Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2022 Volume 28 Issue 4: 1003–1021
https://doi.org/10.3846/tede.2022.16736

DOES URBANIZATION IMPROVE ENERGY EFFICIENCY? EMPIRICAL EVIDENCE FROM CHINA

Yantuan YU[1*], Nengsheng LUO[2]

[1]*School of Economics and Trade, Guangdong University of Foreign Studies, Guangzhou, China*
[2]*School of Economics and Trade, Hunan University, Changhsa, China*

Received 07 October 2021; accepted 25 February 2022; first published online 20 May 2022

Abstract. An analysis of urbanization's effects on energy efficiency (EE) is presented in this paper. We develop an input-oriented data envelopment analysis method to estimate EE in the presence of non-convex metafrontier, and examine how urbanization affects China's EE using data from 251 cities for the period 2003 to 2016. The findings indicate that demographic urbanization (DU), land urbanization (LU), and economical urbanization (EU) significantly exert positive effects on EE. Specifically, estimates from a Tobit model with random effects show that a unit increase in DU, LU and EU would result in an increase in EE by 0.15, 0.15 and 0.45, respectively. These results are robust across econometric specifications, including fixed and correlated random effects Tobit models. Sensitivity analysis of quasi-DID and stochastic frontier estimations also support our findings. The policy implications suggest policymakers should steer urbanization and energy consumption towards becoming more market-oriented and take advantage of how energy market structure complements energy structure, cultivating new energy industries that can greatly improve EE.

Keywords: urbanization, energy efficiency, non-convex metafrontier, Tobit model, stochastic frontier analysis.

JEL Classification: C61, Q32, Q43, Q56, R15.

Introduction

Economic growth in China has progressed greatly since reform and opening up. However, the growth mode of extensive economic mainly relies on factors of production such as labor and resources, is largely at the expense of the environment, resulting in serious damage to the ecological environment and low utilization rate of renewable energy. This unsustainable development mode urges us to explore new green economic growth modes. Policymakers propose that we should accelerate the urbanization of agricultural transfer population and support the economic transformation and development of resource-based areas. Therefore, it

*Corresponding author. E-mail: *yantuanyu@gdufs.edu.cn*

is necessary to give full play to the positive role of urbanization in improving environmental problems and promoting sustainable economic development, organically combine urbanization with environmental protection, continuously eliminate regional economic growth differences, and promote energy transformation and high-quality economic development.

Compared with 56.16% in the world, as of 2020, the urbanization population (% of total population) in China was reached 61.43% (see Appendix, A). Different regions have different levels of urbanization, however, it also has different energy demand (Yu et al., 2020). Thus, there are obvious regional heterogeneity in energy efficiency in varied regions of China. The regions with high energy efficiency are still concentrated in the southeast coastal areas, while the vast areas in the central and western regions are still in a relatively backward position. With the continuous transfer of rural population to cities and towns, the population and economic volume are increasing, and the agglomeration level is constantly improving, which optimizes the energy consumption structure and improves the energy efficiency.

In terms of scale, China's urbanization development speed far exceeds that of developed countries in the same period, but in terms of quality, there is still a significant difference between China's urbanization level and developed countries. Although urbanization brings high-speed economic growth dividend, it also consumes a lot of energy. For example, the construction of urban transportation infrastructure requires a lot of energy such as electricity and gas. However, whether urbanization is conducive to improving energy efficiency is remain unanswered.

To fill this gap, we attempt to examine ongoing practice of urbanization construction in Chinese cities by examining the pattern and dynamics of urbanization and its impacts on energy efficiency. The purpose is threefold, namely, (1) to identify the pattern and processes of urbanization in Chinese cities; (2) to evaluate the relationship between urbanization and energy efficiency using econometrics analysis method apart from stylized fact analysis; (3) to ascertain whether the measures of urbanization levels have significant influence on the results. This paper will provide policy implications for developing countries to promote new urbanization and energy transformation, especially those developing countries that are similar to China's actual situation. Moreover, it has policy guidance for policymakers and practioners to actively explore manners to improve energy efficiency. In addition, urbanization has played a pivotal position in an economic system. Thus, it is of vital importance to investigate the relationship between urbanization and energy efficiency.

The rapid movement of rural populations to urban regions and the transition of industries from primary to secondary (tertiary) tiers, sees urbanization affecting energy efficiency (EE) through different channels. A growing volume of research strongly points to the affect urbanization has on EE. Until now, this research has followed two main paths. The first involves the evaluation of EE, making use of parametric or nonparametric techniques. The most commonly employed methods are data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (He et al., 2018; Boyd & Lee, 2019; Haider & Mishra, 2021).

Mardani et al. (2017) reviewed the DEA models employed worldwide for the development of EE and found that although there are a variety of procedures and methods employed, there is still significant agreement among the empirical results. For example, China's EE shows significant regional heterogeneity, whose factors can be considered by conducting metafrontier analysis in the empirics (Wang et al., 2013; Zhang et al., 2015; Ouyang et al., 2021). However, the resulting metafrontiers produced by extant studies were found to be convex. This includes the "infeasible input-output combinations" (Tiedemann et al., 2011; Huang et al., 2013) that in turn lead to efficiency scores being underestimated when compared to non-convex metafrontiers and biases while estimating the technology gap ratio (Afsharian, 2017; Asfsharian & Podinovski, 2018). Yu et al. (2018) extended the convex metafrontier to include non-convex ones and measured the ecological efficiency of China's industrial sector based on the proposed model. Using a DEA model incorporating non-convex metafrontier and undesirable outputs as well as super efficiency (Anderson & Peterson, 1993) in slacks-based measures (Tone, 2001) (NCMeta-US-SBM)[1], we propose a comprehensive and accurate way to compute China's EE at the prefecture level.

The second path involved examining the actual impacts on EE resulting from urbanization from an econometric perspective, with the associated research providing mixed results. For instance, according to Markandya et al. (2006), making use of an analysis of 12 Eastern European countries undergoing a transition to market economies, urbanization is seen to exert a positive impact on EE. In a study of how urbanization affects provincial EE for the case of China during the period 2003–2014, Li et al. (2018) found that urbanization has an overall negative impact on EE. On the contrary, based on a sample set of 22 emerging economies, Rafiq et al. (2016) found urbanization to be associated with decreased EE, while Sheng et al. (2017) showed from their study of 78 countries that urbanization is also negatively associated with EE. Furthermore, Bilgili et al. (2017) reported that in India and China, urbanization leads to increased EE, although it results in decreased EE in Nepal, Vietnam, the Philippines, South Korea and Thailand. Furthermore, Lv et al. (2020) found that the urbanization effects on both short and long run EE are significantly negative in China.

The objective of this work is to present a more comprehensive DEA model for measuring EE. We also attempt to provide an empirical assessment of what affects urbanization has on the EE of China. This is done making use of a dataset derived from 251 Chinese cities for the period 2003 to 2016.

