(0.0107)
t^2	-0.0042***	-0.005***	-0.0047***
	(0.00039)	(0.00037)	(0.0004)
constant	2.8352**	-5.9043***	----------
	(1.15177)	(0.23583)	

Note: Standard errors in parentheses. ***,**,* denote 1%, 5% and 10% significance levels.

3.2 Estimation of energy efficiency scores

Table 3 contains the descriptive statistics of energy efficiency. The italicized figures in the parentheses are Chen's consistent TFEM estimates. Generally, the results are robust. The mean transient energy efficiency is 0.95, while the mean persistent energy efficiency is 0.563.[5] The relatively higher persistent inefficiency suggests that, in China, the problem of energy inefficiency is structural in nature. Therefore, energy security and environmental sustainability will benefit more from policies aimed at the long term than the short term (Adom et al., 2018). We also assess the regional distribution of energy efficiency in China (see Table 4). There is evidence of regional heterogeneity, and Eastern China emerges as the best performing region,

[5] Though Zhang (2017) and Filippini and Zhang (2016) applied different methods, their estimate of transient energy efficiency (i.e. 0.962 and 0.967, respectively) is very consistent with what is obtained in this study. In terms of persistent efficiency, however, the current study's estimate is lower than that obtained in Zhang (i.e. 0.630–0.751) and Filippini and Zhang (i.e. 0.682–0.808). The possible reason for this discrepancy could stem from the differences in methodology, sample size, and model set-up.

followed by Central China. This confirms the conclusions of Lin and Zhang (2017) and Lin and Du (2013).

Table 3: Average energy efficiency scores by type

Type	Mean	Std. dv	Min	Max	Obs
Transient efficiency	0.9502 *(0.9361)*	0.0421 *(0.0325)*	0.6206 *(0.7222)*	0.9925 *(0.9899)*	390
Persistent efficiency	0.5633	0.1584	0.3060	1	390
Overall efficiency	0.5358 *(0.5275)*	0.1531 *(0.1498)*	0.2480 *(0.2678)*	0.9829 *(0.9727)*	390

Note: Values in parentheses are the estimated efficiency scores based on Chen et al. (2014).

Table 4: Average energy efficiency scores by region

Province	Transient energy efficiency	Persistent energy efficiency	Overall energy efficiency
Eastern China	0.9536 *(0.9373)*	0.6071	0.5778 *(0.5687)*
Western China	0.9436 *(0.9343)*	0.5029	0.4762 *(0.4704)*
Central China	0.9545 *(0.9370)*	0.5863	0.5600 *(0.5495)*

Note: Values in parentheses are the estimated efficiency scores based on Chen et al. (2014).

At the provincial level, there is also evidence of provincial heterogeneity. For transient energy efficiency, all provinces except Xinjian have average scores of more than 0.9, which confirms Zhang (2017). In the case of persistent energy efficiency, provinces like Guangxi, Jiangxi, Anhui, Beijing, and Hainan record mean values of above 0.7, while provinces such as Inner Mongolia, Shanxi, Hebei, Liaoning, Shanghai, Shandong, Guizhou, Gansu, Qinghai, Ningxia, and Xinjiang score below 0.7, on average. The mean overall efficiency performances for the provinces of Guangxi, Jiangxi, Anhui, Beijing, and Hainan are 0.7 or greater. A significant number of provinces recorded between 0.5 and 0.65 (e.g. Shanghai, Jilin, Zhejian, and Guangdong) and below 0.5 (e.g. Guizhou, Gansu, Shanxi, Qinghai, and Ningxia).

There may be several reasons for the observed heterogeneity. Energy efficiency policies differ among the provinces. For example, the government energy intensity reduction targets differ across the provinces. Also, differences in the institutional environment can affect rates of compliance with energy efficiency policies. Differences in human capital, FDI, urban concentration, etcetera might also account for the provincial heterogeneity in energy efficiency across China. The next section explores this question by investigating the drivers of overall energy efficiency in China.

3.3 Endogeneity in efficiency score estimation

We are also aware of the existence of endogeneity issues in the energy demand frontier model. Following a similar strategy to Filippini and Zhang (2016), a two-step approach is adopted in this section to address the potential effects of the endogenous regressor (GDP) on the estimated efficiency scores.

