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Lvn, Yulan, Chen, Wei and Cheng, Jianquan (D) (2020) Effects of urbanisation on energy efficiency in China: new evidence from short run and long run efficiency models. Energy Policy, 147. 111858 ISSN 0301-4215

DOI: https://doi.org/10.1016/j.enpol.2020.111858

Publisher: Elsevier

Version: Accepted Version

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

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9 Abstracts:

Energy efficiency in China has been the cause for increasing concern for national and 10 11 local sustainable development due to rapid economic development and large-scale energy consumption. Using panel data of 30 provinces between 1997 and 2016, this 12 study explores the effects of urbanisation on different types of energy efficiency. First, 13 the measurement of energy is disentangled, with long-run and short-run efficiencies 14 derived. The results of energy efficiency analysis highlight that the predominant long-15 run efficiency is low, with disparate energy efficiency present between provinces. It is 16 verified that improving energy efficiency will be a long run challenge in China. Second, 17 the effects of urbanisation were found to be significantly negative on short-run, long-18 run and overall energy efficiency. Comparatively, the effect of urbanisation on long-run 19 efficiency was shown to have recently grown, implying an urgent call for energy 20 conservation during rapid urbanisation. Finally, this study outlines broader implications 21 and suggests policies to improve energy efficiency. Here, the application of energy 22 conservation technology, industrial structure upgrading and efficiency information 23 disclosure to urban residents are thought to be smart ways to improve energy efficiency. 24

25 Key words:

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

27 **1. Introduction**

The production and use of energy are necessary for economic development, as such 28 energy consumption is an increasing trend in China given its current development stage. 29 Outpacing the US, China has become the largest energy consumer since 2009 due to 30 rapid urbanisation (Liu et al., 2017) and Industrialisation (Li and Lin, 2015). The issues 31 32 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 33 considerable amount of pressure on energy security and contributed to climate change 34 and environment pollution (Guan et al., 2012). To address these problems, it is argued 35 36 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).

6 Cities have become central for many human activities, with mass migration (from 7 rural to urban areas) stimulated by an increasing desire to achieve an improved quality 8 of life along with access to better education and medical services. Urbanisation of China 9 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 10 process after it launched the reform and open-up policy in 1978 and its urbanisation is 11 expected to continue rising (Lv et al., 2019b). However, energy consumption per capita 12 in urban areas of China has been found to be almost six times of that in rural areas 13 (Dhakal, 2009), which implies the pressure on energy brought by urbanisation. 14 Urbanisation should not be at the cost of intensive energy use and environment 15 pollution. In March 2014, the Central Committee of the Communist Party of China 16 (CPC) and the State Council jointly released the "National New-type Urbanisation Plan 17 (2014–2020)", with the aim to promote energy efficient with urbanisation. Energy 18 intensity has also been used since 2006 as the constrained indicator of energy 19 20 conservation policy in the five-year plan of China (NPC, 2006¹). The development mode of urbanisation is related to the achievement of the target of energy intensity. To 21 22 design energy conservative policies during urbanisation in China, it is important and urgent to explore the relationship between urbanisation and energy efficiency. 23

Above all, as the effectiveness of energy efficiency to constrain energy 24 consumption and the importance of urbanisation to economic development, the 25 following questions have caused much concern in China. How does energy efficiency 26 in China evolve over time? Does the energy efficiency in China have a long term or 27 28 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 29 answers to these questions have important implications for urbanisation policy and 30 energy governance. There is rare study about the impact of urbanisation on long- and 31 short- run energy efficiency, which is related to the long and short change of energy 32 utilization behavior caused by urbanisation. To address these questions, this study will 33 focus on adopting several means to measure energy efficiency and investigating the 34 impacts of urbanisation on different types of energy efficiency. It validates the 35 measurement of total factor energy efficiency, explores the evolution of energy 36

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

2 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 3 4 frontier model, where individual effects are disentangled and long- and short-run inefficiencies are measured at the provincial level in China. The disparity between 5 6 individual heterogeneity, long run efficiency, short run efficiency and disturbance term, 7 which contributes to exact estimation and recognition of efficiency, has been specified 8 within stochastic frontier model in recent years (Acosta and De los Santos-Montero, 9 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 10 characteristics between provinces. While previous studies have not fully considered 11 12 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 13 obsolete capacity in China (Li and Lin, 2016). Second, previous literature, which 14 investigates the impact of urbanisation on energy efficiency, has been found to be 15 mostly focused on energy intensity (Lin and Zhu, 2017; Song and Zheng, 2012; Yan, 16 2015). In contrast, this study explores the impact of urbanisation on different types of 17 total factor energy efficiency. That is, this study compares the effect of urbanisation on 18 both short- and long-run energy efficiency, from which quantitative evidence for 19 20 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.