The rest of this paper is arranged as follows. Section 1 presents the development of an input-oriented NCMeta-US-SBM model to measure EE, providing an econometric strategy for investigating the impact of urbanization. Data used for the empirical analysis is presented in Section 2, with Section 3 summarizing the main findings of this analysis. The last Section concludes the paper.

[1] Although the abbreviation is the same as the model proposed by Yu et al. (2018), their model is based on non-oriented which commonly used to measure ecological efficiency, while the model used in this study is mainly on input-oriented which adopted to measure EE. This is because energy consumption is treated as the input variable, so the input-oriented DEA model should be adopted when measuring EE.

1. Methodology

1.1. Measuring energy efficiency with input-oriented NCMeta-US-SBM model

Assuming that the decision making units (DMUs) and technology hegerogeneous groups[2] are N and G, and N_g DMUs in Group g, we obtain $\sum_{g=1}^{G} N_g = N$. The DMUs use the inputs: $\boldsymbol{x} = \left[x_1, x_2, \ldots, x_M\right] \in R_+^M$ to produce desirable (good) outputs: $\boldsymbol{y} = \left[y_1, y_2, \ldots, y_R\right] \in R_+^R$ and undesirable (bad) outputs: $\boldsymbol{b} = \left[b_1, b_2, \ldots, b_J\right] \in R_+^J$. Considering the variable returns of scale (VRS) assumption, the convex and non-convex production technologies for the oth DMU in Group $g\left(o = 1, 2, \cdots, N_g, g = 1, 2, \cdots, G\right)$ in terms of the convex metafrontier could be expressed as follows:

$$
\begin{aligned}
P^{c-meta} = \Big\{ \left(x_m, y_r, b_j\right) &: x_{mg'o} \geq \sum_{g=1}^{G} \sum_{n \in g',\, n \neq o \text{ if } g = g'} \lambda_{gn} x_{mgn}, m = 1, 2, \cdots, M; \\
y_{rg'o} &\leq \sum_{g=1}^{G} \sum_{n \in g',\, n \neq o \text{ if } g = g'} \lambda_{gn} y_{rgn}, r = 1, 2, \cdots, R; \\
b_{jg'o} &\geq \sum_{g=1}^{G} \sum_{n \in g',\, n \neq o \text{ if } g = g'} \lambda_{gn} b_{jgn}, j = 1, 2, \cdots, J; \\
&\sum_{g=1}^{G} \sum_{n \in g',\, n \neq o \text{ if } g = g'} \lambda_{gn} = 1; \lambda_{gn} \geq 0;\ g = 1, 2, \cdots G; n \in g', n \neq o \text{ if } g = g' \Big\},
\end{aligned} \tag{1}
$$

where λ_{gn} represents the nonnegative weighting vector of the n^{th} DMU in Group g in terms of the convex metafrontier, which is encapsulated within all group frontiers (Battese et al., 2004).

The non-convex metafrontier production technology could also be written as:

$$
\begin{aligned}
P^{nc-meta} = \Big\{ \left(x_m, y_r, b_j\right) &: x_{mg'o} \geq \sum_{g=1}^{G} \sum_{n \in g', n \neq o \text{ if } g = g'} \gamma_{gn} x_{mgn}, m = 1, 2, \cdots, M; \\
y_{rg'o} &\leq \sum_{g=1}^{G} \sum_{n \in g', n \neq o \text{ if } g = g'} \gamma_{gn} y_{rgn}, r = 1, 2, \cdots, R; \\
b_{jg'o} &\geq \sum_{g=1}^{G} \sum_{n \in g', n \neq o \text{ if } g = g'} \gamma_{gn} b_{jgn}, j = 1, 2, \cdots, J; \\
&\sum_{g=1}^{G} \sum_{n \in (g'=1), n \neq o \text{ if } g = g'} \gamma_{gn} = \phi_1, \sum_{g=1}^{G} \sum_{n \in (g'=2), n \neq o \text{ if } g = g'} \gamma_{gn} = \phi_2, \cdots, \\
&\sum_{g=1}^{G} \sum_{n \in (g'=G), n \neq o \text{ if } g = g'} \gamma_{gn} = \phi_G; \\
&\sum_{g=1}^{G} \phi_g = 1; \phi_g = 1 \text{ or } 0; \gamma_{gn} \geq 0; n \in g', n \neq o \text{ if } g = g' \Big\},
\end{aligned} \tag{2}
$$

where γ_{gn} represents a nonnegative weighting vector of the n^{th} DMU in Group g in terms of the non-convex metafrontier. Assuming VRS, the optimal objective value for the o^{th} DMU in Group g' (o = 1, 2, ..., N_g; g' = 1, 2, ..., G) in terms of the non-convex metafrontier is given by:

[2] We divided our sample into three groups (i.e., eastern region, central region and western region) based on the geographical location and economic growth mode, which was also employed in previous studies.

$$\begin{aligned}
\rho_{g'o}^{nc-meta*} = \min\Bigg(& 1+\frac{1}{M}\sum_{m=1}^{M}\frac{s_{mg'o}^{x}}{x_{mg'o}}\Bigg) \\
& \text{s.t. } x_{mg'o}-\sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \text{ if } g=g'}\gamma_{gn}x_{mgn}+s_{mg'o}^{x}\geq 0,\ m=1,2,\cdots,M; \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \text{ if } g=g'}\gamma_{gn}y_{rgn}-y_{rg'o}\geq 0,\ r=1,2,\cdots,R; \\
& b_{jg'o}-\sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \text{ if } g=g'}\gamma_{gn}b_{jgn}\geq 0,\ j=1,2,\cdots,J; \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=1),\, n\neq o \text{ if } g=g'}\gamma_{gn}=\phi_1,\sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=2),\, n\neq o \text{ if } g=g'}\gamma_{gn}=\phi_2,\cdots, \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=G),\, n\neq o \text{ if } g=g'}\gamma_{gn}=\phi_G; \\
& \sum_{g=1}^{G}\phi_g=1;\phi_g=1 \text{ or } 0;\gamma_{gn},\, s_{mg'o}^{x}\geq 0\Big\}, \qquad (3)
\end{aligned}$$

where $s_{mg'o}^{x}$ are the input slacks. The super efficiency model and the standard model differ in that the DMU_{go} in the super efficiency model's reference set is excluded (Andersen & Petersen, 1993), which is then denoted by $n \neq o$.

In Model (3), the resulting optimal values are sometimes treated as a measure of EE, however, they are related to the averages of the slacks of all inputs, while maximizing the average improvements in all of the relevant factors for the evaluated DMU in order to reach the non-convex metafrontier. To estimate EE, we should concentrate on the slack in the energy sector rather than the average slack of all inputs.Assuming that the actual energy input is x_e, with the energy slacks referring to the non-convex metafrontier as estimated by Model (3) is $S_e^{nc-meta}$, then the EE of the non-convex metafrontier can be calculated as:

$$EE^{nc-meta}=\frac{\left(x_e-S_e^{nc-meta}\right)}{x_e}. \qquad (4)$$

Eq. (4) defines our SBM based energy efficiency measure for the empirical analysis. Since $0\leq S_e^{nc-meta}<x_e$, thus $EE^{nc-meta}\in(0,1]$.

