Effects of urbanisation on energy efficiency in China: new evidence from short run and long run efficiency models

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Abstracts:

Energy efficiency in China has been the cause for increasing concern for national and local sustainable development due to rapid economic development and large-scale energy consumption. Using panel data of 30 provinces between 1997 and 2016, this study explores the effects of urbanisation on different types of energy efficiency. First, the measurement of energy is disentangled, with long-run and short-run efficiencies derived. The results of energy efficiency analysis highlight that the predominant long-run efficiency is low, with disparate energy efficiency present between provinces. It is verified that improving energy efficiency will be a long run challenge in China. Second, the effects of urbanisation were found to be significantly negative on short-run, long-run and overall energy efficiency. Comparatively, the effect of urbanisation on long-run efficiency was shown to have recently grown, implying an urgent call for energy conservation during rapid urbanisation. Finally, this study outlines broader implications and suggests policies to improve energy efficiency. Here, the application of energy conservation technology, industrial structure upgrading and efficiency information disclosure to urban residents are thought to be smart ways to improve energy efficiency.

Key words:

Total factor energy efficiency, urbanisation, short run, long run, China

1. Introduction

The production and use of energy are necessary for economic development, as such energy consumption is an increasing trend in China given its current development stage. Outpacing the US, China has become the largest energy consumer since 2009 due to rapid urbanisation (Liu et al., 2017) and Industrialisation (Li and Lin, 2015). The issues of energy consumption and energy performance in China have caused much concern. Large-scale energy consumption and a coal-dominated energy structure have placed a considerable amount of pressure on energy security and contributed to climate change and environment pollution (Guan et al., 2012). To address these problems, it is argued that cost-effective ways to reduce energy intensity or improve energy efficiency should be implemented (Ang et al., 2010), reopening debates on both energy efficiency and its dynamics (Le Pen and Sévi, 2010). Energy efficiency has been subject to growing attention within governments and in academia, particularly within developing countries. With respect to China, the evolution of energy intensity and regional disparity has seen energy demand increase dramatically (Wu, 2012a; Zeng et al., 2014).

Cities have become central for many human activities, with mass migration (from rural to urban areas) stimulated by an increasing desire to achieve an improved quality of life along with access to better education and medical services. Urbanisation of China is one of the two key issues affecting the 21st century as stated by Joseph Eugene Stiglitz (Chen and Lu, 2016). China has experienced an unprecedented urbanisation process after it launched the reform and open-up policy in 1978 and its urbanisation is expected to continue rising (Lv et al., 2019b). However, energy consumption per capita in urban areas of China has been found to be almost six times of that in rural areas (Dhakal, 2009), which implies the pressure on energy brought by urbanisation. Urbanisation should not be at the cost of intensive energy use and environment pollution. In March 2014, the Central Committee of the Communist Party of China (CPC) and the State Council jointly released the "National New-type Urbanisation Plan (2014–2020)", with the aim to promote energy efficient with urbanisation. Energy intensity has also been used since 2006 as the constrained indicator of energy conservation policy in the five-year plan of China (NPC, 2006[1]). The development mode of urbanisation is related to the achievement of the target of energy intensity. To design energy conservative policies during urbanisation in China, it is important and urgent to explore the relationship between urbanisation and energy efficiency.

Above all, as the effectiveness of energy efficiency to constrain energy consumption and the importance of urbanisation to economic development, the following questions have caused much concern in China. How does energy efficiency in China evolve over time? Does the energy efficiency in China have a long term or short term effect and how does the corresponding policy respond to these effects? What is the role and effect of urbanisation on long- and short-run energy efficiency? The answers to these questions have important implications for urbanisation policy and energy governance. There is rare study about the impact of urbanisation on long- and short- run energy efficiency, which is related to the long and short change of energy utilization behavior caused by urbanisation. To address these questions, this study will focus on adopting several means to measure energy efficiency and investigating the impacts of urbanisation on different types of energy efficiency. It validates the measurement of total factor energy efficiency, explores the evolution of energy

[1] National People's Congress (NPC), Available online: http://www.npc.gov.cn/wxzl/gongbao/2006-03/18/content_5347869.htm (In Chinese)

efficiency and analyzes the effect of urbanisation on energy efficiency in China.

The main contributions of this study are twofold. For the first time, total factor energy efficiency will be defined and measured by distinguishing the components in stochastic frontier model, where individual effects are disentangled and long- and short-run inefficiencies are measured at the provincial level in China. The disparity between individual heterogeneity, long run efficiency, short run efficiency and disturbance term, which contributes to exact estimation and recognition of efficiency, has been specified within stochastic frontier model in recent years (Acosta and De los Santos-Montero, 2019; Musau et al., 2020), but lacks detailed empirical evidence on China. Here, individual effect is used as a different term from efficiency and reveal heterogeneity in characteristics between provinces. While previous studies have not fully considered long-run inefficiency, it can be shown to make up a key proportion of overall inefficiency and has been caused primarily by lagged technology, and excessive and obsolete capacity in China (Li and Lin, 2016). Second, previous literature, which investigates the impact of urbanisation on energy efficiency, has been found to be mostly focused on energy intensity (Lin and Zhu, 2017; Song and Zheng, 2012; Yan, 2015). In contrast, this study explores the impact of urbanisation on different types of total factor energy efficiency. That is, this study compares the effect of urbanisation on both short- and long-run energy efficiency, from which quantitative evidence for national policy making will be presented.

The rest of this paper is organized as follows. Section 2 presents a review of the literature, focusing on studies that measure energy efficiency and the impact of urbanisation. Section 3 describes the methodological approach for measuring energy efficiency and modelling the impact of urbanisation and introduces all the data sets used. Section 4 presents and discusses the empirical results from analyses and models. From which the main conclusions, policy implications and limitations of this study are drawn and presented in section 5.

