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Effect of land price distortion on land use efficiency: Evidence from China

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ABSTRACT

Land price distortion will not only lead to a series of economic problems such as widening regional economic gap, local government debt risk and serious ecological deterioration, but also lead to the imbalance of macro allocation of land resources and irrational spatial structure, and the land input-output efficiency will also be affected. This article studies the impact of land price distortion on China's land use efficiency using a dataset of 103 cities in China during the years 2008–2015. The results show that there exist significant spatiotemporal disparities of land use efficiency. The land use efficiency has significant spatiotemporal differences. Empirical results document that increases in land price distortion leads to significant decreases in land use efficiency. Our findings are robust to alternative measures of land price distortion, different subsamples and instrumental variable estimations.

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1. Introduction

Extensive research has been devoted to analyzing factor market distortion, which will lead to productivity loss by reducing the efficiency of resource allocation (Banerjee & Moll, 2010; Brandt et al., 2013; Buera et al., 2011; Dai & Cheng, 2016; Gabler & Poschke, 2013; Ranasinghe, 2014; Yang et al., 2018). Classical economic theory suggests the production of a nation primarily depends on the quantity of land, capital, and labour (Solow, 1957). As the most fundamental production factor, not only land is of significance asset under the control of central/local governments (Qin et al., 2016), but an essential policy tool to stimulate economic growth.

Recently, several scholars focus on studying the price distortion in China (Cui & Wei, 2017; Ju et al., 2017; Ouyang et al., 2018; Ouyang & Sun, 2015). To the best of our knowledge, however, few studies focus on land price distortion (henceforth LPD), especially its impact on land use efficiency (henceforth LUE). Practically, local governments have used distorted industrial land prices and land supply to attract

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investment to provide industrial park infrastructure, which has contributed to rapid industrialisation and made China a world-class manufacturing factory. Generally, the land pricing system has significant impacts on improving urban land productivity (Du et al., 2016). Both building permit policy (Asabere & Huffman, 2001) and interregional subsidy competition (Xu et al., 2017) will be distorted land price, furthermore, the zoning of land at a lower density that would occur in a competitive land market with landowners raise land values to a Pareto optimal level. To correct LPD is conducive to improve LUE and realise the effective allocation of land resources, ensuring that the regional development process is consistent with the policymakers' long-term planning, diminishing externalities of land use. More importantly, the implementation effect of land use planning presented significant regional or temporal heterogeneity.

It is necessary to clarify the definition of price distortion and the relationship between price distortion and resource misallocation. Factor price distortion indicates the bias or deviation between the market price of production elements and its marginal outputs or opportunity costs (Chacholiades, 1978). Positive (negative) distortion denotes the factor prices are larger (smaller) than the equilibrium prices determined by the marginal outputs or opportunity costs. Since land is commonly treated as a kind of resources, for ease of discussion, LPD also means land resource misallocation (LRM) to some extent in this study. Our study is helpful to better understand the causes of low LUE in China, and also provides theoretical and empirical basis for the negative impact of LPD on China's land market. To some extent, it also enriches the related research on LPD and LUE. Information about how and to what extent LPD affects LUE is beneficial for both policymakers and practitioners to promote the marketisation reform of land elements. Policymakers should also fully perfect the construction of laws and regulations related to the use of urban construction land and standardise the pricing method of urban construction land. To achieve land sustainable development, the efficiency loss effect of LPD should be vigilant. Therefore, this study can provide some empirical references for the improvement of LUE through reduce the LPD in other developing countries.

This article makes a first empirical attempt to examine the impact of LPD on China's LUE using a dataset of 103 cities during the years 2008–2015. We also develop a data envelopment analysis (DEA) model which has several advantages over conventional models to measure LUE. Of relevance to the present discussion is that the new model can be excluded the infeasible input-output combinations (Tiedemann et al., 2011), the measures of LUE may be more reasonable while taking input-oriented into account. Estimates of Tobit regression show that the LPD shows significant negative impact on LUE from both statistically and economically perspective.

The rest of this article proceeds as follows. Section 2 briefly reviews the literature on misallocation of resources (land misallocation) and measurement of LUE, followed by a discussion of the method in Section 3. Section 4 describes the data and empirical results. Finally, Section 5 summarises and concludes.

2. Literature review

A multitude of studies on analyzing the misallocation of resources has been conducted in the academic community. Misallocation implies high marginal products for constrained countries/regions and therefore a strong pressure for accumulation and to eliminate the distortion. Resources misallocation can lower aggregate total factor productivity (Ha et al., 2016; Hsieh & Klenow, 2009; Restuccia & Rogerson, 2013) because inputs are misallocated across heterogeneous production units, particularly for capital and land (Chinn, 1977). The land utilisation pattern and/or land misallocation may vary across countries. Empirical results show that if the total factor productivity of revenue (TFPR) for China is the same as that of the United States, the total factor productivity of manufacturing enterprises will increase by 30–50%; and if the market distortions are eliminated then it can be increased by 86.6–115% (Ha et al., 2016). Unlike the works of Chinn, (1977) and others, previous study also finds that lifting restrictions on land transferability lowers agricultural employment by 19% and increased GDP by 7% (Gottlieb & Grobovšek, 2019). In addition, several scholars pay attention to land price information or industrial LPD and their impacts, such as Wu et al. (2014).

Another strand of literature focuses on measuring LUE in terms of single-factor analysis and multi-output productivity approach. Nevertheless, due to the advantages of being free from functional form for the frontier or the distribution of inefficiency and its nonparametric treatment of the frontier, the DEA method has been frequently adopted in plenty of pioneer studies (Ding et al., 2022; Lu et al., 2018; Zhang et al., 2018). Since land utilisation has been considered as an input-output system, the essential characteristics of land use have been fully considered by employing DEA method. Regarding the stylise facts of industrialisation and urbanisation in China, tremendously fast economic growth has been achieved with the heavy costs of excessive resource consumption and environmental deterioration. Thus, the undesirable outputs such as industrial pollutants should not be neglected, the directional distance function which considers environmental emissions as undesirable outputs and then brings them into the production process has been widely applied (Chung et al., 1997). However, this kind of directional distance function is a radial and oriented DEA model. The directional distance function model is suffered the limitation of overestimating LUE, because it ignores the non-radial input/output slacks. To overcome this issue, non-radial model was proposed to treat improvements non-proportionally with slacks directly, which is called slack-based measure (SBM) model by (Tone, 2001).

Although a large portion of studies have observed resource misallocation and its impacts on TFP, to date, rare study concentrates on LPD and LUE. Since a study of this topic would be very useful and timely, it is the purpose of this article to fill this gap by focussing on examining the impact of LPD on LUE (relative efficiency evaluation with multiple inputs and outputs). Concerned with the interaction and relationship between LPD and LUE, we make attempt to employ a panel Tobit model to conduct empirical analysis, some policy suggestions are proposed based on the empirical results.