1.2. The Panel Tobit model

Since EE estimated in this study falls in $(0,1]$, there may be a bias and inconsistencies in the resulting ordinary least square (OLS) estimates with a censored dependent variable. This type of data can be dealt with by the Tobit regression, a limited variable model, by using Maximum Likelihood Estimation (MLE). To estimate how urbanization affects EE, a range of limited variable model specifications are used to deal with the problems that arise from possible endogeneity issues. This sees the baseline Tobit model being specified as:

$$\begin{aligned}
& EE_{it}^{*}=x_{it}\beta+ur_{it}\gamma+\delta_t+\pi_i+\mu_{it}; \\
& EE_{it}=\max\left(0,EE_{it}^{*}\right)=\max\left(0,x_{it}\xi+ur_{it}\theta+\delta_t+\pi_i+\mu_{it}\right); \\
& \mu_{it}\left|x_{it},\pi_i\sim N\left(0,\sigma_\mu^2\right),i=1,2,\cdots,N;t=1,2,\cdots,T,\right. \qquad (5)
\end{aligned}$$

where EE_{it} represents EE for city i in year t, x_{it} denotes the control variables that affect EE, and ξ is the parameter vector. The key variables of interest, ur_{it}, measures urbanization for city i in year t and θ denote the parameter vector. Finally, δ_t indicates the year-fixed effects, π_i covers the unobserved heterogeneity, and μ_{it} is the normal distributed error term.

Including fixed effects in a limited dependent variable model leads to the well-known incidental parameters problem in MLE (Greene, 2011). This sees the coefficients of the fixed effects Tobit model being likely to result in inconsistent slope coefficients estimates. Another approach other than the Tobit model is to employ a more general random effects mode. This allows the correlation between π_i and x_i (Wooldridge, 2010), where it assumes that: $\pi_i \left| x_i \sim N\left(\varphi + \overline{x}_i \eta, \sigma_a^2\right)\right.$, where σ_a^2 is the variance of a_i in $\pi_i = \varphi + \overline{x}_i \eta + a_i$. Considering these factors, Eq. (5) may be rewritten as:

$$\begin{aligned} & EE_{it}^{*} = x_{it}\xi + ur_{it}\theta + \delta_t + \pi_i + \mu_{it}; \\ & EE_{it} = \max\left(0, EE_{it}^{*}\right) = \max\left(0, x_{it}\xi + ur_{it}\theta + \delta_t + \overline{x}_i \eta + a_i + \mu_{it}\right); \\ & \mu_{it} \left| x_{it}, a_i \sim N\left(0, \sigma_\mu^2\right), i = 1,2,\cdots,N; t = 1,2,\cdots,T;\right. \\ & a_i \left| x_{it} \sim N\left(0, \sigma_a^2\right), i = 1,2,\cdots,N; t = 1,2,\cdots,T,\right. \end{aligned} \tag{6}$$

where $\overline{x}_i$ is a set of time-constant explanatory variables for each time step, representing the panel averages of all of the model's time-varying variables. Combining this to a traditional random effects Tobit model will in turn solve the unobserved heterogeneity problem, providing consistent model parameter values (Wooldridge, 2010).

2. Data

2.1. Input and output variables for the DEA model

To comprehensively and accurately measure EE, all input and output variables that are relevant to the energy sector need to be taken into account, dependent of course on data availability. These variables, which are used to estimate EE, are outlined below.

Capital stock. This variable is estimated from the annual fixed investment data making use of the perpetual inventory method (PIM), where the nominal investment data is first defined relative to the 2003 CNY (Chinese Yuan) by employing province-specific investment deflators (Huang et al., 2018).

Labor force. The total number of employees, depending on how much data is available, for each prefecture-level city was treated as a proxy for this parameter. We use linear interpolation method to estimate the missing data.

Land input. The total land area of each administrative region was used as the proxy since this data was available.

Energy consumption. Huang et al. (2018) first estimated the primary energy consumption of 191 prefecture-level cities for the period of 2003–2013 using the bottom-up method. We estimated the primary energy consumption of the rest of the prefecture-level cities based on the same approach and extended the study to the years 2003 to 2016.

Desirable output. Gross city product (GCP) was selected as the proxy for this parameter (using 2003 as the base year).

Undesirable outputs. The various environmental pollutants form the proxy for the undesirable outputs. These pollutants have similarities and differences, so a composite environmental pollution index (EPI) which makes use of the entropy method and considers four pollutants, i.e., wastewater, SO_2, soot-dust and CO_2, was developed so as to reduce the effect of extreme or singular values.

2.2. Interested and control variables in econometric framework

Urbanization can be categorized into three groups, namely demographic urbanization (DU), land urbanization (LU), and economically driven urbanization (EU). In addition to the rapid migration of people from rural to urban settings, urbanization also is characterised by the continuous expansion of construction land in urban areas, resulting in secondary and tertiary industries replacing primary industries. Due to data availability, DU is measured as the proportion of urban population of total population, and LU is proxied as the proportion of land used for urban construction in land used for urban development. Finally, the proportion of the secondary and tertiary industries value added to the GCP is treated as a proxy for EU.

Following previous studies, we further control for the economic development (Sadorsky, 2013), the foeign direct investment (FDI) (Al-Mulali & Tang, 2013), the technological innovation (Kou & Liu, 2017), the industrial structure (Elliott et al., 2017), and the urban levels of income (Huang & Hua, 2018). These variables are proxied by real per capita GCP (GCP), the proportion of FDI that makes up GCP (SFDI), the technological innovation index (TECH), the proportion of the secondary industry's value added in the GCP (SIND), and the disposable income of urban residents (DINC).

2.3. Data descriptions

The sample consists of 251 prefectures in China (2003–2016), and cities located in Tibet, Taiwan, Hong Kong, and Macau are excluded due to unavailability of data. Data was collected from several official sources, including *China City Statistical Yearbook* (2004–2019), *China Energy Statistical Yearbook* (2004–2019), *China Statistical Yearbook* (2004–2019), etc. Table 1 presents descriptive statistics of various variables, while the independent variables' correlation coefficients are listed in Table 2.

Table 1. Descriptive statistics of various variables

	Variables	Unit	Observations	Mean	Standard deviation	Minimum	Maximum
DEA model							
	Capital	Billion CNY	3514	1696.4220	2477.0770	27.7746	30734.9700
	Labor	10000 persons	3514	52.2813	75.9818	5.4900	986.8700
	Land	km^2	3514	16547.6500	23060.9100	1113.0000	253356.0000
	Energy	10000 Tons of SCE	3514	1507.9060	1510.5200	46.5611	12100.0000
	GCP	Billion CNY	3514	1317.8330	1825.3890	41.1659	20728.7000
	EPI	–	3514	2.8458	4.8614	0.0356	181.2617

End of Table 1

	Variables	Unit	Observations	Mean	Standard deviation	Minimum	Maximum
Econometric model	EE	–	3514	0.5532	0.2308	0.1008	1.0000
	DU	–	3499	0.0570	0.0707	0.0043	1.0000
	LU	–	3460	0.0627	0.0374	0.0001	1.000
	EU	–	3514	0.8621	0.0890	0.5011	0.9997
	PGCP	CNY/person	3514	2.9523	3.1972	0.2390	32.9734
	SFDI	–	3514	0.1492	0.1622	0.0000	0.9383
	TECH	–	3514	0.0783	0.4120	0.0000	10.6137
	SIND	–	3514	0.4921	0.1081	0.1495	0.9097
	DINC	CNY, logarithm value	3514	10.2302	0.5958	2.2834	11.7179

Note: SCE denotes standard coal equivalent.