First, we identify appropriate instrumental variables for GDP. The instruments considered in this empirical study include life expectancy, the size of green parkland, and real investment in forestry. The Cragg-Donald Wald F test statistic is used to test for weak instruments. The value of this statistic is 12.3, which is higher than the critical value at the 10% level of significance suggested by Stock and Yogo (2003). Therefore, we reject the hypothesis that the instruments are weak. The Hansen J statistic for over-identification is 4.1 (with p-value 0.13), indicating that our choices are valid instruments. All the results confirm that the instruments used in this study are appropriate. The residual estimated from the first step is then included in the second step for frontier estimation.[6]

To compute the persistent and transient efficiency scores, we re-estimate FEM and TFEM using the two-step approach, and label the re-estimations FEM-2 and TFEM-2,. The Spearman rank correlation coefficients between FEM and FEM-2 are 0.9933 for persistent efficiency and 0.9989 for transient efficiency. Therefore, we confirm that the potential endogeneity does not affect our estimated energy scores and we will use the results from Section 3.2 for analysis in the following sections.

[6] As acknowledged in Filippini and Zhang (2016), this procedure is not completely satisfactory for SFA. The regression results are available upon request from the authors.

3.4 Drivers of energy efficiency

Table 5 shows the drivers of energy efficiency. FDI has a significant positive effect on energy efficiency, which implies that FDI via technological spillover and knowledge transfer enhances the technical processes of production, resulting in an improvement in energy efficiency. Liu et al. (2017) and Wang et al. (2017) find a similar result. Education and urbanization also stimulate energy efficiency improvements in China, which confirms Du et al. (2016) and Liu et al. (2017). While human capital development promotes environmental awareness and hence causes investment in green technology, the concentration of the population in one place generates economies of scale and shifts demand from unclean energy sources to clean energy sources.

The effect of price is significantly negative, which implies that, in China, the price of energy does not promote energy efficiency. Du et al. (2016), Liu and Lin (2018), and Liu et al. (2017) found a similar result for China. The possible explanation for this is that the energy price is highly regulated in China, which results in a lower and consistent decline in price that subsequently discourages investment in energy-efficient equipment to promote energy efficiency. Thus, in order for the price of energy to induce energy efficiency investment in China, it has to be deregulated.

Further, higher income per capita compromises energy efficiency improvements. Du et al. (2016) and Liu and Lin (2018) found a similar result for China. As mentioned earlier, in China, the price of energy is highly regulated, which makes it not worthwhile to invest in energy-efficient technologies with their required higher capital outlay. Consequently, higher incomes only intensify the use of the already existing equipment or appliances that may have lower efficiency standards, possibly due to depreciation. Lastly, the regional dummies are statistically significant.

Table 5: Estimation results

	Overall efficiency	**Overall efficiency_robust**
log（FDI）	0.0368*** (0.00792)	0.0339*** (0.0078)
$\log(EDU)$	0.4712*** (0.1519)	0.5132*** (0.1491)
$\log(per \cdot capita \cdot GDP)$	-0.3230*** (0.0465)	-0.3183*** (0.0457)
$Urbanization \cdot rate$	0.0033*** (0.0012)	0.0032*** (0.0012)
$\log(Green \cdot land)$	-0.0107 (0.0112)	-0.0115 (0.0110)
$price$	-0.0013*** (0.0002)	-0.0013*** (0.0002)
$regional \cdot dummy \cdot central$	-0.1136*** (0.0256)	-0.1150*** (0.0251)
$regional \cdot dummy \cdot west$	-0.1363*** (0.0287)	-0.1353*** (0.0281)
$const$	-1.1641*** (0.3235)	1.0148*** (0.3431)
$F-stats$	16.46***	16.01***

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

The positive effect of education and FDI on energy efficiency implies that differences in the performance of these variables might account for the provincial heterogeneity in energy efficiency. Figures 2 and 3 plot the deviation of provincial means from the national average for education and FDI. Generally, the poorest provinces of Guizhou, Gansu, Qinghai, Ningxia, Anhui, Sichuan, and Yunnan perform poorly in these indicators. Thus, to bridge the gap in energy efficiency, government policies in the areas of education and FDI should target these poor provinces.