3. Methodologies

3.1. Measuring LPD based on production function

The measurement of LPD is an evaluation tool of the degree of deviation from the land market price and its opportunity cost. The absolute distortion of land price refers to the land input price deviates from its marginal productivity. Since China's market economic system has been basically established, the allocation of resources and the production of the enterprises are principally market-oriented. If the output level is determined by endogenous factors, choosing the production function method has a comparative advantage. Moreover, the theory of economic growth suggests that the volume of production in a country or region depends on the amount of land, capital and labour involved in the production process. In this article, based on these three basic factors of production, the energy input has introduced to the flexibility Cobb-Douglas production function, which aims to reveal the energy structure change on the influence of economic output. C-D production function can be expressed as:

$$y_{it} = AL_{it}^{\beta_l}K_{it}^{\beta_k}U_{it}^{\beta_u}E_{it}^{\beta_e} \tag{1}$$

where y_{it} represents the economic output of city i at time t; A represents the technology used; L_{it}, K_{it}, U_{it} and E_{it} represent, respectively, the labour, capital, urban construction land and energy input of city i at time t; and β_l, β_k, β_u and β_e represent the elasticities of labour, capital, urban construction land and energy, respectively. The log-log form of equation (1) is as follows:

$$lny_{it} = lnA + \beta_l lnL_{it} + \beta_k lnK_{it} + \beta_u lnU_{it} + \beta_e lnE_{it} + \varepsilon_{it} \tag{2}$$

To maximise the output, we have:

$$\begin{gathered} \max y_{it} = f(L_{it}, K_{it}, U_{it}, E_{it}) \\ s.t.\ p_{L_{it}}L_{it} + p_{K_{it}}K_{it} + p_{U_{it}}U_{it} + p_{E_{it}}E_{it} = C_{it} \end{gathered} \tag{3}$$

where $p_{L_{it}}$, $p_{K_{it}}$, $p_{U_{it}}$ and $p_{E_{it}}$ denote the real price of labour, capital stock, land[1] and energy of city i at time t, respectively. C_{it} represents the total consumption level of city i at time t.

This article analyzes from the perspective of urban construction land input, and the first order condition of maximum output is given by:

$$p_{U_{it}} = MP_{U_{it}} = A\beta_u L^{\beta_l}K^{\beta_k}U^{\beta_u - 1}E^{\beta_e} = \beta_u \frac{y_{it}}{U_{it}} \tag{4}$$

where $MP_{U_{it}}$ represents the marginal output of urban construction land input of city i at time t. Under the framework of equilibrium, to obtain the maximum output of urban construction land, the price of land should be equal to it's the marginal output, otherwise, the price of land will be distorted. The definition of LPD is given by:

$$LPD_{it} = \frac{MP_{U_{it}}}{p_{U_{it}}} \tag{5}$$

where LPD_{it} measures the intensity of LPD of city i at time t. Specifically, $LPD_{it} = 1$ means that there is no LPD for city i at time t; $LPD_{it} > 1$ implies $p_{U_{it}} < MP_{U_{it}}$, representing there exists positive LPD for city i at time t; and $LPD_{it} < 1$ hints $p_{U_{it}} > MP_{U_{it}}$, denoting there exists negative LPD for city i at time t.In terms of positive LPD, the distortions could be corrected by reducing the supply of land used or expansionary policy and monetary policy stated by government, reducing the cost of investment or increasing the demand for urban construction land. With respect to negative LPD, the policies can be transferred to improve the marginal output of urban construction land through increasing both the level of productivity technology and the level of land utilisation intensive. In sum, the government can adopt administrative measures or economic policies to control the urban construction land supply and demand balance, or by improving the level of productivity technology to correct LPD, and comprehensively improve the LUE.

3.2. Measuring LUE with input-oriented NCMeta-US-SBM model

Assuming that there are N decision making units (DMUs), G technology-heterogeneous groups[2] and N_g DMUs in Group g, we have $\sum_{g=1}^{G} N_g = N$. Each DMU uses inputs: $\boldsymbol{x} = [x_1, x_2, \ \ldots, x_M] \in R_+^M$ to produce desirable (good) outputs: $\boldsymbol{y} = [y_1, y_2, \ \ldots, y_R] \in R_+^R$ and undesirable (bad) outputs: $\boldsymbol{b} = [b_1, b_2, \ \ldots, b_J] \in R_+^J$. With variable returns to scale (VRS) assumption, the convex and nonconvex production technologies for the oth DMU in Group $g(o = 1, 2, \ldots, N_g, g = 1, 2, \ldots, G)$ with reference to metafrontier can be respectively expressed as follows:

$$\begin{aligned} P^{c-meta} = \{ (x_m, y_r, b_j) : x_{mg'o} \geq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \lambda_{gn} x_{mgn}, m = 1,2,\ldots,M; \\ y_{rg'o} \leq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \lambda_{gn} y_{rgn}, r = 1,2,\ldots,R; \\ b_{jg'o} \geq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \lambda_{gn} b_{jgn}, j = 1,2,\ldots,J; \\ & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \lambda_{gn} = 1; \lambda_{gn} \geq 0; g = 1,2,\ldots G; n \in g', n \neq o \ \ if \ \ g = g' \} \end{aligned} \tag{6}$$

where λ_{gn} is a nonnegative weighting vector of nth DMU in Group g with reference to convex metafrontier which enveloped by all group frontier technologies.

We can also express the nonconvex metafrontier production technology as follows:

$$\begin{aligned} P^{c-meta} = \{ (x_m, y_r, b_j) : x_{mg'o} \geq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \gamma_{gn} x_{mgn}, m = 1, 2, \ \ldots, M; \\ y_{rg'o} \leq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \gamma_{gn} y_{rgn}, r = 1, 2, \ \ldots, R; \\ b_{jg'o} \geq & \sum_{g=1}^{G} \sum_{n \in g', n \neq o \ \ if \ \ g=g'} \gamma_{gn} b_{jgn}, j = 1, 2, \ \ldots, J; \\ & \sum_{g=1}^{G} \sum_{n \in (g'=1), n \neq o \ \ if \ \ g=g'} \gamma_{gn} = \phi_1, \\ & \sum_{g=1}^{G} \sum_{n \in (g'=2), n \neq o \ \ if \ \ g=g'} \gamma_{gn} = \phi_2, \ \ldots, \\ & \sum_{g=1}^{G} \sum_{n \in (g'=G), n \neq o \ \ if \ \ g=g'} \gamma_{gn} = \phi_G; \\ & \sum_{g=1}^{G} \phi_g = 1; \phi_g = 1 \ \ or \ \ 0; \gamma_{gn} \geq 0; n \in g', n \neq o \ \ if \ \ g = g' \} \end{aligned} \tag{7}$$