Table 2. Correlation coefficients among independent variables

	EE	DU	LU	EU	PGCP	SFDI	TECH	SIND
DU	0.0810***	1.0000						
LU	0.1180***	0.1270***	1.0000					
EU	–0.0370**	0.4420***	0.0710***	1.0000				
PGCP	0.2660***	0.6310***	0.1060***	0.5470***	1.0000			
SFDI	0.3530***	0.3600***	0.2430***	0.3120***	0.4730***	1.0000		
TECH	0.1230***	0.4420***	–0.0030	0.2170***	0.4650***	0.2410***	1.0000	
SIND	–0.2120***	0.0580***	0.0000	0.6050***	0.1580***	–0.0220	–0.1410***	1.0000
DINC	0.1180***	0.1790***	0.0220	0.4600***	0.5250***	0.1120***	0.2640***	0.1550***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3. Empirical results

3.1. Stylized facts

The urban construction land (UCL, 100 km^2), urban residential population (URP, million persons), and per capital energy consumption (PEC, Tons of SCE/person) in China shows a trend of synchronous growth (see Figure 1). More specifically, UCL has increased from 28972 km^2 to 52761 km^2 with average annual growth rate of 4.72%, URP has increased from 338 million persons to 403 million persons with an average annual growth rate of 1.36%, and PEC has increased from 1.53 per capita Tons of SCE to 3.15 per capita Tons of SCE, with average annual growth rate of 5.71%. Evidently, the fluctuation of UCL expansion is relatively large, and formed two turning points of slowing down in 2004 and 2008. It can be inferred that the growth rate of URP lags behind that of UCL, resulting in an imbalanced development of DU and LU over the long term.

Based on the estimation of EE, it is clear that there is a positive relationship between DU (LU) and EE, while a negative correlation is observed between EU and EE (see Figure 2). On the basis of the available findings and stylized facts, there is no evidence that LU or DU exert significant positive impacts on EE, or EU exert significant negative impacts on EE. Because of these factors, conducting an empirical analysis of urbanization's impact on EE is necessary to provide a comprehensive assessment.

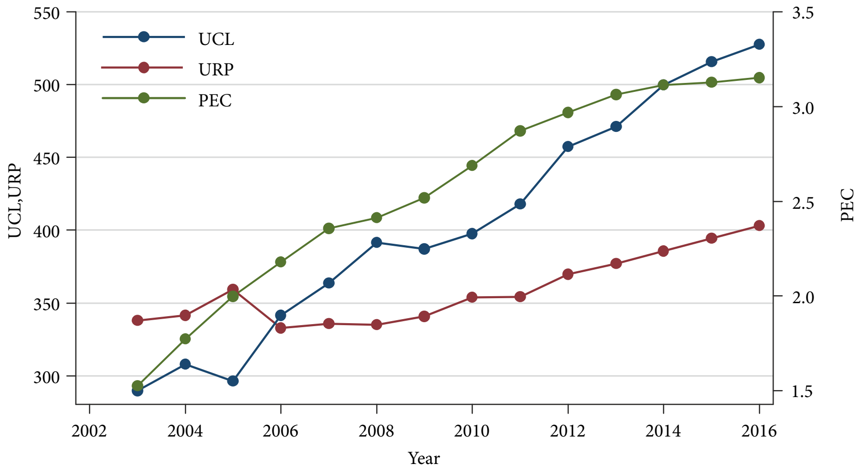

Figure 1. Evolution of UCL, URP and PEC in China over 2003–2016

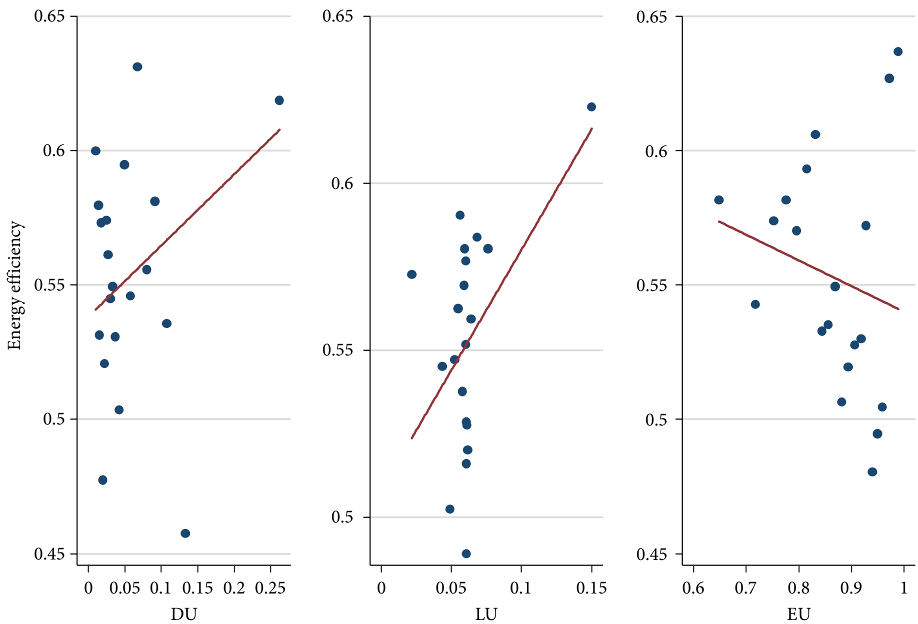

Figure 2. Correlation between urbanization and energy efficiency

3.2. Impacts of urbanization on energy efficiency

The panel Tobit model follows a random effects (RE) scheme with regards to the linear panel data model, where it is assumed that there is no correlation between the time-invariant error term and the independent variables. Table 3 presents the results from the panel Tobit model with RE. It is seen that urbanization contributes to the advancement of EE in China, indicating that urbanization has a significant and positive effect on EE. Specifically, if DU, LU, and EU increased by one unit, then EE would have increased by 0.15, 0.15, 0.45, respectively.