28 **2. Literature review**

29 2.1. Measurement of energy efficiency

30 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 31 energy efficiency policy, the first step is to make an accurate measurement of energy 32 efficiency. Thereby, it is necessary to define a more reliable indicator to measure energy 33 efficiency. Commonly, energy intensity (a single factor energy efficiency indicator) is 34 used and calculated as the division of energy consumption by GDP. Due to high easiness 35 of understanding and calculating it, a wide range of studies have used energy intensity 36 as an indicator of energy efficiency (Hajko, 2014; Li and Shi, 2014; Lin and Zheng, 37 2017; Markandya et al., 2006). Although extensively used, it has been criticized as an 38 insufficient indicator (Ang et al., 2010; Proskuryakova and Kovalev, 2015). Energy 39

1 intensity, which focuses on the relationship between energy input and output, has 2 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 3 and Wang, 2006). Total Factor Energy Efficiency (TFEE) has been acknowledged as a 4 viable alternative due to an enhanced benchmarking performance (Zhou and Ang, 2008), 5 thus leading to increased debate. Two main frontier methods that have been widely 6 utilized to establish TFEE measurements are: non-parametric and parametric frontier 7 analysis. The former, Data Envelopment Analysis (DEA), was first applied by Hu and 8 Wang (2006). A series of subsequent studies have since extended this method to create 9 the non-parametric frontier approach (as shown in Table 1). Employing DEA has been 10 shown to be limited in measuring energy efficiency due to statistical noise being 11 ignored, blended unobservable heterogeneity among individual effects and unfeasible 12 statistical tests (Filippini and Hunt, 2015). 13

As an alternative technique, Stochastic Frontier Analysis (SFA), has an advantage 14 over DEA by including stochastic error terms and a statistical test. Furthermore, the 15 assumption of a unique deterministic frontier in DEA has been argued as being too 16 strong, a limitation not identified in SFA (Filippini and Hunt, 2015). Based on the 17 pioneering work of Aigner et al. (1977) and Meeusen and van Den Broeck (1977), 18 Stochastic Frontier Models (SFM) have been well developed, with models extended in 19 20 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) 21 22 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 23 fixed effect. However, they are pooled and therefore not true panel data models with 24 individual effects. This problem is critical in policy design because unobservable 25 heterogeneity has been highlighted as a major reason for poor selection (Colombi et al., 26 2017). Confusion concerning the conceptualization and terminology of heterogeneity 27 and inefficiency has been shown to greatly distort inefficiency measures (Greene, 28 2005a). As a result, Greene (2005b) has suggested that individual heterogeneity be 29 isolated from inefficiency using a "true" random or fixed effects SFM. Thus, estimated 30 inefficiencies can vary in time (i.e. be transient) and long-run impacts can be 31 incorporated into individual effects. Estimation of "true" SFM was improved by Chen 32 et al. (2014) and Wang and Ho (2010). As only time varying components are included 33 in the inefficiency term of "true" SFM, with long-run inefficient impacts contained to 34 individual effects, a downward bias in overall inefficiency is produced (Colombi et al., 35 2014). As a consequence, it is important to disentangle long-run inefficiencies from 36 models (Greene (2005b). Nascent research has started to focus on disentangling 37 individual heterogeneity, long-run (time invariant, persistent) and short-run (time 38 varying, transient) efficiencies within models (Colombi et al., 2014; Kumbhakar et al., 39 2014). Generally, persistent inefficiencies, which reveal rigidities in production 40 processes, are caused by obsolete equipment that has not been replaced for long periods, 41

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).