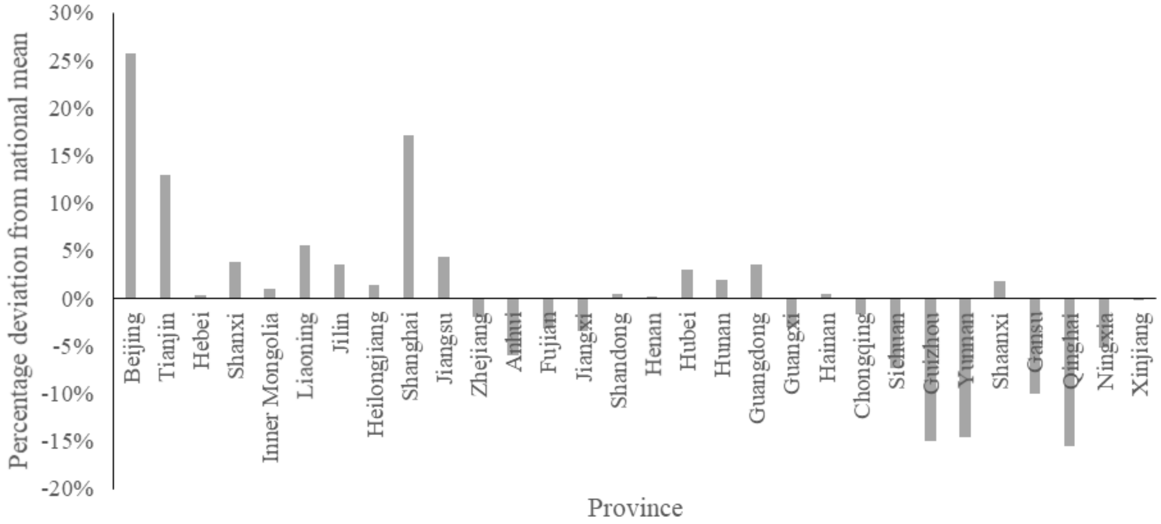

Figure 2: Plot of deviation of provincial means from national mean – Education

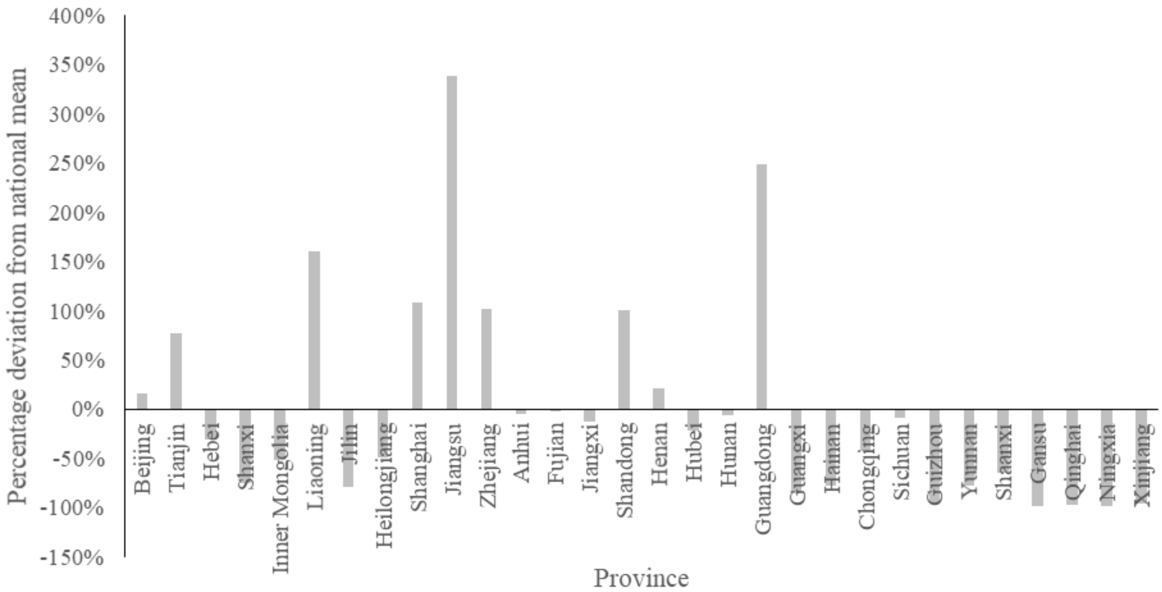

Figure 3: Plot of deviation of provincial means from national mean – FDI

4. Results from Markov-switching Model

4.1 Definition of energy-efficient states

Since the transient energy efficiency measurement captures the efficiency dynamics over time, we define different thresholds to categorize provinces into different states. Table 6 contains the definition of states and the classification of provinces into different states according to their mean values. Of the total sample, no province, on average, fell into the first category during

2003–2015 (Note: this is an average for the period, which suggests that some provinces did indeed reach this state in the process of time). Thus, on average, energy efficiency levels in China can either be described as moderately or less energy-efficient during 2003–2015. As shown in the table, 60% of the sample falls within the moderately energy-efficient state while the remaining 40% falls within the less energy-efficient state, on average.