Table 3. Estimation results of Tobit models with random effects

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DU	0.1881**			0.1814**	0.1317+		0.1245
	(2.0881)			(1.9829)	(1.4698)		(1.3720)
LU		0.1832**		0.2221***		0.1715**	0.2154**
		(2.1488)		(2.5899)		(2.0237)	(2.5297)
EU			0.5729***		0.5911***	0.5657***	0.5858***
			(5.7008)		(5.8347)	(5.6183)	(5.7734)
AME(DU)	0.1504**			0.1451**	0.1024+		0.0970
	(2.1000)			(2.0000)	(1.4800)		(1.3800)
AME(LU)		0.1476**		0.1777**		0.1346**	0.1678**
		(2.1500)		(2.5800)		(2.0200)	(2.5200)
AME(EU)			0.4491***		0.4598***	0.4439***	0.4563***
			(5.8500)		(5.9800)	(5.7600)	(5.9200)
PGCP	0.0169***	0.0180***	0.0154***	0.0174***	0.0148***	0.0158***	0.0153***
	(8.5591)	(9.0909)	(7.7191)	(8.7638)	(7.4464)	(7.8815)	(7.6444)
SFDI	–0.0175	–0.0210	–0.0429	–0.0292	–0.0467	–0.0527	–0.0581
	(–0.4255)	(–0.5069)	(–1.0450)	(–0.7027)	(–1.1316)	(–1.2682)	(–1.3938)
TECH	0.0339***	0.0333***	0.0339***	0.0329***	0.0335***	0.0328***	0.0326***
	(3.8740)	(3.6676)	(3.8726)	(3.6486)	(3.8569)	(3.6361)	(3.6347)
SIND	–0.3817***	–0.3895***	–0.5912***	–0.3811***	–0.5867***	–0.5901***	–0.5850***
	(–8.5105)	(–8.7016)	(–10.3905)	(–8.4776)	(–10.3253)	(–10.3320)	(–10.2597)
DINC	0.0207***	0.0172***	0.0032	0.0198***	0.0052	0.0026	0.0046
	(3.8658)	(3.1960)	(0.5401)	(3.6893)	(0.8754)	(0.4403)	(0.7628)
Constant	0.4747***	0.5122***	0.2825***	0.4704***	0.2381***	0.2840***	0.2361***
	(9.1007)	(9.8984)	(4.3176)	(8.9858)	(3.6139)	(4.3300)	(3.5749)
Year effects	No	No	No	No	No	No	No
City effects	No	No	No	No	No	No	No
Observations	3499	3501	3514	3486	3499	3501	3486
Log-Likelihood	1544.1245	1529.1329	1550.2440	1540.3200	1561.1908	1544.9816	1557.0294
Wald Chi2	477.5000	460.8200	505.2600	472.3200	515.9100	497.0800	509.9300

Notes: 1) Z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, + $p < 0.15$;
3) AME denotes average marginal effects.

Considering that two types of urbanization are possible to develop simultaneously, we examine if the outcome still indicates a significant impact of urbanization on EE (see columns (4)–(6) of Table 3). Exactly what we expected, EE is significantly and positively associated with PGCP, TECH, and DINC, but significantly negatively associated with SIND. It is evident from SFDI coefficients that foreign direct investment negatively affects EE thus indicating that there may be pollution haven effects as a result of the process of urbanization in China.

Next, the fixed effects Tobit model which controls for both yearly and city effects is considered in order to estimate the impacts of urbanization on EE (see Table 4). It may be seen

Table 4. Estimation results of Tobit models with fixed effects

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DU	0.1346+			0.1219	0.1178		0.1053
	(1.5026)			(1.3380)	(1.3294)		(1.1711)
LU		0.2606***		0.3007***		0.2463***	0.2897***
		(3.2946)		(3.7783)		(3.1338)	(3.6652)
EU			0.6397***		0.6603***	0.6297***	0.6519***
			(6.0132)		(6.2004)	(5.9155)	(6.1213)
AME(DU)	0.1223+			0.1108	0.1070		0.0957
	(1.5000)			(1.3400)	(1.3300)		(1.1700)
AME(LU)		0.2367***		0.2732***		0.2238***	0.2633***
		(3.3000)		(3.7800)		(3.1300)	(3.6700)
AME(EU)			0.5810***		0.6000***	0.5721***	0.5924***
			(6.0100)		(6.2000)	(5.9200)	(6.1200)
PGCP	0.0135***	0.0146***	0.0139***	0.0143***	0.0135***	0.0146***	0.0143***
	(5.8842)	(6.3423)	(6.0977)	(6.2179)	(5.9495)	(6.3787)	(6.2561)
SFDI	0.0199	0.0078	0.0119	0.0071	0.0119	0.0002	-0.0007
	(0.4622)	(0.1802)	(0.2765)	(0.1638)	(0.2781)	(0.0055)	(-0.0167)
TECH	0.0336***	0.0320***	0.0331***	0.0318***	0.0327***	0.0313***	0.0311***
	(4.1465)	(3.8142)	(4.0875)	(3.8057)	(4.0683)	(3.7564)	(3.7513)
SIND	−0.1113**	−0.1139**	−0.3474***	−0.1055**	−0.3467***	−0.3416***	−0.3390***
	(−2.2842)	(−2.3474)	(−5.6375)	(−2.1639)	(−5.6303)	(−5.5307)	(−5.4922)
DINC	0.0122	0.0133	0.0085	0.0121	0.0072	0.0086	0.0071
	(1.1614)	(1.2588)	(0.8039)	(1.1444)	(0.6845)	(0.8127)	(0.6746)
Constant	0.2711**	0.2896**	−0.2038	0.2637**	−0.2436*	−0.2044	−0.2437*
	(2.2647)	(2.4505)	(−1.4163)	(2.1954)	(−1.6787)	(−1.4172)	(−1.6761)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3499	3501	3514	3486	3499	3501	3486
Log-Likelihood	2321.8912	2314.5122	2333.4508	2322.5407	2340.9797	2331.8933	2341.1477
Wald Chi2	11887.8200	11812.7600	12006.1600	11852.2100	12045.6800	11956.2000	12006.5600

Notes: 1) Z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, + $p < 0.15$;
3) AME denotes average marginal effects.

that for all the controls, the average marginal effects of DU (LU, EU) shows significance at the 15% (1%, 1%) level, with the corresponding coefficient equal to 0.1223 (0.2367, 0.5810), indicating DU (LU, EU) and EE have a positive relationship. Compared to the RE model, no major change in the coefficient for urbanization is seen. These results indicate that urbanization is conducive to improving China's EE. Additionally, it appears that EU exerts a greater impact on EE than both DU and LU, *ceteris paribus*. We also find that EE promotion will benefit from economic development and technology innovation.

Finally, to check whether our findings still hold without the time-invariant error term being uncorrelated with the independent variables assumption, the correlated random effects (CRE) approach is applied to the Tobit model (Wooldridge, 2008). In particular, the means of the independent variables are controlled for, and then Eq. (9) is determined (see Table 5). The empirical results imply that there is not a significant difference between the CRE and RE Tobit models.