6 As previously noted, SFM has been used widely to measure energy efficiency (see 7 Table 1), whereas only a limited number of nascent studies have focused on 8 disentangling heterogeneity, long-run and short-run efficiencies (Badunenko and 9 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 10 obsolete production capacities. The elimination of obsolete capacity and removal of 11 excessive capacity are two ways in which industrial structural change and upgrade can 12 improve energy efficiency (Li and Lin, 2016). The industrial sector has already 13 experienced several rounds of excess capacity since 1990 and thereby excess capacity 14 has become a long-run structural problem, which suffers from recurrence in the 15 production process (Yu and Shen, 2020). Due to the above-mentioned obsolete and 16 excess production capacities, energy inefficiencies may have sustained over a long 17 period, hence, the detection of long-run inefficiencies is crucial for understanding the 18 quality of urbanisation across China. In addition, both urbanization and energy 19 20 consumption (e.g. energy endowment, climate) have demonstrated strong regional heterogeneity at province level across China. However, previous studies on energy 21 22 efficiency in China have not considered these heterogeneous and dynamic effects, even though distinctions between them have been found to contribute to the accurate 23 measurement and estimation of energy efficiency. Therefore, models that disentangle 24 heterogeneity, persistent and transient inefficiencies are used in this study to investigate 25 both types of inefficiencies in China's energy consumption simultaneously. 26

1 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)

1 2.2. Urbanisation and energy efficiency

2 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 3 concern in policy making. Poumanyvong and Kaneko (2010) summarise the theories 4 on the relationship between urbanisation and environment into three strands: ecological 5 modernization, urban environmental transition and compact city theories. In addition, 6 the sustainable development and consumer behavior preference theories are 7 instrumental in explaining the relationship, as the construction of sustainable 8 urbanisation highlights energy conservation and one indispensable aspect of 9 urbanization, which is internal migration from rural to urban areas, incurs consumer 10 preference altered. In the study of Madlener and Sunak (2011) and Sadorsky (2013), 11 the transmission mechanisms of urbanisation on energy use are explained in detail from 12 four perspectives including urban production process, mobility and transportation, 13 14 infrastructure and urban density, and private households. As a process accompanied by industrialisation and economic development, urbanisation has an intrinsic motivation 15 to affect energy demand and efficiency from different aspects. On one side, urbanisation 16 is a process associated with internal migration from rural to urban with changing 17 consumer behavior and lifestyle and growing adoption of electric appliances, economic 18 structure change with agriculture mechanization and enlargement of energy intensive 19 20 industry, infrastructure construction and maintenance, transportation growth by long distance mobility and commuting, as well as urban logistics and service. Thereby, it is 21 22 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 23 process accompanied by technological advantages and economies of scale that can 24 improve energy efficiency and decrease overall energy use (Madlener and Sunak, 2011; 25 Wang, 2014). The net effect of urbanisation on energy efficiency is unclear and need 26 further empirical investigation. 27

28 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 29 urbanisation are likely to converge to higher levels of energy consumption. Mrabet et 30 al. (2019) suggest a positive impact of urbanisation on non-renewable energy demand 31 32 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 33 China, how to achieve efficient energy consumption and sustainable urban growth is of 34 importance. Among the series of studies focusing on China, Zhang and Lin (2012) show 35 that the positive impacts of urbanisation on energy consumption vary across regions 36 and decline continuously from the western region to the central and eastern regions. 37 Wang et al. (2014) find a one-way positive causal relationship from urbanisation to 38 energy consumption. Zhou et al. (2015) present that urbanisation increases energy 39 40 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.

4 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 5 efficiency (Farajzadeh and Nematollahi, 2018; Sadorsky, 2013). Song and Zheng (2012) 6 7 reported a positive impact of urbanisation on energy intensity using data at provincial 8 level of China. This is consistent with the study by Yan (2015), where a varied elasticity 9 of urbanisation was revealed on aggregated and disaggregated energy intensity. Ma (2015) reports diversification in the impact of urbanisation on energy intensity between 10 disaggregated energy, but is not robust enough in terms of analytical methods. Huang 11 and Yu (2016) confirm the unequal effect of urbanisation on energy intensity across 12 regions. Lin and Zhu (2017) reveal an inverted U-shaped effect of urbanisation on 13 energy intensity in China. Lv et al. (2019a) distinguish the direct and indirect effects of 14 urbanisation on energy intensity across Chinese cities by adopting the spatial Durbin 15 modelling approach. The inconsistent results may be caused by different sampling 16 periods and estimation methods. Among these studies, which take energy intensity as 17 an indicator of energy efficiency, the substitution between energy and other production 18 factors has been ignored, which induces a biased estimation of energy efficiency. To the 19 20 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 21 22 account long- and short-run scales, as a limitation this study will address.