2. Literature review

2.1. Measurement of energy efficiency

To assess policies of energy conservation and design price tools (such as allowance and tax) and non-price instruments as incentives and to evaluate the effectiveness of energy efficiency policy, the first step is to make an accurate measurement of energy efficiency. Thereby, it is necessary to define a more reliable indicator to measure energy efficiency. Commonly, energy intensity (a single factor energy efficiency indicator) is used and calculated as the division of energy consumption by GDP. Due to high easiness of understanding and calculating it, a wide range of studies have used energy intensity as an indicator of energy efficiency (Hajko, 2014; Li and Shi, 2014; Lin and Zheng, 2017; Markandya et al., 2006). Although extensively used, it has been criticized as an insufficient indicator (Ang et al., 2010; Proskuryakova and Kovalev, 2015). Energy intensity, which focuses on the relationship between energy input and output, has ignored the factor substitution with other inputs during the production process. In turn, this ignorance can cause an issue of partial factor energy efficiency measurement (Hu and Wang, 2006). Total Factor Energy Efficiency (TFEE) has been acknowledged as a viable alternative due to an enhanced benchmarking performance (Zhou and Ang, 2008), thus leading to increased debate. Two main frontier methods that have been widely utilized to establish TFEE measurements are: non-parametric and parametric frontier analysis. The former, Data Envelopment Analysis (DEA), was first applied by Hu and Wang (2006). A series of subsequent studies have since extended this method to create the non-parametric frontier approach (as shown in Table 1). Employing DEA has been shown to be limited in measuring energy efficiency due to statistical noise being ignored, blended unobservable heterogeneity among individual effects and unfeasible statistical tests (Filippini and Hunt, 2015).

As an alternative technique, Stochastic Frontier Analysis (SFA), has an advantage over DEA by including stochastic error terms and a statistical test. Furthermore, the assumption of a unique deterministic frontier in DEA has been argued as being too strong, a limitation not identified in SFA (Filippini and Hunt, 2015). Based on the pioneering work of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), Stochastic Frontier Models (SFM) have been well developed, with models extended in many aspects. When considering unobserved heterogeneity, panel data models have the advantage, where original panel SFM, such as Pitt and Lee (1981); Zhou et al. (2010) and Schmidt and Sickles (1984), have mixed individual effects with long-run inefficiency, and the inefficiency term has been regarded as an individual, random or fixed effect. However, they are pooled and therefore not true panel data models with individual effects. This problem is critical in policy design because unobservable heterogeneity has been highlighted as a major reason for poor selection (Colombi et al., 2017). Confusion concerning the conceptualization and terminology of heterogeneity and inefficiency has been shown to greatly distort inefficiency measures (Greene, 2005a). As a result, Greene (2005b) has suggested that individual heterogeneity be isolated from inefficiency using a "true" random or fixed effects SFM. Thus, estimated inefficiencies can vary in time (i.e. be transient) and long-run impacts can be incorporated into individual effects. Estimation of "true" SFM was improved by Chen et al. (2014) and Wang and Ho (2010). As only time varying components are included in the inefficiency term of "true" SFM, with long-run inefficient impacts contained to individual effects, a downward bias in overall inefficiency is produced (Colombi et al., 2014). As a consequence, it is important to disentangle long-run inefficiencies from models (Greene (2005b). Nascent research has started to focus on disentangling individual heterogeneity, long-run (time invariant, persistent) and short-run (time varying, transient) efficiencies within models (Colombi et al., 2014; Kumbhakar et al., 2014). Generally, persistent inefficiencies, which reveal rigidities in production processes, are caused by obsolete equipment that has not been replaced for long periods, old production machines, old buildings, old road systems and systematic behavioral failures (Filippini and Hunt, 2015). Transient inefficiencies, on the other hand, are caused by short-run moral hazards such as inefficient supplier selection, sub-optimal resource allocation and trial-and-error processes in unknown situations (Colombi et al., 2017).

As previously noted, SFM has been used widely to measure energy efficiency (see Table 1), whereas only a limited number of nascent studies have focused on disentangling heterogeneity, long-run and short-run efficiencies (Badunenko and Kumbhakar, 2016; Colombi et al., 2014; Kumbhakar et al., 2014). Two major problems that could lead to risks in the development of Chinese economy are excessive and obsolete production capacities. The elimination of obsolete capacity and removal of excessive capacity are two ways in which industrial structural change and upgrade can improve energy efficiency (Li and Lin, 2016). The industrial sector has already experienced several rounds of excess capacity since 1990 and thereby excess capacity has become a long-run structural problem, which suffers from recurrence in the production process (Yu and Shen, 2020). Due to the above-mentioned obsolete and excess production capacities, energy inefficiencies may have sustained over a long period, hence, the detection of long-run inefficiencies is crucial for understanding the quality of urbanisation across China. In addition, both urbanization and energy consumption (e.g. energy endowment, climate) have demonstrated strong regional heterogeneity at province level across China. However, previous studies on energy efficiency in China have not considered these heterogeneous and dynamic effects, even though distinctions between them have been found to contribute to the accurate measurement and estimation of energy efficiency. Therefore, models that disentangle heterogeneity, persistent and transient inefficiencies are used in this study to investigate both types of inefficiencies in China's energy consumption simultaneously.