Table 6: Classification of provinces according to efficiency scores (based on the mean values of transient energy efficiency)

Classification	States	Cluster of provinces
1>= 75 percentile (0.973)	Highly energy efficient (HEE)	NULL(*)
>= mean (0.950) but < 75 percentile	Moderately energy efficient (MEE)	Hebei, Liaoning, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Guangdong, Guangxi, Sichuan, Yunnan, Shaanxi(**), Hunan
<mean (0.950)	Less energy efficient (LEE)	Beijing, Tianjin, Shanxi(**), Inner Mongolia, Jilin, Hainan, Chongqing, Guizhou, Gansu, Qinghai, Ningxia, Xinjiang

* As the efficiency scores used for the classification in this table are based on the mean values of transient energy efficiency, the category for HEE is empty. However, some provinces move into and away from HEE over time as the transient efficiency scores change.
** Shanxi is a province of North China, capital Taiyuan, while Shaanxi is a northwestern Chinese province, capital Xi'an.

4.2 Energy efficiency transition

4.2.1 Assuming exogeneous transition intensities

To estimate the transition probabilities, first, we test our data against whether it satisfies a time-homogeneous Markov model or time-inhomogeneous Markov model, assuming for the moment there are no covariates. The test reveals no significant time-inhomogeneity in the transition probabilities (see Appendix B). Table 7 contains information about the state table (the number of counts a state is followed by another state), transition intensities, probability of each state being next (state table in probability terms. Note: This is not the same as the transition probabilities), and transition probabilities.

Assuming a one-year time interval, there is a 67% chance of a province remaining in either the HEE or LEE state. The probability of remaining in the MEE state is 53%, suggesting that, comparatively, the HEE and LEE states are more persistent. The same column reveals that energy efficiency transition is very systematic or ladder-like in nature. Given that the current state is HEE, the most likely location out of this state is MEE. Also, the most likely state out of MEE and LEE is LEE and MEE, respectively. The transition probabilities characterize the following paths $HEE \rightarrow MEE$, $MEE \rightarrow LEE$, and $HEE \rightarrow LEE$ are relatively higher than those that characterize the paths $MEE \rightarrow HEE$, $LEE \rightarrow MEE$, and $LEE \rightarrow HEE$. This suggests that movements away from the frontier are more persistent than those towards the frontier. The persistent nature of HEE and LEE implies these states are more sustainable. The former could be due to the fact that technologies take time to depreciate and energy efficiency policies are more robust in the first year. In the latter case, the benefits of technological diffusion take time and depend on learning experiences, adaptation processes, and absorptive capacity.

Next, we increase the time intervals to two, three, and four and then estimate the transition probabilities (see Table 7). Generally, states become less persistent as we increase the time of transition. For a four-year time interval, the degree of persistency reduces by 45.2%, 34.5%, and 38.8% for the HEE, MEE, and LEE states, respectively. In the case of LEE, the reduction indicates that enough time provides the opportunities for learning, adaptation, and development of absorptive capacity, and this increases the probability of transitioning from this state. In the case of HEE and MEE, the decline suggests that technology depreciates with time, and the efficacy of energy efficiency policies also reduce with time, which compromises the standards. For HEE and LEE, the result shows that the former is less sustainable, which implies that the benefits of energy efficiency improvements are likely to be short-lived in China. Further, the nature of transitions out of the states is ladder-like, and the movements towards the frontier are less persistent than from the frontier. The bottom part of Table 7 shows the average duration of states in years over the sample period.