where γ_{gn} is a nonnegative weighting vector of nth DMU in Group g with reference to the nonconvex metafrontier. With convex metafrontier and nonconvex metafrontier defined, we can now define input-oriented super efficiency SBMs for both frontiers. Unlike Huang et al. (2018), we extend the convex metafrontier to nonconvex one which enable us to exclude the infeasible input-output combinations. Assuming VRS, the optimal objective value for the oth DMU in Group g' ($o = 1, 2, \ldots, N_g$; $g' = 1, 2, \ldots, G$) with reference to the nonconvex metafrontier is estimated as:

$$\begin{aligned}
\rho_{g'o}^{nc-meta*} = \min & \left(1 + \frac{1}{M}\sum\nolimits_{m=1}^{M}\frac{s_{mg'o}^{x}}{x_{mg'o}}\right) \\
& s.t.\ x_{mg'o} - \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \ \ if \ \ g=g'}\gamma_{gn}x_{mgn} + s_{mg'o}^{x} \geq 0, m = 1, 2, \ldots, M; \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \ \ if \ \ g=g'}\gamma_{gn}y_{rgn} - y_{rg'o} \geq 0, r = 1, 2, \ldots, R; \\
& b_{jg'o} - \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in g',\, n\neq o \ \ if \ \ g=g'}\gamma_{gn}b_{jgn} \geq 0, j = 1, 2, \ldots, J; \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=1),\, n\neq o \ \ if \ \ g=g'}\gamma_{gn} = \phi_1, \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=2),\, n\neq o \ \ if \ \ g=g'}\gamma_{gn} = \phi_2, \ldots, \\
& \sum\nolimits_{g=1}^{G}\sum\nolimits_{n\in(g'=G),\, n\neq o \ \ if \ \ g=g'}\gamma_{gn} = \phi_G; \\
& \sum\nolimits_{g=1}^{G}\phi_g = 1; \phi_g = 1 \ \ or \ \ 0; \gamma_{gn}, s_{mg'o}^{x} \geq 0
\end{aligned} \tag{8}$$

where $s_{mg'o}^{x}$ represents the input slacks. The difference between the super efficiency model and the standard model is that DMU_{go} in the reference set in the super efficiency model is excluded, which is denoted by $n \neq o$.

The optimal object values estimated in Model (8) are sometimes taken as the measure of LUE. However, these values relate to the averages of the slacks of all inputs and maximize the average improvements of all relevant factors for the evaluated DMU to reach the nonconvex metafrontier. Given that, one should focus on the slack of land instead of the average slack of all inputs when measuring LUE. Suppose the actual land input is x_l, and the land slacks corresponding to the nonconvex metafrontier by solving the Model (8) is $S_l^{nc-meta}$, then the nonconvex metafrontier LUE can be calculated by:

$$LUE^{nc-meta} = \frac{(x_l - S_l^{nc-meta})}{x_l} \tag{9}$$

Eq. (9) defines our SBM based land efficiency measure for the empirical analysis. Since $0 \leq S_l^{nc-meta} < x_l$, and $LUE^{nc-meta} \in (0, 1]$.

3.3. Panel Tobit model

In the presence of super efficiency, the efficiency values may greater than one, the panel Tobit model might be inappropriate. However, LUE considered in this study falls in $(0, 1]$, which are censored. The ordinary least square (OLS) estimates with a censored dependent variable may be biased and inconsistent. Tobit regression, one of limited dependent variable models, can effectively handle this type of data with the Maximum Likelihood Estimation (MLE). Given that, we adopt panel Tobit model.

To estimate the effectiveness of LPD on LUE, we employ a variety of limited variable model specifications to overcome challenges presented by potential endogeneity concerns. In particular, the baseline Tobit model can be specified as:

$$LUE_{it}^{*} = x_{it}\beta + LPD_{it}\gamma + \delta_t + \pi_i + \mu_{it} \tag{10}$$

$$\begin{gathered} LUE_{it} = \max(0, LUE_{it}^{*}) = \max(0, x_{it}\xi + LPD_{it}\theta + \delta_t + \pi_i + \mu_{it}) \\ \mu_{it}|x_{it}, \pi_i \sim N\left(0, \sigma_{\mu}^{2}\right), \ \ i = 1, 2, \ldots, N; \ \ t = 1, 2, \ldots, T \end{gathered} \tag{11}$$

where LUE_{it} represents LUE for city i at year t denotes the time; x_{it} is the independent variables and ξ represents the parameter vector. The key variables of interest, LPD measures funded by LPD (LPD_{it}) and θ represents the parameter vector. Finally, δ_t represents year fixed effects, π_i captures unobserved heterogeneity and μ_{it} is the normal distributed error term.

The inclusion of fixed effects in a limited dependent variable model poses the well-known incidental parameters problem in MLE. Consequently, the coefficients of the fixed effects Tobit model are likely imprecise resulting in inconsistent estimates of the slope coefficients. An alternative specification to the fixed effects Tobit model is a more general random effects model, which allow π_i and x_i to be correlated (Wooldridge, 2010). This model assumes: $\pi_i|x_i \sim N\left(\varphi + \overline{x_i}\eta, \sigma_a^2\right)$ where σ_a^2 is the variance of a_i in the equation $\pi_i = \ \varphi + \overline{x_i}\eta + a_i$. Under this specification the model defined in (10) becomes:

$$LUE_{it}^{*} = x_{it}\xi + LPD_{it}\theta + \delta_t + \pi_i + \mu_{it} \tag{12}$$

$$\begin{gathered} LUE_{it} = \max\left(0, LUE_{it}^{*}\right) = \max\left(0, x_{it}\xi + LPD_{it}\theta + \delta_t + \overline{x_i}\eta + a_i + \mu_{it}\right) \\ \mu_{it}|x_{it}, a_i \sim N\left(0, \sigma_{\mu}^{2}\right), \ \ i = 1, 2, \ldots, N; \ \ t = 1, 2, \ldots, T \\ a_i|x_{it} \sim N\left(0, \sigma_a^2\right), i = 1, 2, \ldots, N; \ \ t = 1, 2, \ldots, T \end{gathered} \tag{13}$$

where $\overline{x_i}$ represents an additional set of time constant explanatory variables appearing in each time period. Specifically, they represent panel averages of all-time varying variables in the model. Adding to a traditional random effects Tobit model solves the unobserved heterogeneity problem and results in consistent estimates for model parameters.

4. Empirical analysis

4.1. Variables and data

Our sample consists of panel 103 major prefecture-level cities[3] in China over the period of 2008–2015. Taiwan, Hong Kong, and Macau are excluded temporally due to unavailability of data. We collect data from several official sources, including *China Statistical Yearbook*, *China Environment Yearbook*, *China Energy Statistical Yearbook*, *China Yearbook for Regional Economy*, *China Industrial Economy Statistical Yearbook*, *Statistical Yearbook of the Chinese Investment in Fixed Assets*, *China Land and Resources Statistical Yearbook* and *China Urban Construction Statistical Yearbook*.