23 **3. Methods and data**

24 **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:

28
$$T = \{(K, L, E, Y): K, L, E \text{ can produce } Y\}$$
(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.

31
$$D_E(L,K,E,Y) = \sup_{\theta} \left\{ \theta : \left(L,K,\frac{E}{\theta},Y\right) \in T \right\}$$
 (2)

According to the definition, $\frac{E}{D_E}$ is the hypothetical energy use and the TFEE can be

1 defined as the ratio between hypothetical and actual energy use:

$$2 TFEE = \frac{1}{D_E} (3)$$

3 To find out a numerical energy efficiency, the definition of Shephard energy distance 4 function need to be expressed in functional representation. Here, a trans-log 5 transformation function is used.

6
$$D_E(L, K, E, Y) = \exp\left(\beta_0 + \sum_{n=1}^4 \beta_n \ln(X_n) + \frac{1}{2} \sum_{m=1}^4 \sum_{n=1}^4 \beta_{mn} \ln(X_m) \ln(X_n) + \nu\right)$$
 (4)

7 Where X_i represent K, L, E, Y and v is the statistical noise and measurement 8 error.

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

10
$$D_E(L,K,\lambda E,Y) = \lambda D_E(L,K,E,Y)$$
 (5)

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

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

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

16 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 17 $e^{-\ln D_E(L,K,E,Y)}$ in equation (6). The equation (6) belongs to SFM and some specification 18 methods of SFM are chosen to estimate TFEE. However, there are no clear criteria to 19 choose a unique specification of SFM (Farsi et al., 2006). For comparison, three kinds 20 of specification are chosen to develop the model (1). First, one of the earliest time 21 invariant panel data SFM developed by Schmidt and Sickles (1984) is chosen and time 22 invariant (long run) efficiency scores are derived from their model. Second, the true 23 fixed effects model by Greene (2005b) is used and time varying true efficiency scores 24 are estimated. Third, the four-component model by Kumbhakar et al. (2014) is chosen 25 to disentangle individual effects, persistent and transient inefficiency. All these models 26

1 are specified in the following equations:

3

4

$$-e_{it} = \beta + \beta_{Y} y_{it} + \beta_{L} l_{it} + \beta_{K} k_{it} + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + v_{it} - u_{i}$$
(7.1)

$$-e_{it} = \beta + \beta_{Y} y_{it} + \beta_{L} l_{it} + \beta_{K} k_{it} + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + \mu_{i} + v_{it} - u_{it}$$
(7.2)

$$-e_{it} = \beta + \beta_{Y} y_{it} + \beta_{L} l_{it} + \beta_{K} k_{it} + \beta_{YL} y_{it} * l_{it} + \beta_{KL} k_{it} * l_{it} + \beta_{KY} k_{it} * y_{it} + \beta_{KK} y_{it}^{2} + \beta_{LL} l_{it}^{2} + \beta_{YY} k_{it}^{2} + \mu_{i} + v_{it} - u_{i} - u_{it}$$
(7.3)

where i=1, 2,n; t=1.....T. Variables in lowercase correspond to logarithm of 5 variables in (6), μ_i is the individual term and V_{it} is the error term. In model (7.1), 6 U_{i} is the inefficiency term. In model (7.2) U_{it} is the time varying inefficiency term. 7 In model of (7.3), U_{it} and U_i are the transient and persistent inefficiency terms 8 respectively. Three kinds of time varying efficiency scores were derived; 9 GREENE2005 from (7.2), TRANSIENT from (7.3) and OVERALL from (7.3). Two 10 kinds of time invariant efficiency scores were also derived; SS1984 from (7.1) and 11 PERSISTENT from (7.3). 12

13 **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.

17
$$EE_{it} = \alpha + \beta_1 URB_{it} + \beta_2 X_{it} + \varepsilon_{it}$$
(8)

Where EE is energy efficiency corresponding to several types of energy efficiency 18 defined above. Here, time varying efficiency can be indicated by SS1984 and 19 PERSISTENT, and time invariant efficiency can be indicated by GREENE2005 and 20 TRANSIENT, and OVERALL. In total, five models using five types of energy 21 efficiency as dependent variables are developed. URB indicates urbanisation and X 22 represents the chosen control variables. All variables were transformed into log 23 variables to alleviate heteroscedasticity and order of magnitude thereby producing 24 comparable results by elasticity. As dependent variable in the model is limited and can 25 26 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.