Table 7 Transition probabilities from time-homogeneous Markov model

State switch	State table	Prob. being next	Transition intensities	Transition probabilities			
				Time interval in years			
				One	Two	Three	Four
$HEE \rightarrow HEE$	86	0	-0.4655 (-.6488, -.3340)	0.6721 (.4729, .7372)	0.5072 (.3082, .5910)	0.4182 (.2075, .5118)	0.3682 (.1748, .4648)
$HEE \rightarrow MEE$	31	0.9151 (.4400, .9950)	.4260 (.2763, .6567)	0.2433 (.1812, .3234)	0.3134 (.2462, .3942)	0.3338 (.2707, .4067)	0.3399 (.2784, .4066)
$HEE \rightarrow LEE$	11	0.0849 (.0050, .5600)	0.0395 (.0030, .5279)	0.0846 (.0611, .2966)	0.1794 (.1336, .3913)	0.2480 (.1816, .4489)	0.2919 (.2199, .4762)
$MEE \rightarrow HEE$	25	0.4116 (.2708, .5845)	0.3393 (.2098, .5487)	0.1988 (.1377, .2697)	0.2617 (.1774, .3432)	0.2834 (.1763, .3809)	0.2917 (.1633, .3926)
$MEE \rightarrow MEE$	67	0	-0.8244 (-1.1365, -.5980)	0.5303 (.4330, .6088)	0.3963 (.3285, .4741)	.3581 (.2951, .4319)	0.3472 (.2861, .4175)
$MEE \rightarrow LEE$	34	0.5884 (.4155, .7292)	0.4851 (.3207, .7338)	0.2709 (.2064, .3628)	0.3419 (.2607, .4370)	0.3585 (.2674, .4702)	0.3611 (.2684, .4830)
$LEE \rightarrow HEE$	9	0.1293 (.0219, .4653)	0.0064 (.0132, .3148)	0.0839 (.0492, .2008)	0.1615 (.1097, .3073)	0.2151 (.1397, .3474)	0.2490 (.1526, .3685)
$LEE \rightarrow MEE$	26	0.8707 (.5347, .9781)	0.4332 (.2695, .6963)	0.2463 (.1715, .3345)	0.3160 (.2459, .3978)	0.3356 (.2651, .4070)	0.3410 (.2785, .4136)
$LEE \rightarrow LEE$	71	0	-0.4976 (-.7249, -.3415)	0.6698 (.5360, .7519)	0.5225 (.3865, .6141)	0.4493 (.3184, .5556)	0.4100 (.2899, .5246)
-2loglikelihood			639.2728				
	HEE	**MEE**	**LEE**				
Duration of States	5.0672 (3.0729, 6.2639)	4.1766 (3.4468, 5.0105)	3.7559 (2.7381, 5.7945)				

Note: HEE (Highly energy efficient), MEE (Moderately energy efficient), and LEE (Less energy efficient). Figures in parentheses are the lower and upper confidence intervals at 97.5%.

4.2.2 Endogenizing the transition intensities

In the foregoing section, we ignored the effect of explanatory variables on the transition intensities. Where such effects are significant, failing to account for them could bias the estimate of the transition intensities and the transition probabilities. In this section, we control for the effects of human capital development, FDI, real income per capita, and GPL. To verify this, we test the time-homogeneous model with covariates against the time-homogeneous model with no covariates, using the log-likelihood ratio test. The result supports the former (see Appendix C). This means that the time-homogeneous model with covariates provides a better fit.

Table 8 contains the results. A comparison of the results in Tables 7 and 8 reveals changes in the values of the transition probabilities, but the conclusion is similar. For the one-year time interval, the HEE state seems more persistent, with a transition probability of 68%. This is followed by the LEE and MEE states, with transition probabilities of 66% and 51%, respectively. The transitions are systematic in nature, and the movements towards the frontier seem less persistent than the movements away from the frontier. The latter suggests that energy efficiency progress in China has not been sustainable.

By increasing the time interval, we also witness a consistent decline in the degree of persistence of the HEE, MEE, and LEE states. The degree of persistence decreases by 51%, 14.8%, and 30.3% for HEE, MEE, and LEE, respectively, for the four-year time interval. Over the four-year period, HEE becomes the least persistent state compared to the LEE state. Thus, in comparison, it is relatively more difficult for China to escape the LEE state than the HEE state. Adom and Adams (2018) and Adom (2016) found a similar result in Nigeria and Cameroon. However, observing the probabilities over time, some progress is made with time. As revealed in the table, there is a consistent improvement in the transition from the LEE to other states as well as from the MEE to HEE state, albeit the movement towards the frontier seems less persistent than the movements away from the frontier. In the case of China, the desire to get out of the LEE state to either the MEE or HEE state could be due to international pressure to mitigate greenhouse gas emission or domestic pressure to improve the local environment and remain competitive internationally. The bottom part of the table contains information about the average duration of states in years over the sample period.