To measure LUE comprehensively and accurately, all the input and output variables relevant to land supply system should be considered as much as possible to the extent that the data are available. The input and output variables for measuring LUE are described as follows:

1. Desirable output: The real gross domestic product (GDP) is chosen as good output with the data at constant 2008 prices, wherever applicable throughout this article.
2. Undesirable outputs: Like most existing literature, environmental pollutants are treated as the bad outputs. The LUE of prefecture-level cities in China will be overestimated without considering environmental loss. In this study, three variables are selected according to data availability, namely, volume of industrial wastewater discharged, volume of sulphur dioxide emission and volume of industrial soot-dust removed. To alleviate the influence of extreme values, we employed the entropy weight method to generate a composite environmental pollution index (EPI) of these pollutants.
3. Labour force: According to data availability, the total number of employees is used as proxy here. China does not currently provide complete statistics on the number of years of education and wages of the labour force in each city. Thus, we could not further estimate the human capital at city level. Nevertheless, we adopt the number of employees to measure labour force which commonly used in the existing literature (He et al., 2020; Tan et al., 2021).
4. Capital input: The method used frequently to estimate capital input is the perpetual inventory method (Wu et al., 2014).The capital stock can be calculated as $K_{i,t} = I_{i,t} + (1 - \sigma_{i,t})K_{i,t-1}$, where $K_{i,t}$ is the capital stock of region i in year t, and $\sigma_{i,t}$ is the depreciation rate of fixed assets of region i in year t. We estimate capital stock based on the procedure provided by (Huang et al., 2018).
5. Land input: This article adopts the area of land used for urban construction as the proxy for land use due to the accessibility of data. The mean value of the land input was only 81.880 square kilometres in 2003, while it was almost 1.8 times that in 2015 at 149.658 square kilometres. Such a considerable change implies that land use is of importance during the process of industrialisation and urbanisation in China.
6. Energy input: According to data availability, we calculate the total energy consumption based on water supply, annual electricity, total gas supply (coal gas,

natural gas) and liquefied petroleum gas supply and convert it to standard coal equivalent (SCE) units – the standard energy metric used in Chinese energy statistics.

Key variables and controls used in panel Tobit model are presented as follows. As mentioned above, we are aim at investigating the mutual influencing effects between LPD and LUE in which measured by equations (3) and (6), respectively. In addition, to control for the characteristics of each city, six control variables are included in the econometric estimation: (1) population density (POPD), the shares of total population at year-end in total land area of administrative region (Xue et al., 2022; Yu et al., 2019); (2) Foreign capital level (SFOV), the shares of gross industrial output value from foreign founded enterprises in total gross industrial output value (Jiang et al., 2021; Xue et al., 2022); (3) openness (OPEN), we consider opening-up for internal market which proxied by the shares of total retail sales of consumer goods in GRP (Yang et al., 2017; Yu et al., 2019); (4) industrial land use structure (SIND), the shares of area for industrial operation in total area of urban construction land use, as suggested by (Chen et al., 2019; Tu et al., 2014), the industry sub-type exerts more impact on industrial land use than policy intervention; (5) transportation condition (ROAD, PBUS), we use two proxies in this study, per capita urban road area and the number of buses per ten thousand persons (Xue et al., 2022). The transportation infrastructure is expected to have a significant positive impact on LUE. Additionally, we also add three dummies (i.e. EAST, RECITY and TCZ) to control the geographic conditions, resource-based city and environmental policies (Huang et al., 2018), respectively. EAST equals to 1 indicates the cities are in the eastern of China; RECITY equals to 1 means the cities are listed as resource-based (RB) cities[4]; TCZ equals to 1 represents the cities are listed as two control zones (TCZ) cities[5]. Based on the aforementioned analysis and the existing literature (Chen et al., 2019; Huang et al., 2018; Xue et al., 2022; Yang et al., 2017; Yu et al., 2019; Zhang et al., 2018), we predict that the POPD, SFOV, PBUS, RECITY exert positive impact on LUE, and the OPEN, SIND, ROAD, EAST and TCZ impose negative effect on LUE. Table 1 reports descriptive statistics of the variables for DEA and Tobit models.

4.2. Measuring LUE

Figure 1 demonstrates the geographical distribution of study sample for average efficiency values during 2008–2015. Two features stand out. First, although the average efficiency values are obviously different from each other, there are three high efficiency value agglomeration regions, namely the northeast region, the Beijing-Tianjin-Hebei region and the central of China. On average, Langfang city has the highest efficiency (0.9994), whereas Zhengzhou city presents the lowest value (0.3198). Second, compared with the cities with high LUE, it seems that the cities with low LUE is more efficient to some extent for the growth rate of LUE of these cities is much higher. This is mainly because from east to west in China, urban element endowments, location conditions, and development levels show spatial characteristics of gradual deterioration. Especially in the western region, the economic

Table 1. Summary statistics.

Variable	Obs.	Unit	Mean	Std. Dev.	Min.	Max.
Panel A: DEA model						
Labour	824	10,000 persons	68.1544	99.6064	6.7900	777.3450
Capital	824	100 million RMB	1859.7930	2421.4250	57.2456	18000.0000
Land	824	Sq.km	250.7689	323.9037	36.0000	2915.5600
Energy	824	10,000 tons SCE	21.7174	26.0198	1.4518	181.9641
GDP	824	100 million RMB	2049.3110	3008.1830	92.4664	21000.0000
EPI	824	–	0.1214	0.1399	0.0016	2.5391
Panel B: Tobit model						
LUE	824	–	0.6890	0.2087	0.1091	1.0000
LPD	824	–	0.2013	0.3673	0.0120	9.7920
LRM	824	–	0.5068	0.3490	0.0000	6.7200
POPD	824	10,000 persons/Sq.km	0.1363	0.1035	0.0039	1.1449
SFOV	824	–	0.2390	0.1991	0.0028	0.8400
OPEN	824	–	0.3420	0.1000	0.0437	0.9470
SIND	824	–	0.2100	0.0750	0.0063	0.4333
ROAD	824	Sq.m	13.5861	7.4766	2.9100	73.0400
PBUS	824	Unit	11.2131	9.2374	1.1300	110.5200
EAST	824	–	0.4466	0.4974	0.0000	1.0000
RECITY	824	–	0.2913	0.4546	0.0000	1.0000
TCZ	824	–	0.7670	0.4230	0.0000	1.0000

Source: Authors calculation.