9 (1) Economic development (per capita GDP, PERGDP) has been found to support 10 the development of energy conservation technology and the application of energy 11 saving electric appliances in the home. Where, Wu (2012) and Yu (2012) find a negative 12 effect of income on energy intensity in China. To explore the existence of Kuznets curve, 13 the quadratic per capita GDP (PERGDP2) has also been included. Here, the value of 14 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.

36 (6) International trade (TRADE) has been increasing in China since the37 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 8 technology, application of advanced equipment, innovation and patents. Huang and Yu 9 (2016) reveal that research and development (R&D) is a powerful tool to decrease 10 energy intensity in China. However, due to the inherent difficulties of measuring 11 technology (Wang et al., 2012), there is no coherent indicator for technology. One 12 solution is to choose a proxy, such as R&D expenditure, R&D researchers, application 13 14 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 15 16 technology progress.

17 **3.3. Data sources and descriptions**

18 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 19 three input variables (labor, capital and energy) were collected for the measurement of 20 model (1). The output variable was represented by gross domestic product (GDP) and 21 was converted to the 1997 price using a GDP deflator. Labor was represented by persons 22 employed in an urban area at the year-end. The data for capital stock was calculated 23 using the perpetual inventory method (PIM), as described by Zhang et al. (2004) and 24 was adjusted by the price index of investment of fixed assets. Data was collected from 25 National Bureau of Statistics of China and the China Energy Statistical Yearbook (1998-26 2017). 27

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.

Variables	mean	std	min	median	max	cv	
e	8.898	0.836	5.966	8.962	10.570	0.094	
У	7.719	0.861	5.312	7.806	9.311	0.112	
1	7.522	0.825	5.561	7.617	8.814	0.110	

35 Table 2 Descriptive statistics of all variables.

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.						

2 4. Empirical results and discussion

3 4.1. Description of efficiency scores

The summary statistics for energy efficiency scores derived from the three SFA 4 models (1.1), (1.2) and (1.3) are presented into Table 3. First, the mean efficiency 5 scores from the true fixed effects model (GREENE2005) and the mean transient 6 efficiency scores from the four component models (TRANSIENT) were found to be 7 similar. This can be attributed to both measures only addressing the short-run (time 8 varying) part of energy efficiency. Second, the estimated mean value of TRANSIENT 9 efficiency was found to be larger than that of PERSISTENT efficiency. This indicates 10 a significant difference between long-run and short-run inefficiency values. Energy 11 inefficiency was found to be caused by persistent political and economic factors such 12 13 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 14 PERSISTENT efficiency was more volatile than TRANSIENT efficiency, indicating 15 larger inequality between provinces in PERSISTENT efficiency. Third, the scores of 16 PERSISTENT and SS1984 were found to be different. This verifies the necessity to 17 separate heterogeneity from the model. The PERSISTENT model excludes the 18 individual effect, while the SS1984 model does not consider such distinctions. To 19 alleviate bias when calculating energy efficiency, it is necessary to incorporate 20 heterogeneity as a term of individual effect into the model. Fourth, OVERALL was 21 found to be lower than GREENE2005, which verifies the existence of possible 22 persistent efficiency. The OVERALL model includes both persistent and transient 23 efficiencies. However, the true fixed effect SFM was only found to cover short-run 24 efficiency, ignoring long-run efficiencies and thus introducing an upward bias in 25 efficiency. Finally, standard errors reported for the two kinds of time invariant 26 efficiency scores (SS1984 and PERSISTENT) were found to be two of the largest, 27 indicating a relatively high disparity in long-run efficiency between provinces. 28

29 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 2 correlation coefficients between the five efficiency scores. First, the correlation 3 coefficient between TRANSIENT and GREENE2005 was found to be high and 4 5 significant. This suggests a consistent estimation for the short-run efficiency from both models. Second, the correlation between PERSISTENT and TRANSIENT was found 6 to be insignificant and very low. This suggests that they are completely different parts 7 of efficiency and thus, it is necessary to separate and distinguish between them when 8 developing policy to improve energy efficiency. Until now, there has been no such 9 distinction in regulation policy for improving energy efficiency, with no clear targets 10 set to improve persistent and / or transient efficiencies. Third, high correlation was 11 found between OVERALL and PERSISTENT but with respect to OVERALL and 12 TRANSIENT, correlation was found to be insignificant. This highlights the 13 predominant status of the time invariant part within the model. Thus, to improve energy 14 efficiency and alleviate the disparity between provinces, impetus should be placed on 15 the promotion of persistent efficiency. 16

	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***	

17 Table 4 Correlation coefficients between the energy efficiency scores.

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

18

19 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.