Table 5. Estimation results of Tobit models with correlated random effects

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DU	0.3306***			0.3346***	0.2869***		0.2889***
	(3.1657)			(3.1080)	(2.8285)		(2.7762)
LU		0.1679*		0.2092**		0.1558*	0.2014**
		(1.9384)		(2.4011)		(1.8139)	(2.3358)
EU			0.8004***		0.8231***	0.7940***	0.8179***
			(7.3062)		(7.5113)	(7.2323)	(7.4500)
AME(DU)	0.2730***			0.2766***	0.2372***		0.2391***
	(3.1600)			(3.1000)	(2.8200)		(2.7700)
AME(LU)		0.1386*		0.1730**		0.1288*	0.1667**
		(1.9400)		(2.4000)		(1.8100)	(2.3300)
AME(EU)			0.6615***		0.6805***	0.6568***	0.6768***
			(7.2400)		(7.4400)	(7.1700)	(7.3800)
PGCP	0.0161***	0.0166***	0.0145***	0.0167***	0.0144***	0.0149***	0.0149***
	(7.5028)	(7.6545)	(6.7567)	(7.7011)	(6.7406)	(6.8996)	(6.9235)
SFDI	–0.1376***	–0.1505***	–0.1448***	–0.1495***	–0.1419***	–0.1551***	–0.1537***
	(–2.9732)	(–3.2003)	(–3.1432)	(–3.1946)	(–3.0944)	(–3.3260)	(–3.3160)
TECH	0.0375***	0.0378***	0.0383***	0.0365***	0.0369***	0.0373***	0.0361***
	(4.2175)	(4.0793)	(4.2979)	(3.9791)	(4.1818)	(4.0501)	(3.9617)
SIND	–0.3567***	–0.3664***	–0.6305***	–0.3550***	–0.6251***	–0.6292***	–0.6230***
	(–7.3979)	(–7.5875)	(–10.5251)	(–7.3446)	(–10.4699)	(–10.4579)	(–10.3922)
DINC	0.0203***	0.0174***	–0.0041	0.0193***	–0.0027	–0.0048	–0.0034
	(3.6524)	(3.1234)	(–0.6537)	(3.4679)	(–0.4356)	(–0.7510)	(–0.5454)
Constant	2.5499***	2.4193***	1.9669**	2.5684***	2.2151***	1.9813**	2.2543***
	(3.5220)	(3.3402)	(2.5465)	(3.5484)	(2.8069)	(2.5635)	(2.8557)
Year effects	No	No	No	No	No	No	No

End of Table 5

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
City effects	No	No	No	No	No	No	No
Observa-tions	3499	3501	3514	3486	3499	3501	3486
Log-Likelihood	1580.7651	1560.8780	1593.6349	1576.9146	1609.2742	1587.9946	1604.8927
Wald Chi2	566.4500	537.6400	608.9100	560.9000	631.8800	599.7700	625.0300

Notes: 1) Z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, + $p < 0.15$;
3) AME denotes average marginal effects.

3.3. Sensitivity analysis

The robustness of the empirical results determined in the previous sections are now assessed. On the one hand, the quasi-DID method (Nunn & Qian, 2011; Yang et al., 2017) is used to examine both the average and dynamic effects of urbanization on the EE as a result of the New National Urbanization Plan (NNUP) (2014–2020), outlined by the Chinese government in 2014 (see Table 6). It can be observed that the DU × I and LU × I coefficients are significantly positive, which implies that the NNUP's implementation since 2014 has positively promoted EE, especially for DU and LU. The dynamic effects of the NNUP on EE also show the positive effects of the policy, with urbanization exerting a positive influence on EE for the period from 2014 to 2016. Regarding the relative strength of the influence, it appears that LU exerts a greater impact on EE than DU and LU.

Table 6. Estimation results of quasi-DID method

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Lag(EE)	0.8618***	0.8586***	0.8633***	0.8561***	0.8611***	0.8525***
	(277.4570)	(301.9917)	(376.8476)	(288.7997)	(285.6983)	(263.8392)
DU × I	0.0509***					
	(8.4447)					
DU × I_{2014}		0.1749***				
		(44.4050)				
DU × I_{2015}		–0.0670***				
		(–10.4122)				
DU × I_{2016}		0.3062***				
		(25.2976)				
LU × I			1.8548***			
			(22.1609)			
LU × I_{2014}				0.4216***		
				(28.6566)		
LU × I_{2015}				3.8632***		
				(7.4189)		
LU × I_{2016}				1.2838***		
				(13.9980)		

End of Table 6

Variables	(1)	(2)	(3)	(4)	(5)	(6)
EU × I					0.0160	
					(1.4315)	
EU × I_{2014}						0.0275***
						(26.9173)
EU × I_{2015}						0.0034
						(0.2848)
EU × I_{2016}						0.0569**
						(2.1576)
Constant	−0.3339***	−0.3285***	−0.3355***	−0.2791***	−0.3281***	−0.2698***
	(−34.8366)	(−33.0480)	(−39.7780)	(−33.2648)	(−37.0225)	(−31.0312)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
AR (1)	−3.7900***	−3.7600***	−3.8100***	−3.7900***	−3.8000***	−3.7400***
AR (2)	1.0300	1.0500	1.0100	1.0400	1.0200	1.0400
Hansen test chi2	226.8900	224.6700	226.6700	232.1100*	226.3000	228.1700*
Observations	3253	3253	3251	3251	3263	3263

Notes: 1) Z-statistics in parentheses; 2) *** p < 0.01, ** p < 0.05, * p < 0.1.

Furthermore, as an alternative EE evaluation approach, we utilize a panel data stochastic frontier analysis (SFA) model in order to examine how urbanization impacts on EE. Both production and efficiency functions are estimated in this model. Table 7 presents the results of the SFA models and the technical inefficiency terms assumed to exponential distribution (see Appendix B for further details). Across all econometric specifications, the estimated coefficients of DU, LU and EU show how urbanization imposes significant negative impacts on technical inefficiency, indicating it exerts positive effects on EE (see Eq. (C.4)). Given these results, it may be said that the evidence generally supports our findings.

Table 7. Estimation results of SFA models with dependent variable technical inefficiency

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DU	−3.2914**			−3.0792*	−3.1813*		−2.3773
	(−2.1180)			(−1.7342)	(−1.7540)		(−1.4205)
LU		−9.7293***		−8.6985***		−8.7435***	−8.1994***
		(−3.9485)		(−3.5960)		(−3.6413)	(−3.4009)
EU			−3.9751**		−3.0220**	−1.6413	−1.7229
			(−2.4202)		(−2.0896)	(−0.7888)	(−0.8410)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3499	3501	3514	3486	3499	3501	3486
Log-Likelihood	−20253.9090	−29153.2210	−1348.5294	−28263.5300	−7613.0266	−25623.699	−24498.096
Wald Chi2	538.4500	397.5100	6036.6000	395.0400	1425.5900	444.3200	451.6000

Note: 1) Z-statistics in parentheses; 2) *** p < 0.01, ** p < 0.05, * p < 0.1.