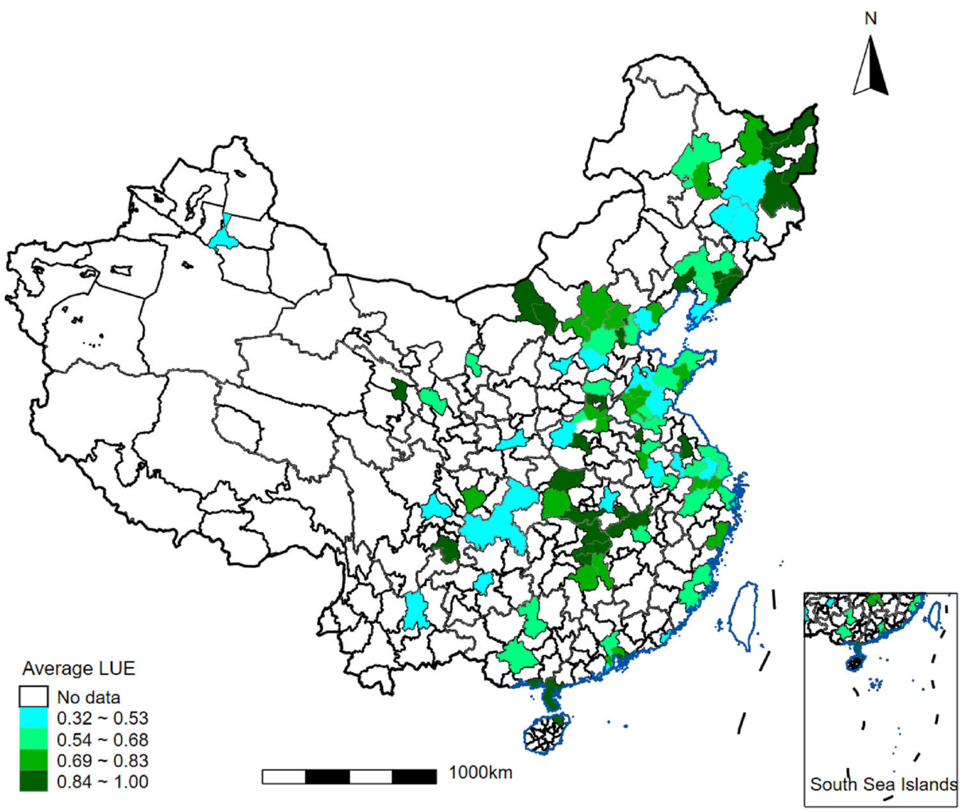

Figure 1. Spatial distribution of average efficiency values and geometric change rate of 103 major cities in China during 2008–2015. (Color figure online).
Source: authors' elaboration.

development of most of its cities is still relatively backward, the industrialisation process is still in the middle stage of rapid development of industrialization, and most of the cities have no obvious location advantages, imperfect infrastructure, low quality of labour force, and relatively weak industrial foundation. In addition, compared with the central and western regions, the competition for land investment among cities in the eastern region is more intense, and the competition among governments to intervene in the sale of industrial land is greater, resulting in a deeper distortion of land prices and lower land use efficiency. Besides, lower LUE may be offset by high efficiency of other input(s). For example, the LUE of the eastern region is lower, but its capital use efficiency is significantly higher than that of the central and western regions. Specifically, the capital input per unit of GDP for easter region is 0.855, which is much lower than that of central region (1.019) and western region (1.013). Moreover, although the LUE are relatively low in eastern region, the geometric growth rates are much higher than that of central and western regions, indicating that there exist the catching up effect and it plays a positive role in improving LUE in China.

Figure 2 illustrates that the mean of LUE in different regions shifted to the left from 2008 to 2015, showing the mean value of LUE decreased continuously. The kernel density estimation of LUE in different regions showed a 'flat' distribution in 2008 and 2011, however, the 'lofty' characteristics were presented in 2015. Furthermore, the kernel density curve of the three regions has obviously moved upward over time, as a result, the LUE gap among different regions has decreased. More specifically, the LUE in the eastern and western regions are mainly concentrated in [0.4, 0.6], and the central region is in [0.6, 0.8]. It also shows that the LUE in the central region is higher than the rest regions.

The above findings show that there exist significant regional differences of LUE in China, to explore the driving forces impose impact on LUE is of importance for policy makers to implement the urban land planning and land resource allocation from both theoretical and practical aspects. Thus, it is necessary to investigate the influence factors exert on the LUE by using econometric tools which discussed in the section 3.3 and the estimation results are presented in next subsection.

4.3. Estimation results

The panel Tobit model is a random effects (RE) approach to linear panel data model, which assumes that the time-invariant error term is uncorrelated with independent variables. Estimation results of panel Tobit model are presented in the first column of Table 2. The result show that LPD is significantly and negatively (at 5% level of significance) associated with LUE, suggesting that LPD is not conducive to improve the LUE in China. A unit increase in LPD would lead to a decrease in LUE score by 0.0224 (See the third row of Table 2). One of the possible explanations is that higher LPD results in lower productivity, it is not propitious for further expansion of the economy and the optimal allocation of land resources. Consistent with our expectation, LUE is positively and significantly associated with the shares of gross industrial output value from foreign founded enterprises in total gross industrial output value

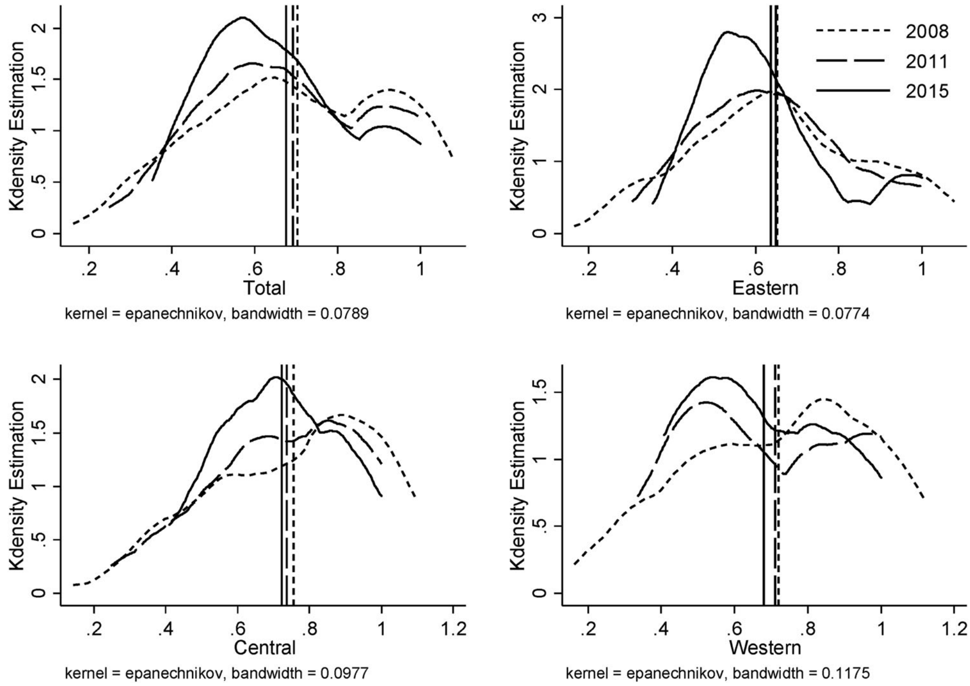

Figure 2. Kernel density estimation of LUE for different regions.
Source: authors' elaboration.