6 The coefficients of per capita GDP were shown to be significantly positive in all 7 periods, ranging from 2.295 to 9.983. This is consistent with the reports by Ma (2015) 8 and Yu (2012). The coefficients of quadratic per capita GDP were found to be negative 9 and significant across all periods, excluding 2001-2005. Overall, the results show an 10 inverted U-shaped relationship between economic development and persistent 11 efficiency, supporting the EKC hypothesis (Jiang et al., 2014).

12 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 13 14 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 15 conservation policy in industry is efficient and that the strategy of industrial upgrading 16 and adjustment in China is playing a vital role. This implies that inherent technology 17 and technology that is embodied in existing equipment and transport systems can be 18 characterized as mostly old with low capacity. Thus, the strategy of accelerating the 19 20 process of eliminating old and backward equipment in China is meaningful in increasing overall energy efficiency. 21

22 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 23 24 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 25 the finding by Liu et al. (2017) but is in contradiction with those by Huang and Yu 26 (2016) and Wang (2017). However, this contradiction may be caused by different 27 sample sizes and modeling methods. For example, Huang and Yu (2016) focused on 28 energy intensity, while the data set used by Wang (2017) only spanned the years 2001 29 to 2013. The aim of increasing energy prices is to encourage the producer to decrease 30 energy consumption and to apply more energy efficient technologies. It calls for further 31 price reform and reveals the role of energy price in supply and demand although this 32 may have a long way to go. 33

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.

1 Lastly, the effects of urbanisation on energy efficiency were analyzed. Taking the 2 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 3 with the result created by Li et al. (2018) and Ma (2015), although in these studies 4 energy intensity was used to measure energy efficiency. Significantly negative effects 5 6 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 7 notable that elasticity has an increasing trend, indicating a high magnitude of effect in 8 recent years. Same results were found for the long-run efficiency indicated by SS1984. 9 As a result, this reveals that urbanisation impedes improvements to long-run energy 10 efficiency in China. Due to its role in industrial restructuring, factor allocation 11 optimization and economy of scale, urbanisation has been identified as a potential 12 solution to overcome excess capacity and to improve long-run efficiency. However, 13 14 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 15 migrant workers placement and the lagged replacement of household appliances. 16

Results for time varying efficiency are displayed in **Table 6**. Firstly, the results of 17 economic development were found to be consistent with results of long-run efficiency. 18 Secondly, Industrialisation and the tertiary sector were found to improve the short-run 19 20 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 21 22 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, 23 2016; Ma and Yu, 2017), indicating that the industry is energy intensive and dominated 24 by the extension of energy intensive industries and the construction of energy 25 consuming infrastructure. According to Ma and Yu (2017), construction of 26 infrastructure that is demanded by urbanisation also increases the demand of energy-27 intensive products (Du et al., 2018). Thirdly, the effects of energy price on two short-28 run efficiencies and overall efficiency were found to be all significantly negative, which 29 is similar to the findings from long-run efficiency models. Fourthly, the effects of FDI 30 and trade were found to be insignificantly negative for short-run efficiency, but 31 significantly positive for OVERALL efficiency (Lv et al., 2016). Improving the 32 absorption ability of advanced technology brought by directly FDI and that indirectly 33 embodied in imported products is critical in improving energy efficiency. The 34 insignificant effects of FDI and trade on short-run efficiency also highlight the need to 35 encourage foreign investment into the energy conservation industry. Fifthly, R&D was 36 found to be significantly negative for short-run efficiency, with an opposite result for 37 overall efficiency (Lv et al., 2016) and time invariant efficiency. Two reasons were 38 found to explain the negative contribution of R&D to short-run efficiency. First, when 39 investment in research increases, investment in energy technology does not increase at 40 the same rate. Second, the transfer of technology was found to lag behind the 41

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.