4.2.3 Three-state versus two-state

From the outset, we imposed a three-state model. In this section, we redefine a two-state model – above mean level (HEE) and below mean level (LEE) – and then test this model against a three-state model, assuming for now a time-homogeneous model with no covariates. The likelihood ratio test favours the two-state model, which implies one of the three states is redundant (see Appendix D for the results). Also, we test the two-state time-homogeneous model against the two-state time-inhomogeneous model, and the test supports the latter (see Appendix E for the results). Finally, we test this model with no covariates against the model with covariates, and the test favours the former (see Appendix F for the results).

Based on the above, we proceed to estimate transition intensities and transition probabilities. Table 9 shows information on the state table, transition intensities, and transition probabilities. For the one-year time interval, the LEE state is more persistent than the HEE state, with transition probabilities of 86% and 66%, respectively. Again, the movements away from the frontier seem more persistent than the movements towards the frontier, with transition probabilities of 34.5% and 14.4%, respectively. By changing the time interval, the results seem very consistent. The degree of persistency of the HEE and LEE states declines, and the extent of decline over the four-year time interval is higher for the former (i.e. 47.6%) than the latter (i.e. 15.3%). This supports the result that the HEE state is less sustainable than the LEE state. As shown in the table, the transition probability of remaining in the HEE state is lower than that of remaining in the LEE state. Thus, it is relatively more difficult to get out of the LEE state than the HEE state. Also, the movement away from the frontier is more persistent than the movement towards the frontier. The lower part of the table shows the average duration of both states over the sample period.

4.3 Reasons for the unsustainable nature of the HEE state

In the case of China, there are several reasons that might account for the unsustainable nature of the HEE state or the sustainable nature of the LEE state. First, the less persistent nature of HEE suggests that there are still gaps in terms of the stringency or robustness nature of energy efficiency policies in China. These gaps cut across the different array of policies implemented, and they reflect in areas such as implementation, monitoring, evaluation, compliance, flexibility, scope, and sustainability. Expectations and standards do change with time. Therefore, the definition of standards for energy efficiency should be flexible to accommodate behavioural changes that might affect consumption and production patterns over time. However, presently, there are fixed definitions of standards for energy efficiency that are adjusted after a certain period of time. For example, the definition of energy conservation targets is for a fixed five-year period, after which an adjustment is made. This could be problematic, as expectations and standards can change within this period, which could work against the progress of energy efficiency. Moreover, these binding targets do not provide opportunities for local governments to go beyond the limit set. Another possible problem with the energy conservation targets that might affect the sustainability of the HEE state is the use of energy intensity as the sole indicator of achieving energy efficiency enhancements. This makes it possible for local governments to still increase their consumption of energy and meet the target as long as the gross domestic product does not increase at a slower rate. In terms of scope, great attention has been focused on selected sectors and products that are deemed to be energy-intensive, but other household energy-use services have been overlooked. It was not until 2016 that the government expanded the energy efficiency labelling standards to cover most public energy-use services. Therefore, untapped efficiency potentials in major sectors such as buildings, transportation, and industry still remain. For example, in the transportation sector, energy efficiency is lagging with regard to inland waterways, air transportation, and trucks.

The second possible reason could be due to the low energy price regime in China, which discourages energy efficiency investment. Third, energy efficiency policies could be part of the problem itself as a result of Jevons paradox, where improvement in energy efficiency will lower the energy price but facilitate a rise in energy consumption, which is referred to as the rebound effect. In China, Zhang and Lin Lawell (2017) found evidence of a significant macroeconomic price rebound effect for each province in China. Other factors such as the low level of energy technology and lack of capacity building for energy saving might account for the unsustainable nature of the HEE state.

Table 8 Transition probabilities from time-homogeneous Markov (with covariates)