Table 2. Estimation results of baseline models with dependent variable: *LUE.*

	Tobit model		CRE Tobit model
Variables	(1)	(2)	(3)
LPD	−0.0311** (-2.0580)	−0.0329** (-2.1443)	−0.0290* (-1.9034)
AME(LPD)	−0.0224** (-2.0500)	−0.0270** (-2.1500)	−0.0212* (-1.9000)
POPD	0.0070 (0.0726)	0.1058 (1.0164)	0.1198 (1.0773)
SFOV	0.1351* (1.9004)	0.1357 (1.6342)	0.1293 (1.4988)
OPEN	−0.2253*** (-2.6377)	−0.1511* (-1.7239)	−0.1761* (-1.8934)
SIND	−0.2738** (-2.3654)	−0.3675*** (-3.0569)	−0.3684*** (-2.8653)
ROAD	−0.0055*** (-3.4314)	−0.0073*** (-3.4748)	−0.0079*** (-3.9687)
PBUS	0.0037*** (2.8254)	0.0040*** (2.8109)	0.0042*** (2.7401)
EAST	−0.0487 (-1.1765)	0.2776*** (3.9766)	−0.0364 (-0.7966)
RECITY	0.0755* (1.8062)	0.4061*** (6.1954)	0.0489 (1.0508)
TCZ	−0.1180*** (-2.6047)	−0.5209*** (-7.1361)	−0.1314*** (-2.8462)
Constant	0.9427*** (14.9562)	1.0861*** (15.0597)	1.0422*** (7.2117)
Year fixed effects	No	Yes	No
City fixed effects	No	Yes	No
Obs.	824	824	824
Log-likelihood	197.0892	398.1492	201.8065

Source: authors' elaboration.

(SFOV) and the number of buses per ten thousand population (PBUS), but negatively and significantly associated with opening-up for internal market (OPEN), the shares of area for industrial operation in total area of urban construction land use (SIND) and per capita urban road area (ROAD). Estimated results of control variables are different from previous studies. For example, Yu et al. (2019) argued that market openness has positive influence on the LUE. Xue et al. (2022) suggested that the increase of secondary industry will significantly promote the LUE. However, Xue et al. (2022) also found that the population density can promote the LUE because of its agglomeration effect. Perhaps this is because that the sample and period, estimation methods are varied in these studies.

Next, we adopt the FE model that controls for year fixed effects and city fixed effects simultaneously to estimate the impact of LPD on LUE and report the results in the second column of Table 2. With all the controls, the LPD is significant at the 5% level, with a coefficient of −0.0329, showing a negative relationship between LPD and LUE. Compared to RE model, there is no dramatic change of coefficient on LPD, although coefficient on LPD becomes smaller, it is still significant at the 5% level. Those results indicate that LPD does not improve China's LUE. In addition, the land performance of cities in which located in the east of China seems to be more efficient than others since EAST exerts positive impact on LUE.

Finally, to check whether our results can still hold without the assumption that the time-invariant error term is uncorrelated with independent variables, we adopt the correlated random effects (CRE) approach to the Tobit model. Specifically, we further control for the means of independent variables and estimate Eq. (12), showing in the third column of Table 2. The empirical results suggest that there is no large difference between the CRE Tobit model and the RE Tobit model to estimate the impact of LPD on LUE. Our empirical findings are consistent with Lyu et al. (2022) who found that LPD is not conducive to improving green development efficiency.

4.4. Robustness checks

In terms of robustness, further analysis has been conducted from two aspects.

First, we use land resource misallocation (LRM) as another proxy for LPD. Considering the comparability of data, the LRM is measured by different datasets in different phases[6], i.e. the shares of granting area through agreement in total granting area are used before 2008, and for 2009–2015, the shares of land for industry, mining, and warehousing in total amount of land supplied are used. The estimation results are presented in column (2) of Table 3. We find that there is no dramatic change of the estimated coefficients, both signs and significances. Thus, it seems that the claim of the LPD impose significantly negative impact on LUE is verified. The empirical results are in line with Lin et al. (2020) who suggested that the minimum price policy related to land market decreases the LUE.

Second, two subsamples are used for testing the relationship between LPD and LUE. To check whether the LPD of the four municipalities (Beijing, Tianjin, Shanghai, Chongqing) is overestimated the marginal effects on LUE, we use the first subsample which excluded the four municipalities and obtain the robustness results, as presented in Table 4. To investigate whether the outliers impose significant marginal effects on LUE, we employ the second subsample of prefecture-level cities between 1th percentile and 99th percentile of LUE and obtain the robustness results, as presented in Table 5. Since the estimation results do not change dramatically, indicating that our conclusions are robust to alternative measurement of key variable and subsamples.

Table 3. Robustness check: alternative measures of LPD.

	Tobit model		CRE Tobit model
Variables	(1)	(2)	(3)
LRM	−0.0063** (-2.4462)	−0.0156** (-2.1872)	−0.0111*** (-2.7832)
AME(LRM)	−0.0128** (-2.4500)	−0.0128** (-2.1900)	−0.0082*** (-2.7800)
Control variables	Yes	Yes	Yes
Year fixed effects	No	Yes	No
City fixed effects	No	Yes	No
Obs.	824	824	824
Log-likelihood	195.0745	396.5590	202.3386

Notes: 1) z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) AME represents average marginal effect; 4) The land resource misallocation (LRM) is treated as an alternative measure of LPD.
Source: authors' elaboration.

Table 4. Estimation results of the 1st subsample with dependent variable: *LUE*.

	Tobit model		CRE Tobit model
Variables	(1)	(2)	(3)
LPD	−0.0302** (-2.0504)	−0.0279* (-1.8810)	−0.0283* (-1.9120)
AME(LPD)	−0.0271** (-2.0500)	−0.0230* (-1.8800)	−0.0207* (-1.9100)
Control variables	Yes	Yes	Yes
Year fixed effects	No	Yes	No
City fixed effects	No	Yes	No
Obs.	792	792	792
Log-likelihood	210.6559	408.7277	216.0832

Notes: 1) z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) AME represents average marginal effect; 4) Four municipalities (Beijing, Tianjin, Shanghai, Chongqing) are excluded in the 1st subsample.
Source: authors' elaboration.

Table 5. Estimation results of the 2nd subsample with dependent variable: *LUE*.

	Tobit model		CRE Tobit model
Variables	(1)	(2)	(3)
LPD	−0.0334** (-2.3076)	−0.0367** (-2.5166)	−0.0315** (-2.1618)
AME(LPD)	−0.0301** (-2.3100)	−0.0304** (-2.2500)	−0.0231** (-2.1600)
Control variables	Yes	Yes	Yes
Year fixed effects	No	Yes	No
City fixed effects	No	Yes	No
Obs.	816	816	816
Log-likelihood	221.9311	429.4734	226.1061

Notes: 1) z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) AME represents average marginal effect; 4) The prefecture-level cities between 1th percentile and 99th percentile are reserved in the 2nd subsample.
Source: authors' elaboration.