4 5. Conclusions and policy implications

5 Using a balanced dataset of 30 Chinese provinces from 1997 to 2016, this study 6 has developed stochastic frontier models to disentangled individual effects from long-7 run and short-run inefficiencies. After comparing and evaluating the different types of 8 energy efficiency, the effects of urbanisation on energy consumption is then 9 distinguished between long-run and short-run efficiencies.

The main findings and policy implications of this study are summarized as follows. 10 Firstly, the long-run efficiency is found to play an important part of energy efficiency 11 in China. Long-run efficiency (PERSISTENT or SS1984) achieves lower scores and 12 demonstrated a larger disparity between provinces when compared with short-run 13 efficiency. There is still a long way to go to improve long-run efficiency across the 14 country. Excess and obsolete production capacity, barriers to technology upgrades, and 15 energy management problems in production have remarkably contributed to such low 16 and unequal long-run efficiency. The constrained energy intensity target reported in the 17 five-year plan of China includes a variety of policies to resolve the excess capacity, 18 look to upgrade technology, and transform / upgrade industrial structure, which have 19 been shown to be efficient in controlling long-run inefficiency. 20

Secondly, the effects of urbanisation on short-run, long-run and overall energy 21 efficiency have been proven to be significantly negative (Li et al., 2018; Lv et al., 2017; 22 Ma, 2015; Rafiq et al., 2016; Yan, 2015). Here, it is suggested to improve urban 23 construction plans, utilize the economies of scale with respect to brought production 24 concentration, change and guide the choice of household appliance use and to decrease 25 the effect of urbanisation on excess capacity. Urban structure and construction plans 26 claim to be efficient ways to control energy consumed in transportation and 27 infrastructure (Zhao et al., 2017). While China has already developed many standards 28 and codes for transport and building design, it is recommended that attention to paid to 29 the in-depth integration and coordinated development of urbanisation with information 30 communication technology (ICT) to improve energy efficiency. This is of particular 31 importance within the logistics industry, which has been developed very fast due to the 32 increased clusters of residents. Moreover, as the energy consumption habit of urban and 33 rural residents are different, it is necessary to guide the energy saving behavior of new 34 urban residents to reduce residential energy consumption (Wang et al., 2020; Xie et al., 35 2020). With the exception of implications related to government subsidy policies, such 36 as home appliance going to countryside from 2008 and old-for-new policy of auto and 37 electric appliance from 2009, it is suggested that best use is made of non-price 38 interventions such as social norms and nudges (Allcott, 2011). These polices have been 39 shown to help influence the behavior of energy consumers, both in the short-run and 40

long-run. Indeed, the effects of social nudges have been proven to persist (Brandon et 1 2 al., 2017). The adoption of information disclosure policies such as the China Energy Label (NDRC, 2016²) system and the energy efficiency star catalog for household 3 electric appliances (MIIT, 2012^3) have been shown to mitigate the effect of imperfect 4 market information and can reveal energy efficiency information to consumers thereby 5 contributing to increased energy efficiency. Finally, urbanisation development 6 especially infrastructure construction should take into account and make full use of the 7 capacity level of specific regions to avoid aggravating the issue of excessive and 8 obsolete capacity, which relates to long-run inefficiency. 9

10 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 11 administrative hierarchy, there are over 360 cities at prefectural level. Therefore, 12 developing the statistical models at the finer prefectural level would enable the 13 14 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 15 16 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 17 18 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 19 20 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 21 22 be interesting to compare the patterns of energy consumption efficiency between China and other developing/developed countries, which can help guide the national strategy 23 24 of energy conservation. As a dynamic and spatial process, urbanisation has been 25 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 26 will be meaningful to explore energy flow efficiency and its interactions with 27 28 urbanisation development using the spatial statistical methods by Zhang et al. (2019).

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http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057542/n3057544/c592628 5/content.html

² <u>http://www.ndrc.gov.cn/zcfb/zcfbl/201603/t20160308_792230.html</u>

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PERSISTE	SS1984								
	NT		NT		NT		NT		NT	
	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]
PERGDP	-0.260**	-0.481***	-0.127	-0.153	-0.135*	-0.168*	-0.118***	-0.114***	-0.090	-0.107
2	[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]

1 Table 5 Determinants of time invariant energy efficiency.

	5	0 0, ,		
	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]	

1 Table 6 Determinants of time varying energy efficiency.

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