State switch	Transition intensities	Prob. being next	Transition probabilities			
			Time interval in years			
			One	**Two**	**Three**	**Four**
$HEE \rightarrow HEE$	-0.4466 (-.6286, -.3173)	0	0.6842 (.5758, .7768)	0.5061 (.3663, .6306)	0.3991 (.2661, .5445)	0.3329 (.2137, .4907)
$HEE \rightarrow MEE$	.4093 (.2668, .6279)	1 (.9957, .1)	0.2375 (.1704, .3177)	0.3070 (.2348, .3934)	0.3323 (.2555, .4124)	0.3439 (.2671, .4167)
$HEE \rightarrow LEE$	0.0373 (.0027, .5231)	1.405e-07 (2.914e-12, .00433)	0.0783 (.0466, .1230)	0.1868 (.1228, .2746)	0.2686 (.1785, .3626)	0.3232 (.2200, .4356)
$MEE \rightarrow HEE$	0.2852 (.1667, .4881)	0.2844 (.1526, .4675)	0.1466 (.0755, .2510)	0.1894 (.1009, .3109)	0.2050 (.1071, .3549)	0.2122 (.1161, .3632)
$MEE \rightarrow MEE$	-0.7817 (-1.0810, -.5652)	0	0.5112 (.4235, .5906)	0.3971 (.3214, .4809)	.3700 (.2892, .4474)	0.3632 (.2866, .4411)
$MEE \rightarrow LEE$	0.4965 (.3315, .7436)	0.7156 (.5325, .8474)	0.3422 (.2553, .4350)	0.4134 (.3071, .5157)	0.4250 (.3050, .5299)	0.4246 (.2946, .5385)
$LEE \rightarrow HEE$	0.0606 (.0113, .3243)	1.366e-04 (2.499e-07, .0685)	0.0417 (.0195, .0987)	0.0994 (.0495, .1847)	0.1429 (.0723, .2674)	0.1719 (.0906, .3132)
$LEE \rightarrow MEE$	0.4236 (.2628, .6827)	0.9999 (.9315, 1)	0.2950 (.2126, .3818)	0.3564 (.2726, .4425)	0.3663 (.2762, .4442)	0.3660 (.2853, .4428)
$LEE \rightarrow LEE$	-0.4842 (-.7401, -.3168)	0	0.6633 (.5494, .7562)	0.5442 (.4226, .6503)	0.4907 (.3617, .6052)	0.4621 (.3348, .5761)
-2*log-likelihood	601.9066					
	HEE	**MEE**	**LEE**			
Duration of States	4.4586 (3.06010, 6.4530)	4.2904 (3.3532, 5.2436)	4.2514 (2.8862, 5.5970)			

Figures in parentheses are the lower and upper confidence intervals at 97.5%.

Table 9 Transition probabilities from time-homogeneous Markov (with covariates)

	State table	Transition intensities	Time interval in years			
State switch			**One**	**Two**	**Three**	**Four**
$HEE \rightarrow HEE$	150	-0.3851	0.655	0.4793	0.3892	0.3431
		(-.5176, -.2865)	(.4802, .8011)	(.2912, .6817)	(.2180, .6064)	(.1846, .5672)
$HEE \rightarrow LEE$	54	0.3851	0.3445	0.5207	0.6108	0.6569
		(.2865, .5176)	(.1989, .5198)	(.3183, .7088)	(.3936, .7820)	(.4328, .8154)
$LEE \rightarrow HEE$	45	0.4199	0.1441	0.2178	0.2554	0.2747
		(.3047, .5788)	(.0572, .3364)	(.0849, .4542)	(.1061, .4976)	(.1127, .5247)
$LEE \rightarrow LEE$	111	-0.4199	0.8559	0.7822	0.7446	0.7253
		(-.5788, .3047)	(.6636, .9428)	(.5458, .9151)	(.5024, .8936)	(.4753, .8873)
	HEE	**LEE**				
Duration of States	7.31	5.69				
	(6.3183, 4.7087)	(8.2913, 6.6817)				

Figures in parentheses are the lower and upper confidence intervals at 97.5%

5. Conclusion

This study examines energy efficiency transitions in China using data from 30 provinces that cover 2003–2015. The study combines the stochastic frontier model with the panel Markov-switching regression. The following results emerged from the study.

Persistent energy inefficiency is higher than transient energy inefficiency. This is an indication that, in China, environmental sustainability and energy security will benefit more from policies aimed at the long term, such as energy efficiency regulation, upgrade of technology, and promotion of technical and managerial competencies. Also, overall energy efficiency estimates reveal significant regional and provincial heterogeneities, and most of the current energy efficiency programs are developed and directed towards specific sectors. For example, the Top-1000 Energy-consuming Enterprise Program is dedicated to the industrial sector, while the National Energy Efficiency Design Standard for Public Buildings is aimed at the building sector. Policies dedicated to provincial level seem rare. In the national five-year plans, the provincial targets for energy intensity and emission intensity reduction are specified; however, as discussed in Filippini and Zhang (2016) and Zhang (2017), energy intensity is different to energy efficiency. Therefore, the policy makers need to design provincial-level efficiency measures to close the regional gap.