Conclusions and policy implications

Analyzing efficiency and productivity with heterogeneity technology is important.Analyzing the metafrontier can be useful for considering heterogeneity technology, however, most of the prior literature develops convex metafrontiers that include infeasible combinations of inputs and outputs, leading to biased estimates.Given that, methodologically, the convex metafrontier is extended to a non-convex metafrontier, with China's EE being determined based on a sample set of 251 prefecture-level cities for the period 2003 to 2016. Empirically, we also explore how urbanization influences EE using Tobit regression methods. The following policy implications are thus derived from our findings, and summarized as follows.

We find that DU, LU, and EU all have a positive impact on EE. Specifically, estimates from the Tobit model with random effects show that a unit increase in DU, LU, and EU would result in an increase in EE by 0.15, 0.15 and 0.45, respectively. These results are robust across econometric specifications, including fixed and correlated random effects Tobit models. Sensitivity analyses of stochastic frontier analysis also support our findings.

The New Normal in China is characterized by urbanization as the engine for economic and social development. In order to improve China's EE, it is critical to promote the urbanization strategy and use the dividend released by its urbanization. Through urbanization, it is also possible to promote and realize sustainable development. With reference to the empirical findings, we suggest the following policy implications and suggestions. On the one hand, it is imperative that policymakers take advantage of the complementarity between energy structure and energy market to improve the role that urbanization plays in the energy sector, cultivating new energy industries that can greatly improve EE. During the process of urbanization, the spillover effects of energy technologies are vital, transferring superior energy resources to industrial sectors and regions with comparative advantages, and generating new energy structures that may result. The high traction to the urbanization process and the promotion role of urbanization in EE improvement should be formed and strengthened continuously. The development of urbanization requires further improvement of endogenous power mechanisms. On the other hand, multidimensional heterogeneities, such regional and city size differences, when considering urbanization should be made full use of during the process of introducing high-quality energy. To improve China's EE, the mobility and agglomeration of high-end energy industries, that is, the consideration of environmental protection and energy-saving measures, as well as innovations in information technology and new sources of energy (vehicles), should be promoted. Furthermore, energy consumption/demand levels and energy (types) endowments in different cities also need to be highlighted during the process of new urbanization. The governors should attach great importance to the coordinated development between demographic urbanization, land urbanization, and economic urbanization and EE, especially to the complementary and synergistic effects of all kinds of urbanization.

The following aspects will be studied further. We suggest an extension to the DEA model to measure and compare productivity changes across cities within a group as measured by the Malmquist-Luenberger productivity indicator.These indicators have the same non-convex metafrontier and are comparable and provide insightful information. Moreover, the spatial effects and distance decay effects of urbanization on EE could also be verified using spatial econometrics models, e.g., the SLX model. In addition, it is also a worthy direction to analyze the channels and mechanisms through which urbanization affects energy efficiency.

Acknowledgements

We would like to thank the editor and anonymous referees for their valuable comments and suggestions to improve the quality of this paper. Yantuan Yu thanks the financial support provided by the National Natural Science Foundation of China (71903068).

Conflicts of interest

The authors declare no conflict of interest.

References

Afsharian, M., & Podinovski, V. V. (2018). A linear programming approach to efficiency evaluation in nonconvex metatechnologies. *European Journal of Operational Research*, *268*(1), 268–280. https://doi.org/10.1016/j.ejor.2018.01.013

Afsharian, M. (2017). Metafrontier efficiency analysis with convex and non-convex metatechnologies by stochastic nonparametric envelopment of data. *Economics Letters*, *160*, 1–3. https://doi.org/10.1016/j.econlet.2017.08.006

Al-Mulali, U., & Tang, C. F. (2013). Investigating the validity of pollution haven hypothesis in the gulf cooperation council (GCC) countries. *Energy Policy*, *60*, 813–819. https://doi.org/10.1016/j.enpol.2013.05.055

Andersen, P., & Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis. *Management Science*, *39*(10), 1261–1264. https://www.jstor.org/stable/2632964

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 325–332. https://doi.org/10.1007/BF01205442

Battese, G. E., Rao, D. S. P., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*(1), 91–103. https://doi.org/10.1023/B:PROD.0000012454.06094.29

Bilgili, F., Koçak, E., Bulut, Ü., & Kuloğlu, A. (2017). The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity. *Energy*, *133*, 242–256. https://doi.org/10.1016/j.energy.2017.05.121

Boyd, G. A., & Lee, J. M. (2019). Measuring plant level energy efficiency and technical change in the U.S. metal-based durable manufacturing sector using stochastic frontier analysis. *Energy Economics*, *81*, 159–174. https://doi.org/10.1016/j.eneco.2019.03.021

Elliott, R. J. R., Sun, P., & Zhu, T. (2017). The direct and indirect effect of urbanization on energy intensity: A province-level study for China. *Energy*, 123, 677–692. https://doi.org/10.1016/j.energy.2017.01.143

Greene, W. H. (2011). *Econometric analysis* (7^{th} ed.). Prentice Hall.

Haider, S., & Mishra, P. P. (2021). Does innovative capability enhance the energy efficiency of Indian Iron and Steel firms? A Bayesian stochastic frontier analysis. *Energy Economics*, *95*, 105128. https://doi.org/10.1016/j.eneco.2021.105128

He, Y., Liao, N., & Zhou, Y. (2018). Analysis on provincial industrial energy efficiency and its influencing factors in China based on DEA-RS-FANN. *Energy*, *142*, 79–89. https://doi.org/10.1016/j.energy.2017.10.011

Huang, C. W., Ting, C. T., Lin, C. H., & Lin, C. T. (2013). Measuring non-convex metafrontier efficiency in international tourist hotels. *Journal of the Operational Research Society*, *64*(2), 250–259. https://doi.org/10.1057/jors.2012.52

Huang, J., & Hua, Y. (2018). Eco-efficiency convergence and green urban growth in China. *International Regional Science Review*, *42*(3–4), 307–334. https://doi.org/10.1177/0160017618790032

Huang, J., Yu, Y., & Ma, C. (2018). Energy efficiency convergence in China: Catch-up, lock-in and regulatory uniformity. *Environmental and Resource Economics*, *70*(1), 107–130. https://link.springer.com/article/10.1007/s10640-017-0112-0

Jorgenson, D., Gollop, F. M., & Fraumeni, B. (1987). *Productivity and U.S. economic growth*. Harvard University Press.

Kou, Z., & Liu, X. (2017). *FIND report on city and industrial innovation in China*. Fudan Institute of Industrial Development, School of Economics, Fudan University.