Table 1 Summary of recent methods for measuring energy efficiency

Method	Characteristics	Reference
DEA	Slack and radial adjustments of energy input	Hu and Wang (2006)
	Propose Shephard energy distance function	Zhou et al. (2008)
	Include bad output	Zhou and Ang (2008)
	Treat sectoral **heterogeneity** technology	Wang et al. (2017)
	Consider technology **heterogeneity** across groups	Huang et al. (2018)
	Deal with congestion input	Zhou et al. (2017)
SFA	Use SFA to estimate energy input requirement function	Boyd (2008)
	Estimate USA residential aggregate energy demand using SFM by Aigner et al. (1977), Pitt and Lee (1981), Greene (2005a)	Filippini and Hunt (2012)
	Use Cobb-Douglas function to model Shephard energy distance function	Zhou et al. (2012)
	Use parametric meta-frontier to deal with **heterogeneity** between provinces	Lin and Du (2013)
	Measure the TFEE of Japanese regions based on the method by Zhou et al. (2012)	Honma and Hu (2014)
	Employ latent class stochastic frontier model by considering **heterogeneity** between provinces	Lin and Du (2014)
	Distinguish **heterogeneity, long-run and short-**run efficiency	Filippini and Hunt (2015)

2.2. Urbanisation and energy efficiency

New type urbanisation has emerged as a vital policy for Chinese economic development. As such, the impact of urbanisation on energy use has become a main concern in policy making. Poumanyvong and Kaneko (2010) summarise the theories on the relationship between urbanisation and environment into three strands: ecological modernization, urban environmental transition and compact city theories. In addition, the sustainable development and consumer behavior preference theories are instrumental in explaining the relationship, as the construction of sustainable urbanisation highlights energy conservation and one indispensable aspect of urbanization, which is internal migration from rural to urban areas, incurs consumer preference altered. In the study of Madlener and Sunak (2011) and Sadorsky (2013), the transmission mechanisms of urbanisation on energy use are explained in detail from four perspectives including urban production process, mobility and transportation, infrastructure and urban density, and private households. As a process accompanied by industrialisation and economic development, urbanisation has an intrinsic motivation to affect energy demand and efficiency from different aspects. On one side, urbanisation is a process associated with internal migration from rural to urban with changing consumer behavior and lifestyle and growing adoption of electric appliances, economic structure change with agriculture mechanization and enlargement of energy intensive industry, infrastructure construction and maintenance, transportation growth by long distance mobility and commuting, as well as urban logistics and service. Thereby, it is reasonable to predict high energy demands because of rapid urban development driven by the construction of urbanisation. On the other side, urbanisation is also a complex process accompanied by technological advantages and economies of scale that can improve energy efficiency and decrease overall energy use (Madlener and Sunak, 2011; Wang, 2014). The net effect of urbanisation on energy efficiency is unclear and need further empirical investigation.

A plethora of empirical studies has concentrated on the impact of urbanisation on energy use. Mohammadi and Ram (2012) find that countries with high levels of urbanisation are likely to converge to higher levels of energy consumption. Mrabet et al. (2019) suggest a positive impact of urbanisation on non-renewable energy demand in both developed and emerging countries while it has a higher elasticity in the former group. Regarding the rapid urban development and large amount of energy demand in China, how to achieve efficient energy consumption and sustainable urban growth is of importance. Among the series of studies focusing on China, Zhang and Lin (2012) show that the positive impacts of urbanisation on energy consumption vary across regions and decline continuously from the western region to the central and eastern regions. Wang et al. (2014) find a one-way positive causal relationship from urbanisation to energy consumption. Zhou et al. (2015) present that urbanisation increases energy consumption in the eastern and central regions of China, whereas unclear effects present in the western regions where is less developed with low level of urbanisation. Chen (2018) confirms the resulting findings of Zhang and Lin (2012) in the study of renewable energy consumption.

However, the previous studies have seldom addressed the impact of urbanisation on energy efficiency or have simply used energy intensity as an indicator of energy efficiency (Farajzadeh and Nematollahi, 2018; Sadorsky, 2013). Song and Zheng (2012) reported a positive impact of urbanisation on energy intensity using data at provincial level of China. This is consistent with the study by Yan (2015), where a varied elasticity of urbanisation was revealed on aggregated and disaggregated energy intensity. Ma (2015) reports diversification in the impact of urbanisation on energy intensity between disaggregated energy, but is not robust enough in terms of analytical methods. Huang and Yu (2016) confirm the unequal effect of urbanisation on energy intensity across regions. Lin and Zhu (2017) reveal an inverted U-shaped effect of urbanisation on energy intensity in China. Lv et al. (2019a) distinguish the direct and indirect effects of urbanisation on energy intensity across Chinese cities by adopting the spatial Durbin modelling approach. The inconsistent results may be caused by different sampling periods and estimation methods. Among these studies, which take energy intensity as an indicator of energy efficiency, the substitution between energy and other production factors has been ignored, which induces a biased estimation of energy efficiency. To the best of the authors' knowledge, only Lv et al. (2017) and Li et al. (2018) have analyzed the impact of urbanisation on TFEE. However, current studies have not taken into account long- and short-run scales, as a limitation this study will address.

3. Methods and data

3.1. Definition and measurement of energy efficiency

Suppose there are three inputs, capital (K), labor(L) and energy (E) and one output, gross domestic production (GDP, Y) in the production process. Then, the production technology can be presented as:

$$T = \{(K, L, E, Y) : K, L, E \text{ can produce } Y\} \quad (1)$$

The definition of Shephard energy distance function $D_E(L, K, E, Y)$ by Zhou et al. (2012) is utilized to measure total factor energy efficiency.

$$D_E(L, K, E, Y) = \sup_{\theta}\left\{\theta : \left(L, K, \frac{E}{\theta}, Y\right) \in T\right\} \quad (2)$$

According to the definition, $\frac{E}{D_E}$ is the hypothetical energy use and the TFEE can be defined as the ratio between hypothetical and actual energy use:

$$TFEE = \frac{1}{D_E} \tag{3}$$

To find out a numerical energy efficiency, the definition of Shephard energy distance function need to be expressed in functional representation. Here, a trans-log transformation function is used.

$$D_E(L,K,E,Y) = \exp\left(\beta_0 + \sum_{n=1}^{4}\beta_n \ln(X_n) + \frac{1}{2}\sum_{m=1}^{4}\sum_{n=1}^{4}\beta_{mn}\ln(X_m)\ln(X_n) + \nu\right) \tag{4}$$

Where X_i represent K,L,E,Y and ν is the statistical noise and measurement error.