4.5. Addressing endogeneity

Furthermore, we also consider the endogenous issues. For one thing, we use the tenure of party secretary (Zheng et al., 2014) as an instrument variable (IV) of LPD and obtain the empirical results summarised in column (1) of Table 6, which indicates that the LPD is significantly negatively associated with LUE from the economically perspective. Since the IV estimate is unaffected by the measurement error, which tends to be larger than the OLS estimates. Besides, it's possible that the IV estimate to be larger than the OLS estimate because IV is estimating the local average treatment effect (ATE). OLS is estimating the ATE over the entire population (Card, 2001). For the other, those cities with low LUE often experienced a large scope of

Table 6. Estimation results of endogeneity tests.

	IV Tobit model (1)	Tobit model (2)	Tobit model (3)	CRE Tobit model (4)	Tobit model (5)	Tobit model (6)	CRE Tobit model (7)
LPD	−0.8251**						
	(−2.1600)						
Lagged (LPD)		−0.0115***	−0.0128***	−0.0093***			
		(−2.7201)	(−2.7975)	(−2.5810)			
Leaded (LPD)					−0.0168***	−0.0137***	−0.0174**
					(−2.9869)	(−2.8726)	(−2.0174)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	No	No	Yes	No
City fixed effects	No	No	Yes	No	No	Yes	No
Constant	1.4598	0.9191***	1.0891***	1.0427***	0.9283***	1.0887***	1.0258***
	(0.4750)	(14.0007)	(13.7031)	(7.3023)	(13.4764)	(13.0907)	(6.8243)
Obs.	824	721	721	721	721	721	721
Log-likelihood		147.6410	338.5927	152.1459	164.6263	365.5595	170.5289

Notes: 1) z-statistics in parentheses; 2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; 3) Second stage regression is reported in the first column and the F statistics is 45.6015.
Source: authors' elaboration.

spatial resources misallocation, which will strengthen their motivation to distort the land price, and the cities with lower LPDs may be benefitted from the economic efficiency. It is difficult to measuring the LPD which often accompanied with time-lag effects. Moreover, the government's intervention in micro economy and the distortion of the land price will take some time to transmit to the relevant economic sectors and produce changes in micro production behaviour. Thus, it is necessary to verify the issues of inverse causality and synchrony tests. Based on the model specification of Wei and Zheng (2020), we add the lag- and lead- one period terms of LPD into the empirical models for the counterfactual test and the relaxation of inverse causality between different variables, respectively. The estimation results are shown in columns (2)–(7) of Table 6. Economically, empirical results showed that the evidence of the LPD exerts significant negative effects on LUE is supported. Thus, the LPD exactly impede the promotion of LUE.

5. Conclusions and policy implications

5.1. Conclusions

We explore empirically the effect of LPD on China's LUE using a dataset of 103 cities during the years 2008–2015, Cobb-Douglas production method, input-oriented NCMeta-US-SBM model and Tobit regression approach are applied throughout the article. The main conclusions are summarised as follows:

1. Results of DEA model shows that there exist significant spatiotemporal disparities of LUE, on average, the LUE in central region is relative higher than eastern/western region. With the advantages of geographical location, not only the eastern region has not played the role of growth pole of LUE, but there exist spread-backwash effects of LUE. Thus, the links between different regions should be strengthened, enabling the LUE can be promoted in a coordinated way by improving industrial agglomeration and optimising the resources allocation.

2. Kernel density estimation of LUE indicates that the urban LUE in different regions has obvious gap as time goes on. Some measures should be taken to improve the quality of economic development and the LUE in different regions.
3. Estimates of Tobit regression show that increases in LPD lead to significant decreases in LUE on the prefecture-level, specifically, a unit increase in LPD would results in a decrease in LUE score by 0.0224, reducing to 0.0212 in correlated random effects Tobit model. For a long time, some local governments have adopted land preferential policies or such low-cost means as the provision of infrastructure facilities to attract investment, land supply is not affected by market supply and demand, consequently, land prices are distorted. To correct the LPD and raise the LUE efficiently, the land expropriation compensation system should be established and improved based on market mechanism.
4. Sensitivity analyses suggest that the empirical results are robust to alternative measures of LPD and different subsamples.

5.2. Policy implications

Based on the empirical findings, the policy implications are summarised as follows. First, according to the current implementation of land management, differentiated land management policies could be implemented for different regions and cities. To formulate differentiated construction land utilisation and management policies according to city types can ensure the efficient utilisation of construction land in various regions and various cities, and achieve the goals of intensive land use and sustainable development. Second, since the LPD exert significantly negative effect on LUE, policymakers and governors should perfect the construction of laws and regulations related to the use of urban construction land and standardize the pricing method of urban construction land to solve and correct the price distortion of land resources, and to curb the behaviour of local governments to distort land prices to attract investment. Third, practitioners should actively promote the reform of the market-based allocation of land elements, deepen the reform of the land transfer system, improve the market supply system for industrial land, and promote the participation of collective construction land in market transactions, form a multi-subject land supply pattern, and gradually break the monopoly of land market.

Furthermore, future studies can be conducted from the following three aspects. First, due to data restrictions, the time period covered in this study was only eight years. Therefore, the time span can be increased to cover a longer period, and more information and data can be used to analyze the China's LUE, such as convergence analysis. Second, more precise estimation of LPD can be estimated by using time varying state space model (with panel data). Besides, the proposed DEA model can be extended to measure and compare productivity changes for prefecture-level cities in different groups under the framework of the Malmquist-Luenberger productivity indicator. With the same metafrontier, these indicators are comparable and can provide insightful information. Third, a potential mechanism analysis of LPD on LUE. Moreover, both static and dynamic spatial econometric models should be applied to study the spill-over effects and interaction effects of LPD.

CRediT author statement

Yantuan Yu: Data curation, Visualization, Writing- Original draft preparation, Funding acquisition. Nengsheng Luo: Methodology, Writing- Reviewing and Editing, Funding acquisition.

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Disclosure statement

The authors declare no conflict of interest.