Li, K., Fang, L., & He, L. (2018). How urbanization affects China's energy efficiency: A spatial econometric analysis. *Journal of Cleaner Production*, *200*, 1130–1141. https://doi.org/10.1016/j.jclepro.2018.07.234

Lv, Y., Chen, W., & Cheng, J. (2020). Effects of urbanization on energy efficiency in China: New evidence from short run and long run efficiency models. *Energy Policy*, *147*, 111858. https://doi.org/10.1016/j.enpol.2020.111858

Mardani, A., Zavadskas, E., Streimikiene, D., Jusoh, A., & Khoshnoudi, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews*, *70*, 1298–1322. https://doi.org/10.1016/j.rser.2016.12.030

Markandya, A., Pedroso-Galinato, S., & Streimikiene, D. (2006). Energy intensity in transition economies: Is there convergence towards the EU average? *Energy Economics*, *28*(1), 121–145. https://doi.org/10.1016/j.eneco.2005.10.005

Nunn, N., & Qian, N. (2011). The potato's contribution to population and urbanization: Evidence from a historical experiment. *The Quarterly Journal of Economics*, *126*(2), 593–650. https://doi.org/10.1093/qje/qjr009

Ouyang, X., Chen, J., & Du, K. (2021). Energy efficiency performance of the industrial sector: From the perspective of technological gap in different regions in China. *Energy*, *214*, 118865. https://doi.org/10.1016/j.energy.2020.118865

Rafiq, S., Salim, R., & Nielsen, I. (2016). Urbanization, openness, emissions, and energy intensity: A study of increasingly urbanized emerging economies. *Energy Economics*, *56*, 20–28. https://doi.org/10.1016/j.eneco.2016.02.007

Sadorsky, P. (2013). Do urbanization and industrialization affect energy intensity in developing countries? *Energy Economics*, *37*, 52–59. https://doi.org/10.1016/j.eneco.2013.01.009

Sheng, P., He, Y., & Guo, X. (2017). The impact of urbanization on energy consumption and efficiency. *Energy & Environment*, *28*(7), 673–686. https://doi.org/10.1177/0958305X17723893

Tiedemann, T., Francksen, T., & Latacz-Lohmann, U. (2011). Assessing the performance of German *Bundesliga* football players: A non-parametric metafrontier approach. *Central European Journal of Operations Research*, *19*(4), 571–587. https://doi.org/10.1007/s10100-010-0146-7

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5

Wang, Q., Zhao, Z., Zhou, P., & Zhou, D. (2013). Energy efficiency and production technology heterogeneity in China: A metafrontier DEA approach. *Economic Modelling*, *35*(5), 283–289. https://doi.org/10.1016/j.econmod.2013.07.017

Wooldridge, J. M. (2008). *Nonlinear dynamic panel data models with unobserved effects. Invited lecture*. Canadian Econometrics Study Group, Montreal.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Yang, Z., Fan, M., Shao, S., & Yang, L. (2017). Does carbon intensity constraint policy improve industrial green production performance in China? A quasi-DID analysis. *Energy Economics*, *68*, 271–282. https://doi.org/10.1016/j.eneco.2017.10.009

Yu, Y., Huang, J., & Zhang, N. (2018). Industrial eco-efficiency, regional disparity, and spatial convergence of China's regions. *Journal of Cleaner Production*, *204*, 872–887. https://doi.org/10.1016/j.jclepro.2018.09.054

Yu, Y., Zhang, N., & Kim, J. D. (2020). Impact of urbanization on energy demand: An empirical study of the Yangtze River Economic Belt in China. *Energy Policy*, *139*, 111354. https://doi.org/10.1016/j.enpol.2020.111354

Zhang, N., Kong, F., & Yu, Y. (2015). Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. *Ecological Indicators*, *51*, 165–172. https://doi.org/10.1016/j.ecolind.2014.07.041

APPENDIX

A. Evolution of urban population (% of total population) during 1960–2020

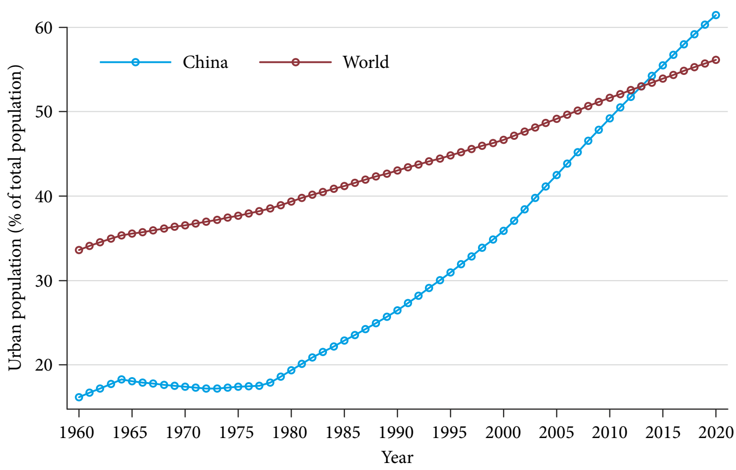

Figure A1. Evolution of urban population (% of total population) in China and the world during 1960–2020 (data sources: the World Bank)

B. SFA-based energy efficiency for sensitivity analysis

Following Battese and Coelli (1995), we investigate the impact of urbanization on energy efficiency which estimated by the panel data stochastic frontier function. Assuming the production possibility function $f(x)$ and the efficiency level $0 < \varepsilon \le 1$, then we have the actual output $y = f(x)\varepsilon$. By introducing the random impact on production output, our output frontier function is expressed as:

$$y = f(x) \cdot \varepsilon \cdot e^{v}, \tag{B.1}$$

where $f(x)$ is assumed to follow the Cobb-Douglas production function in such form as $f(x) = e^{\beta_0} x_1^{\beta_1} \cdots x_n^{\beta_n}$. By taking natural logarithm of both sides of Eq. (B.1), we can obtain:

$$\ln y = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + \ln\varepsilon + v = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + v - u, \tag{B.2}$$

where $u = -\ln\varepsilon > 0$ is a non-negative random variable capturing technical inefficiency, and v is random error independent of u whose distribution is Exponential. When panel data are used for estimation, the panel data stochastic frontier model can be expressed as:

$$\ln y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{nit} + v_{it} - u_{it}, \tag{B.3}$$

where i and t denote year and city, respectively.

Practically, urbanization does not directly enter the production function, it may affect energy efficiency through technical inefficiency term. Ignoring these factors may lead to inaccurate estimation results. Given that, the technical inefficiency equation is estimated as:

$$u_{it} = \delta_0 + \delta_i Z_{it}, \tag{B.4}$$

where Z_{it} denotes urbanization and other influence factors closely affecting the energy efficiency and its coefficients is δ_i. Since the energy efficiency is calculated as $exp(-\hat{u}_{it})$, urbanization and other influence factors exert positive (negative) impacts on energy efficiency if $\delta_i < 0$ ($\delta_i > 0$).

We use capital stock (K), labor force (L), and energy consumption (E) as input factors, gross city product (GCP) as output to construct the panel data stochastic frontier model based on Jorgenson et al. (1987), which specified as:

$$\ln GCP_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln E_{it} + v_{it} - u_{it}, \tag{B.5}$$

where $\ln GCP_{it}$ is the logarithm term of real GCP with constant price at 2003 for city i in year t. K is measured using perpetual inventory method adopted by Ke and Xiang (2012) by taking 2003 as the base year. The total number of employees was used as proxy to labor force L. Additionally, E is energy input measured as total primary energy consumption and the estimation procedure is referred to Huang et al. (2018). K, L, and E are all computed using their logarithm terms. v and u denote random error and technical inefficiency explained above.