Following the definition (2), D_E is linearly homogeneous in energy. So,

$$D_E(L,K,\lambda E,Y) = \lambda D_E(L,K,E,Y) \tag{5}$$

using a trans-log transformation function to represent the distance function, the SFM to measure TFEE is listed as follows:

Taking logarithm of (4) and (5) and then substituting (4) into (5), the following equation is derived:

$$\begin{aligned} -\ln E &= \ln\beta_0 + \beta_Y \ln Y + \beta_L \ln L + \beta_K \ln K \\ &+ \beta_{YL}\ln Y \ln L + \beta_{KL}\ln K \ln L + \beta_{KY}\ln K \ln Y \\ &+ \beta_{YY}(\ln Y)^2 + \beta_{KK}(\ln K)^2 + \beta_{LL}(\ln L)^2 \\ &+ \ln \nu - \ln D_E(L,K,E,Y) \end{aligned} \tag{6}$$

The three kinds of inputs are treated asymmetrically, in order to limit the contraction potential of energy only. TFEE, the focus of this study, is represented as $e^{-\ln D_E(L,K,E,Y)}$ in equation (6). The equation (6) belongs to SFM and some specification methods of SFM are chosen to estimate TFEE. However, there are no clear criteria to choose a unique specification of SFM (Farsi et al., 2006). For comparison, three kinds of specification are chosen to develop the model (1). First, one of the earliest time invariant panel data SFM developed by Schmidt and Sickles (1984) is chosen and time invariant (long run) efficiency scores are derived from their model. Second, the true fixed effects model by Greene (2005b) is used and time varying true efficiency scores are estimated. Third, the four-component model by Kumbhakar et al. (2014) is chosen to disentangle individual effects, persistent and transient inefficiency. All these models are specified in the following equations:

$$
\begin{aligned}
-e_{it} = \ & \beta + \beta_Y y_{it} + \beta_L l_{it} + \beta_K k_{it} \\
& + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} \\
& + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + v_{it} - u_i
\end{aligned} \tag{7.1}
$$

$$
\begin{aligned}
-e_{it} = \ & \beta + \beta_Y y_{it} + \beta_L l_{it} + \beta_K k_{it} \\
& + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} \\
& + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + \mu_i + v_{it} - u_{it}
\end{aligned} \tag{7.2}
$$

$$
\begin{aligned}
-e_{it} = \ & \beta + \beta_Y y_{it} + \beta_L l_{it} + \beta_K k_{it} \\
& + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} \\
& + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + \mu_i + v_{it} - u_i - u_{it}
\end{aligned} \tag{7.3}
$$

where i=1, 2, ……n; t=1……T. Variables in lowercase correspond to logarithm of variables in (6), μ_i is the individual term and v_{it} is the error term. In model (7.1), u_i is the inefficiency term. In model (7.2) u_{it} is the time varying inefficiency term. In model of (7.3), u_{it} and u_i are the transient and persistent inefficiency terms respectively. Three kinds of time varying efficiency scores were derived; GREENE2005 from (7.2), TRANSIENT from (7.3) and OVERALL from (7.3). Two kinds of time invariant efficiency scores were also derived; SS1984 from (7.1) and PERSISTENT from (7.3).

3.2. Modelling the impact of urbanisation on energy efficiency

To explore the effects of urbanisation on different types of energy efficiency, regression models are established by treating energy efficiency as dependent variable and urbanisation as the independent variable of interest.

$$EE_{it} = \alpha + \beta_1 URB_{it} + \beta_2 X_{it} + \varepsilon_{it} \tag{8}$$

Where EE is energy efficiency corresponding to several types of energy efficiency defined above. Here, time varying efficiency can be indicated by SS1984 and PERSISTENT, and time invariant efficiency can be indicated by GREENE2005 and TRANSIENT, and OVERALL. In total, five models using five types of energy efficiency as dependent variables are developed. URB indicates urbanisation and X represents the chosen control variables. All variables were transformed into log variables to alleviate heteroscedasticity and order of magnitude thereby producing comparable results by elasticity. As dependent variable in the model is limited and can be considered as fractional data due to its definition, following the discussion by

McDonald (2009), ordinary least squares estimation is preferred and heteroskedastic-consistent standard errors are calculated .

In addition to urbanisation, extensive studies have examined other factors affecting energy efficiency, which are added to the model as control variables. According to these previous studies, economic development (Filipović et al., 2015), energy price (Herrerias et al., 2013; Löschel et al., 2015), foreign direct investment (FDI) and trade (Adom, 2015; Adom and Amuakwa-Mensah, 2016), technology improvement and economic structure (Sadorsky, 2014) have been proven significant factors.

(1) Economic development (per capita GDP, PERGDP) has been found to support the development of energy conservation technology and the application of energy saving electric appliances in the home. Where, Wu (2012) and Yu (2012) find a negative effect of income on energy intensity in China. To explore the existence of Kuznets curve, the quadratic per capita GDP (PERGDP2) has also been included. Here, the value of GDP is adjusted by GDP inflation index to the base year, 1997.