Notes

1. China Land and Resources Statistical Yearbook (2009-2016) provides integrated price of land, referring to the average price level of lands for different usage (include commercial use, residential use and industrial use) in the same city or area, we use land price index to convert the integrated price of land to constant 2008 prices. The land price index is collected from China Land Price Information Service Platform (in Chinese), available at http://www.landvalue.com.cn/, accessed 25 August 2022. As suggested by Qin et al. (2016), the contribution of the composition effect to raw price gaps varies with the part of the price distribution and differs by the type of land, thus, we utilize the integrated price of land. This also because of the lack information of land input for commercial use and residential use.
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.
3. China Land and Resources Statistical Yearbook (2009-2016) provides prices of land for construction use of 105 major prefecture-level cities (See **Appendix A**), we select 103 of them except Shunde of Foshan City and Lhasa City as the research subject in order to conduct feasible comparison.
4. The first list of 12 RB cities was announced in 2008, while the second list of 32 and the third list of 25 RB cities were announced in 2009 and 2011. The list was substantially expanded to 262 cities and regions, including 126 prefectures. Among the 103 prefectures in our sample, 30 are on the list, cf. http://www.gov.cn/zwgk/2013-12/03/content_2540070.htm (**in Chinese**).
5. The two control zones refer to the sulfur dioxide control zone and acid rain control zone. Prefectures are included into the zones if the recorded emissions exceeded the national standards in the preceding years. The specific classification criteria can be seen http://www.zhb.gov.cn/gkml/zj/wj/200910/t20091022_172231.htm (**in Chinese**).
6. The industrial land must be sold by bidding and auction, and its selling price shall not be lower than the published minimum price standard, which leads to the proportion of transfer of industrial land has dropped rapidly (from 74% in 2007 to 17.2% in 2008).

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Appendix A.AList of 105 major cities in China

Table A1. 105 major prefectural level cities.

Beijing Municipality (1)	Xuzhou City (1)	Jiaozuo City (2)
Tianjin Municipality (1)	Changzhou City (1)	Wuhan City (2)
Shijiazhuang City (1)	Suzhou City (1)	Huangshi City (2)
Tangshan City (1)	Nantong City (1)	Yichang City (2)
Qinhuangdao City (1)	Yangzhou City (1)	Xiangyang City (2)
Handan City (1)	Hangzhou City (1)	Jingzhou City (2)
Baoding City (1)	Ningbo City (1)	Changsha City (2)
Zhangjiakou City (1)	Wenzhou City (1)	Zhuzhou City (2)
Langfang City (1)	Jiaxing City (1)	Xiangtan City (2)
Taiyuan City (2)	Huzhou City (1)	Hengyang City (2)
Datong City (2)	Hefei City (2)	Yueyang City (2)
Hohhot City (3)	Wuhu City (2)	Guangzhou City (1)
Baotou City (3)	Bengbu City (2)	Shenzhen City (1)
Shenyang City (1)	Huainan City (2)	Zhuhai City (1)
Dalian City (1)	Huaibei City (2)	Shantou City (1)
Anshan City (1)	Fuzhou City (1)	Shunde of Foshan City*(1)
Fushun City (1)	Xiamen City (1)	Zhanjiang City (1)
Benxi City (1)	Quanzhou City (1)	Dongguan City (1)
Dandong City (3)	Nanchang City (2)	Zhongshan City (1)
Jinzhou City (3)	Jiujiang City (2)	Nanning City (3)
Fuxin City (3)	Jinan City (1)	Liuzhou City (3)
Liaoyang City (3)	Qingdao City (1)	Beihai City (3)
Changchun City (2)	Zibo City (1)	Haikou City (3)
Jilin City (2)	Zaozhuang City (1)	Chongqing Municipality (3)
Harbin City (2)	Yantai City (1)	Chengdu City (3)
Qiqihar City (2)	Weifang City (1)	Nanchong City (3)
Jixi City (2)	Jining City (1)	Yibin City (3)
Hegang City (2)	Tai'an City (1)	Guiyang City (3)
Daqing City (2)	Linyi City (1)	Kunming City (3)
Yichun City (2)	Zhengzhou City (2)	LhasaCity* (3)
Jiamusi City (2)	Kaifeng City (2)	Xi'an City (3)
Mudanjiang City (2)	Luoyang City (2)	Lanzhou City (3)
Shanghai Municipality (1)	Pingdingshan City (2)	Xining City (3)
Nanjing City (1)	Anyang City (2)	Yinchuan City (3)
Wuxi City (1)	Xinxiang City (2)	Urümqi City (3)

Notes: 1) * denotes the cities are not covered in the study; 2) heterogeneous groups are labelled as 1 (eastern region), 2 (central region) and 3 (western region) in parentheses.
Data sources: China Land and Resources Statistical Yearbook (2016).

Appendix B.Tendency of average LUE for different regions

Incorporating nonconvex metafrontier technique, undesirable outputs, and super efficiency into SBM simultaneously, the LUE is evaluated across each city in China and for each year. Figure B1 presents the average LUE of 103 prefecture-level cities across three different regions in China from 2008 to 2015. The results show that the average LUE in central region is relative higher than that of the eastern and western regions in most years. Additionally, the average LUE of these regions have decreased over the periods of 2008-2015. Moreover, on average, the LUE of eastern cities is approximately 5.2080% lower than that of the whole country, while the LUE of central (western) region is about 5.6094% (1.7918%) higher than the national level. Consequently, the gap of LUE between the eastern and central regions is far greater than that of the western and central regions. One of potential explanations is that the higher land input may result in higher LPD, leading to lower LUE to some extent. Specifically, the mean values of land input for eastern, central, and western regions are 325.7 Sq.km, 171.7 Sq.km, and 222.2 Sq.km, respectively. And the mean values of LPD for these regions are 0.204, 0.202, and 0.195, respectively. Another explanation is that local governments are excessively pursuing economic

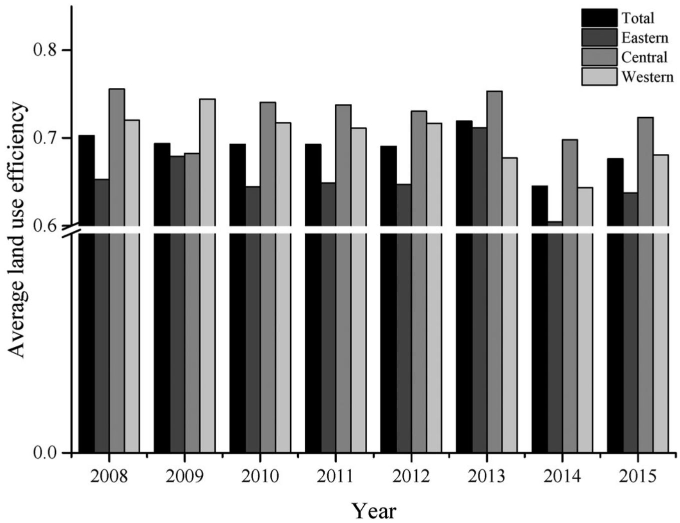

Figure B1. Histogram of average LUE for different regions. (Color figure online).
Source: authors' elaboration.

growth, blindly increasing investment in land, and actively promoting production methods with high energy consumption and high emissions, resulting in low LUE. In addition, this trend also reflects China's broader transition from an earlier focus on high-speed economic development to a focus on high-quality economic development. Having proposed the construction of ecological civilisation, more attention has been paid to green and low-carbon development, and the status of environmental protection has been improved at the same time of continuing economic development, which further improves the LUE. However, the mean value of LUE is decreasing in the western and central regions during 2008-2015, with high efficiency values in the central region, and the efficiency values of the eastern region are low.