Our second-stage analysis shows that human capital development, FDI, and urbanization promote energy efficiency, but income and price reduce it. This suggests the need for several indirect complementary policies for efficiency improvement. Although education level relies on talents, factors of environment, infrastructural gaps, and financial constraints can impact negatively on acquiring the necessary skills and knowledge that are beneficial for energy efficiency enhancement and environmental sustainability. Therefore, policies aimed at removing infrastructural gaps and financial constraints in China may prove useful for enhancing education levels and, hence, improving energy efficiency. For instance, the central government should broaden access to education to poor households in the less developed provinces of Guizhou, Gansu, Qinghai, Ningxia, Anhui, Sichuan, and Yunnan by increasing government financial aid to the poor in these provinces above the current level and expanding the scheme to cover senior high school and other non-fee costs (i.e. travelling and learning materials). Similarly, business opportunities may attract FDI to a location (as mentioned by this reviewer), but this may be conditional on the economic and political risks as well as the level of infrastructure development in these areas. Minimizing these risks and enhancing infrastructure development, complemented with tight environmental regulation, should attract FDIs that will enhance energy efficiency. Also, these provinces need an economic facelift to become preferred FDI destinations. Therefore, prioritizing these areas in the national development agenda is crucial not only for economic growth but also for energy efficiency improvement. Deregulating the price of energy could equally help to stimulate investment in energy efficiency.

Further, the results show that the high energy-efficient state is less sustainable than the lower energy-efficient state; that is, the movement away from the frontier is more persistent than movement towards the frontier, indicating that energy efficiency policies or programs in China lack robustness. In order to increase the persistence of the high energy-efficient state, the government couldconsider the following strategies: (1) national energy efficiency policies should consider the entire economic system instead of focusing on some key sectors or products. In this way, the economy can harness the full benefits of energy efficiency; (2) the set-up of energy efficiency policies should be made flexible, for example by implementing a three-year regular update to accommodate behavioural changes that affect consumption and production patterns. This can provide opportunities for regular review of policies and technological upgrade and repair; (3) beyond the minimum binding target set for energy conservation, the central government should provide incentives such as one that is tied to local budget allocation for provinces that are willing to go beyond the set target; (4) the government should also set energy consumption reduction targets; (5) the government should complement the current energy efficiency policies with energy sufficiency policies that aim at limiting the growth in energy services. This can be achieved either by travelling less, using less light, encouraging lower speeds and building smaller houses, or substituting energy services such as bicycles for cars and thermal underclothing for central heating, etc.

Acknowledgement

This article benefited from the useful comments of five anonymous reviewers and the editor. The usual disclaimer applies. The work described in this paper was substantially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU 21603917) and a startup grant from City University of Hong Kong (7200527).

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Appendix

A. Levin-Lin-Chu unit root test

	EF	lfdi	ledu	lypc	ur	lgpl	P
LLC stats	-9.787***	-7.481***	-10.662***	-7.180***	-14.579***	-9.686***	-7.796***

B. Choice of Markov model

	Time-homogeneous Markov	**Time-inhomogeneous Markov**	**Null hypothesis**	**Log-likelihood ratio statistics**
-2*log-likelihood	639.2728	632.8176	There is no significant time-inhomogeneity	6.4552 (df=6) [0.3742]

C. Choice of Markov model

	Time-homogeneous Markov (no covariates)	**Time-homogeneous Markov (with covariates)**	**Null hypothesis**	**Log-likelihood ratio statistics**
-2*log-likelihood	639.2728	601.9066	Model with no covariates fit better than model with covariates	37.3663 (df=24) [0.0402]

D. Choice of Markov model

	AIC	**-2*log-likelihood**	**Log-likelihood ratio statistics**
2-state model	427.2319	423.2319	-216.0409 (df=4) [1.000]
3-state model	651.2728	639.2728	

E. Choice of Markov model

	Time-homogeneous Markov	**Time-inhomogeneous Markov**	**Null hypothesis**	**Log-likelihood ratio statistics**
-2*log-likelihood	423.2319	418.1325	There is no significant time-inhomogeneity	5.0994 (df=2) [0.0781]

F. Choice of Markov model

	Time-inhomogeneous Markov (no covariates)	**Time-inhomogeneous Markov (with covariates)**	**Null hypothesis**	**Log-likelihood ratio statistics**
-2*log-likelihood	418.1325	409.2736	Model with no covariates fit better than model with covariates	8.8589 (df=8) [0.3543]