(2) Industrialisation (IND) has been found to be a process that accompanies urbanisation, with secondary industry the largest sector for energy consumption. China has been found to place more emphasis on energy conservation during the transformation and upgrading of industry (Feng et al., 2009). Jiang and Ji (2016) and Liao et al. (2007) reveal that industrialisation has boosted energy intensity in China. Industrialisation is indicated by the percentage of industry value added to GDP.

(3) In addition to industry, tertiary (TER) is another sector within the economic structure. Due to urbanisation and the improving living standard of residents, there is great scope for the development of the service industry. Thereby the contribution of the tertiary sector to value added to GDP has grown in China. The effect of tertiary on energy uses causes much concern (Yuxiang and Chen, 2010).

(4) Energy price (PRICE) is a vital variable to energy efficiency, due to its role in production theory. According to "law of diminishing marginal returns" (Birol and Keppler, 2000), the increase in energy price improves the energy efficiency, if the rebound effect of price is small or ignored. In line with the study of Liu et al. (2017), power purchasing price index was adopted as a proxy for energy price.

(5) Foreign direct investment (FDI) plays an important role in the transfer of technology, managerial skills and human capital. FDI affects energy efficiency through scale effect, composition effect and technique effect (HÜBLER and KELLER, 2010). The ratio of FDI to GDP was adopted as a control variable, with FDI converted into Renminbi (RMB) using the exchange rate between RMB and US dollar.

(6) International trade (TRADE) has been increasing in China since the introduction of the open-door policy in 1978. However, the effect of trade on energy

consumption and the environment has been subject to growing concern (Antweiler et al., 2001; Peters et al., 2011). Trade affects energy consumption in a direct way through energy trade and indirectly as energy embodied in products. It is also one way of international technology spillover. While Zheng et al. (2011) confirmed the driving forces of increasing trade on energy intensity, Yu (2012) found no significant effect of export. The indicator for trade was thus calculated as the proportion of import and export to GDP.

(7) Technology progress (R&D) includes upgrades to industrial production technology, application of advanced equipment, innovation and patents. Huang and Yu (2016) reveal that research and development (R&D) is a powerful tool to decrease energy intensity in China. However, due to the inherent difficulties of measuring technology (Wang et al., 2012), there is no coherent indicator for technology. One solution is to choose a proxy, such as R&D expenditure, R&D researchers, application of patents, patents granted, and so on. Following the work by Huang and Yu (2016) and Lin and Zhao (2015), the ratio of R&D expenditure to GDP was chosen as a proxy for technology progress.

3.3. Data sources and descriptions

Considering data availability and consistency, this study collected two-category data from 1997 to 2016 for the 30 provinces of China. **First**, one output variable and three input variables (labor, capital and energy) were collected for the measurement of model (1). The output variable was represented by gross domestic product (GDP) and was converted to the 1997 price using a GDP deflator. Labor was represented by persons employed in an urban area at the year-end. The data for capital stock was calculated using the perpetual inventory method (PIM), as described by Zhang et al. (2004) and was adjusted by the price index of investment of fixed assets. Data was collected from National Bureau of Statistics of China and the China Energy Statistical Yearbook (1998-2017).

Second, in model (2), urbanisation was represented by the percentage of urban population to total population, with the data before 2000 amended by Zhou and Tian (2006). Data for GDP per capita, energy price, FDI, trade, R&D, industry value added, tertiary value added were collected from China Price Statistical Yearbook, China Statistical Yearbook and Statistical Yearbook of provinces (1998-2017) and regional Statistical Yearbook (1998-2017). Descriptive statistics of all variables are presented in Table 2.

Table 2 Descriptive statistics of all variables.

Variables	mean	std	min	median	max	cv
e	8.898	0.836	5.966	8.962	10.570	0.094
y	7.719	0.861	5.312	7.806	9.311	0.112
l	7.522	0.825	5.561	7.617	8.814	0.110

k	9.414	1.174	5.953	9.426	12.020	0.125
URB	3.818	0.323	3.069	3.823	4.495	0.085
IND	3.621	0.251	2.477	3.684	3.971	0.069
TER	3.705	0.168	3.343	3.687	4.385	0.045
PERGDP	8.793	0.464	7.671	8.738	10.060	0.053
PRICE	3.866	0.450	2.560	3.933	4.605	0.116
FDI	0.551	1.069	-3.254	0.694	2.801	1.940
TRADE	2.835	1.008	1.165	2.529	5.148	0.356
R&D	-0.153	0.789	-2.353	-0.115	1.846	-5.169

Notes: all variables are taken logarithm.

4. Empirical results and discussion

4.1. Description of efficiency scores

The summary statistics for energy efficiency scores derived from the three SFA models (1.1), (1.2) and (1.3) are presented into **Table 3**. **First**, the mean efficiency scores from the true fixed effects model (GREENE2005) and the mean transient efficiency scores from the four component models (TRANSIENT) were found to be similar. This can be attributed to both measures only addressing the short-run (time varying) part of energy efficiency. **Second**, the estimated mean value of TRANSIENT efficiency was found to be larger than that of PERSISTENT efficiency. This indicates a significant difference between long-run and short-run inefficiency values. Energy inefficiency was found to be caused by persistent political and economic factors such as management or regulations, where energy inefficiency was better controlled in the short-run period. The standard error (std) and coefficient of variation (cv) show that the PERSISTENT efficiency was more volatile than TRANSIENT efficiency, indicating larger inequality between provinces in PERSISTENT efficiency. **Third**, the scores of PERSISTENT and SS1984 were found to be different. This verifies the necessity to separate heterogeneity from the model. The PERSISTENT model excludes the individual effect, while the SS1984 model does not consider such distinctions. To alleviate bias when calculating energy efficiency, it is necessary to incorporate heterogeneity as a term of individual effect into the model. **Fourth**, OVERALL was found to be lower than GREENE2005, which verifies the existence of possible persistent efficiency. The OVERALL model includes both persistent and transient efficiencies. However, the true fixed effect SFM was only found to cover short-run efficiency, ignoring long-run efficiencies and thus introducing an upward bias in efficiency. **Finally**, standard errors reported for the two kinds of time invariant efficiency scores (SS1984 and PERSISTENT) were found to be two of the largest, indicating a relatively high disparity in long-run efficiency between provinces.

Table 3 Description of efficiency results.

EE	Mean	std	Min	Median	Max	cv
SS1984	0.3610	0.2380	0.0484	0.3130	1.0000	0.6590
GREENE2005	0.9510	0.0231	0.6860	0.9540	0.9790	0.0243
TRANSIENT	0.9570	0.0171	0.7540	0.9600	0.9800	0.0179
PERSISTENT	0.5660	0.2130	0.1190	0.6200	0.8440	0.3760
OVERALL	0.5420	0.2040	0.1090	0.5820	0.8180	0.3770

Table 4 presents Pearson's correlation coefficients and Spearman's rank correlation coefficients between the five efficiency scores. First, the correlation coefficient between TRANSIENT and GREENE2005 was found to be high and significant. This suggests a consistent estimation for the short-run efficiency from both models. Second, the correlation between PERSISTENT and TRANSIENT was found to be insignificant and very low. This suggests that they are completely different parts of efficiency and thus, it is necessary to separate and distinguish between them when developing policy to improve energy efficiency. Until now, there has been no such distinction in regulation policy for improving energy efficiency, with no clear targets set to improve persistent and / or transient efficiencies. Third, high correlation was found between OVERALL and PERSISTENT but with respect to OVERALL and TRANSIENT, correlation was found to be insignificant. This highlights the predominant status of the time invariant part within the model. Thus, to improve energy efficiency and alleviate the disparity between provinces, impetus should be placed on the promotion of persistent efficiency.

Table 4 Correlation coefficients between the energy efficiency scores.

	SS1984	GREENE2005	TRANSIENT	PERSISTENT	OVERALL
SS1984		-0.0239	-0.0270	1.0000***	0.9930***
GREENE2005	0.0312		0.9987***	-0.0239	0.0569
TRANSIENT	0.0262	0.9977***		-0.0270	0.0538
PERSISTENT	0.8875***	0.0275	0.0238		0.9930***
OVERALL	0.8869***	0.0738*	0.0704*	0.9988***	

Notes: (1) Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation.
(2)*** p<0.01, ** p<0.05, * p<0.1

4.2. Results for the effect of urbanisation on energy efficiency

Table 5 presents the results for the two kinds of long-run efficiency. As long-run efficiency is time invariant, regression data (based on a five-year average) was developed to analyse the evolution of influence. Such sample division is in accordance with the five-year plan of China. Thereby, the sample was divided into four sub-samples corresponding with the following periods: 1997-2000, 2001-2005, 2006-2010 and

2011-2016. Here, the dependent variable was the PERSISTENT or SS1984 efficiency for each period and the independent variables used the average value in the corresponding period. For example, column (1) presents the results of the model when a long-run efficiency is taken as the dependent variable and independent variables are averaged between 1997 to 2000.

The coefficients of per capita GDP were shown to be significantly positive in all periods, ranging from 2.295 to 9.983. This is consistent with the reports by Ma (2015) and Yu (2012). The coefficients of quadratic per capita GDP were found to be negative and significant across all periods, excluding 2001-2005. Overall, the results show an inverted U-shaped relationship between economic development and persistent efficiency, supporting the EKC hypothesis (Jiang et al., 2014).

The coefficients of Industrialisation and the tertiary sector on long-run efficiency were found to be all negative, and only exert significant effects in the early periods. The effect of the tertiary sector is consistent with the conclusions drawn by Ma and Yu (2017). The insignificant results found for later time periods show that existing energy conservation policy in industry is efficient and that the strategy of industrial upgrading and adjustment in China is playing a vital role. This implies that inherent technology and technology that is embodied in existing equipment and transport systems can be characterized as mostly old with low capacity. Thus, the strategy of accelerating the process of eliminating old and backward equipment in China is meaningful in increasing overall energy efficiency.

The effect of energy price on long-run efficiency was found to be only significantly negative in the period 1997-2000, with measurement of SS1984, meaning that energy price is only significant in one out of 10 cases. As a result, it should be acknowledged that the effect of energy price on long-run efficiency is insignificant. This is similar to the finding by Liu et al. (2017) but is in contradiction with those by Huang and Yu (2016) and Wang (2017). However, this contradiction may be caused by different sample sizes and modeling methods. For example, Huang and Yu (2016) focused on energy intensity, while the data set used by Wang (2017) only spanned the years 2001 to 2013. The aim of increasing energy prices is to encourage the producer to decrease energy consumption and to apply more energy efficient technologies. It calls for further price reform and reveals the role of energy price in supply and demand although this may have a long way to go.

Regarding the effects of FDI, trade and R&D, coefficients were found to be all positive and significant (Jiang and Ji, 2016; Lv et al., 2016), with the exception of coefficients for trade in the sub samples; 1997-2000 and 2001-2005. From this, it can be concluded that the effect of FDI, trade and R&D on long-run efficiency have become more significant in recent years. Furthermore, the absorption abilities of technology were found to be higher in the long-run period.

Lastly, the effects of urbanisation on energy efficiency were analyzed. Taking the period 1997-2000 as an example, it was confirmed that a 1% increase in urbanisation level led to a 1.458% decrease in the PERSISTENT efficiency of China. This is in line with the result created by Li et al. (2018) and Ma (2015), although in these studies energy intensity was used to measure energy efficiency. Significantly negative effects were also found for the periods of 2001-2005, 2006-2010, 2011-2016 and full sample 1997-2016, with coefficients of -2.428, -2.761, -3.624, -2.602, respectively. Here, it is notable that elasticity has an increasing trend, indicating a high magnitude of effect in recent years. Same results were found for the long-run efficiency indicated by SS1984. As a result, this reveals that urbanisation impedes improvements to long-run energy efficiency in China. Due to its role in industrial restructuring, factor allocation optimization and economy of scale, urbanisation has been identified as a potential solution to overcome excess capacity and to improve long-run efficiency. However, such impacts have so far been limited, due to the abuse of energy intensive materials (such as iron and steel) in blind expansion, the policy burden of firms brought by migrant workers placement and the lagged replacement of household appliances.

Results for time varying efficiency are displayed in **Table 6**. Firstly, the results of economic development were found to be consistent with results of long-run efficiency. Secondly, Industrialisation and the tertiary sector were found to improve the short-run energy efficiency, contributing to energy policy, rules and standards in the management of new-build enterprise and the extension of old enterprises. This was also shown true for new-build transportation systems and buildings. The effects of Industrialisation and tertiary on OVERALL efficiency were found to be significantly negative (Jiang and Ji, 2016; Ma and Yu, 2017), indicating that the industry is energy intensive and dominated by the extension of energy intensive industries and the construction of energy consuming infrastructure. According to Ma and Yu (2017), construction of infrastructure that is demanded by urbanisation also increases the demand of energy-intensive products (Du et al., 2018). Thirdly, the effects of energy price on two short-run efficiencies and overall efficiency were found to be all significantly negative, which is similar to the findings from long-run efficiency models. Fourthly, the effects of FDI and trade were found to be insignificantly negative for short-run efficiency, but significantly positive for OVERALL efficiency (Lv et al., 2016). Improving the absorption ability of advanced technology brought by directly FDI and that indirectly embodied in imported products is critical in improving energy efficiency. The insignificant effects of FDI and trade on short-run efficiency also highlight the need to encourage foreign investment into the energy conservation industry. Fifthly, R&D was found to be significantly negative for short-run efficiency, with an opposite result for overall efficiency (Lv et al., 2016) and time invariant efficiency. Two reasons were found to explain the negative contribution of R&D to short-run efficiency. First, when investment in research increases, investment in energy technology does not increase at the same rate. Second, the transfer of technology was found to lag behind the development of technology. Thereby, it is necessary to accelerate and improve the rate of technology conversion. Finally, the coefficients for urbanisation were found to be significantly negative which is consistent with the result for long-run efficiency.

5. Conclusions and policy implications

Using a balanced dataset of 30 Chinese provinces from 1997 to 2016, this study has developed stochastic frontier models to disentangled individual effects from long-run and short-run inefficiencies. After comparing and evaluating the different types of energy efficiency, the effects of urbanisation on energy consumption is then distinguished between long-run and short-run efficiencies.

The main findings and policy implications of this study are summarized as follows. Firstly, the long-run efficiency is found to play an important part of energy efficiency in China. Long-run efficiency (PERSISTENT or SS1984) achieves lower scores and demonstrated a larger disparity between provinces when compared with short-run efficiency. There is still a long way to go to improve long-run efficiency across the country. Excess and obsolete production capacity, barriers to technology upgrades, and energy management problems in production have remarkably contributed to such low and unequal long-run efficiency. The constrained energy intensity target reported in the five-year plan of China includes a variety of policies to resolve the excess capacity, look to upgrade technology, and transform / upgrade industrial structure, which have been shown to be efficient in controlling long-run inefficiency.

Secondly, the effects of urbanisation on short-run, long-run and overall energy efficiency have been proven to be significantly negative (Li et al., 2018; Lv et al., 2017; Ma, 2015; Rafiq et al., 2016; Yan, 2015). Here, it is suggested to improve urban construction plans, utilize the economies of scale with respect to brought production concentration, change and guide the choice of household appliance use and to decrease the effect of urbanisation on excess capacity. Urban structure and construction plans claim to be efficient ways to control energy consumed in transportation and infrastructure (Zhao et al., 2017). While China has already developed many standards and codes for transport and building design, it is recommended that attention to paid to the in-depth integration and coordinated development of urbanisation with information communication technology (ICT) to improve energy efficiency. This is of particular importance within the logistics industry, which has been developed very fast due to the increased clusters of residents. Moreover, as the energy consumption habit of urban and rural residents are different, it is necessary to guide the energy saving behavior of new urban residents to reduce residential energy consumption (Wang et al., 2020; Xie et al., 2020). With the exception of implications related to government subsidy policies, such as home appliance going to countryside from 2008 and old-for-new policy of auto and electric appliance from 2009, it is suggested that best use is made of non-price interventions such as social norms and nudges (Allcott, 2011). These polices have been shown to help influence the behavior of energy consumers, both in the short-run and long-run. Indeed, the effects of social nudges have been proven to persist (Brandon et al., 2017). The adoption of information disclosure policies such as the China Energy Label (NDRC, 2016[2]) system and the energy efficiency star catalog for household electric appliances (MIIT, 2012[3]) have been shown to mitigate the effect of imperfect market information and can reveal energy efficiency information to consumers thereby contributing to increased energy efficiency. Finally, urbanisation development especially infrastructure construction should take into account and make full use of the capacity level of specific regions to avoid aggravating the issue of excessive and obsolete capacity, which relates to long-run inefficiency.

To address this issue in more detail, further work could be completed in the future. First, this study has been focused on the spatial unit of province. Based on the China's administrative hierarchy, there are over 360 cities at prefectural level. Therefore, developing the statistical models at the finer prefectural level would enable the consideration of intra-province distribution with respects to energy consumption. Also, with availability of newly published statistical data after 2016, the long- and short-run energy efficiency will be examined to explore the dynamic impacts of urbanisation. Second, urbanisation has been indicated by growth of the urban population, which has been driven by migration, FDI, Industrialisation and many other factors (He et al., 2017; Wang et al., 2015; Zhao and Chai, 2015). With better availability of socio-economic and spatial data in the future, spatial effects (e.g. spillover and non-stationarity) could also be considered within the statistical models. Third, in the era of globalization, it will be interesting to compare the patterns of energy consumption efficiency between China and other developing/developed countries, which can help guide the national strategy of energy conservation. As a dynamic and spatial process, urbanisation has been remarkably driven by continuous migration and transport flows between cities and provinces. As a result, with data sets of energy flows between provinces and cities, it will be meaningful to explore energy flow efficiency and its interactions with urbanisation development using the spatial statistical methods by Zhang et al. (2019).

[2] http://www.ndrc.gov.cn/zcfb/zcfbl/201603/t20160308_792230.html

[3] http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057542/n3057544/c5926285/content.html

Table 5 Determinants of time invariant energy efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PERSISTENT	SS1984	PERSISTENT	SS1984	PERSISTENT	SS1984	PERSISTENT	SS1984	PERSISTENT	SS1984
	1997-2000		2001-2005		2006-2010		2011-2016		1997-2016	
URB	-1.458***	-1.861***	-2.428***	-3.563***	-2.761***	-4.370***	-3.624***	-5.935***	-2.602***	-4.047***
	[0.36]	[0.51]	[0.57]	[0.74]	[0.83]	[1.04]	[1.03]	[1.16]	[0.72]	[0.94]
PERGDP	5.795***	9.983***	3.739*	4.503**	2.897**	3.997***	2.899***	3.640***	2.295**	3.094**
	[2.18]	[2.49]	[2.27]	[2.01]	[1.18]	[1.40]	[0.84]	[0.94]	[1.16]	[1.23]
PERGDP2	-0.260**	-0.481***	-0.127	-0.153	-0.135*	-0.168*	-0.118***	-0.114***	-0.090	-0.107
	[0.11]	[0.14]	[0.11]	[0.11]	[0.08]	[0.09]	[0.04]	[0.04]	[0.06]	[0.07]
IND	-0.588*	-0.550	-1.011**	-0.851	-0.633	-0.523	-0.142	0.208	-0.306	-0.110
	[0.31]	[0.43]	[0.51]	[0.57]	[0.46]	[0.60]	[0.21]	[0.32]	[0.34]	[0.49]
TER	-3.337***	-3.800***	-2.645*	-2.664*	-1.028	-1.212	-0.628	-0.376	-1.385	-1.532
	[0.89]	[0.86]	[1.61]	[1.56]	[0.83]	[1.03]	[0.50]	[0.69]	[0.89]	[1.05]
PRICE	-2.672	-6.616***	-0.319	-0.851	-0.072	-0.594	-0.305	-0.668	0.316	-0.096
	[1.67]	[2.20]	[1.01]	[1.11]	[0.41]	[0.59]	[0.39]	[0.45]	[0.67]	[0.79]
FDI	0.200***	0.176*	0.178	0.280*	0.396***	0.472***	0.309***	0.371***	0.409***	0.499***
	[0.06]	[0.10]	[0.13]	[0.16]	[0.12]	[0.15]	[0.07]	[0.08]	[0.09]	[0.12]
TRADE	0.130	0.254	0.140	0.330	0.395**	0.607**	0.371***	0.565***	0.352*	0.556**
	[0.15]	[0.22]	[0.21]	[0.30]	[0.19]	[0.25]	[0.11]	[0.16]	[0.18]	[0.25]
R&D	0.368***	0.417***	0.487**	0.513**	0.509***	0.615***	0.497***	0.633***	0.421***	0.499***
	[0.10]	[0.12]	[0.20]	[0.20]	[0.16]	[0.17]	[0.11]	[0.15]	[0.13]	[0.17]
sigma	0.325***	0.427***	0.386***	0.473***	0.332***	0.424***	0.237***	0.296***	0.303***	0.384***
	[0.05]	[0.05]	[0.09]	[0.08]	[0.06]	[0.06]	[0.04]	[0.04]	[0.06]	[0.04]

Table 6 Determinants of time varying energy efficiency.

	GREENE2005	TRANSIENT	OVERALL
URB	-0.043***	-0.031***	-2.230***
	[0.01]	[0.01]	[0.16]
PERGDP	0.182**	0.131**	2.524***
	[0.08]	[0.06]	[0.25]
PERGDP2	-0.009**	-0.007**	-0.094***
	[0.00]	[0.00]	[0.01]
IND	0.017**	0.012**	-0.464***
	[0.01]	[0.01]	[0.11]
TER	0.050***	0.038***	-1.259***
	[0.01]	[0.01]	[0.21]
PRICE	-0.016***	-0.010***	-0.417***
	[0.00]	[0.00]	[0.06]
FDI	0.001	0.001	0.243***
	[0.00]	[0.00]	[0.02]
TRADE	-0.002	-0.002	0.285***
	[0.00]	[0.00]	[0.04]
R&D	-0.009***	-0.006***	0.328***
	[0.00]	[0.00]	[0.03]
sigma	0.025***	0.018***	0.389***
	[0.00]	[0.00]	[0.02]

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