Impacts of Land Finance on Green Land Use Efficiency - A Spatial Autoregressive Mode

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Abstract. Improving urban green land use efficiency (GLUE) is an inevitable requirement to promote regional sustainable development. This paper uses the Global Malmquist-Luenberger (GML) index to measure the GLUE of 26 cities in the Yangtze River Delta (YRD), and analyzes the influence of land finance on the GLUE and its action mechanism by using the panel data regression model and spatial autoregressive model. The results show that: Firstly, the GLUE of the YRD presents a stable development trend, the overall efficiency level is high, and there is a spatial agglomeration feature. Secondly, land finance has a statistically significant negative impact on GLUE. Thirdly, the mechanism test found that the negative impact of land finance on the GLUE is mainly realized by inhibiting technological progress.

Keywords: land finance · green land use efficiency · Yangtze River Delta

1 Introduction

Land is the spatial carrier of economic and social activities [1]. However, with the rapid expansion of urban construction land, the problems of low efficiency and extensive use of urban land are becoming increasingly serious [2], especially in the areas with dense towns along the eastern coast of China [3]. How to make the limited land resources meet the growing consumption needs of society has become a key issue on the road of sustainable development in the future.

In recent years, many scholars have done a lot of theoretical and empirical research on urban land use efficiency. In terms of definition, land use efficiency is defined as the level of industrial output per unit area of industrial land [4]. In terms of measurement method, Chen et al. used the data envelopment analysis model to analyze the construction land efficiency of 336 cities in China from 2005 to 2012 [5]. Lu et al. measured the overall evaluation of urban land use in 31 provinces and cities of China from 2001 to 2014 using SBM model [6]. Liu et al. used the one-stage stochastic frontier model to evaluate urban land use efficiency [7]. In terms of influencing factors, Xie et al. found that the relationship between per capita GDP and industrial land efficiency is N-shaped [8]. Yu et al. found that the level of economic development and industrial structure had significant effects on land use efficiency [9]. Among these influencing factors, the

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influence of land finance on land use efficiency is particularly important [10]. Liu et al. found that the excessive reliance of local government on land finance led to the rapid expansion of land use [11]. Du et al. found that land pricing system can improve urban land use efficiency by stimulating investment and commercial management [12]. The above literature provide inspiration for this paper, but there are still some deficiencies in the research on the relationship between land finance and land green use efficiency. On one hand, the existing literatures are all analyzed at the provincial level or the individual level of the city, which reduces the credibility of the empirical results. On the other hand, few studies have considered the spatial spillover effect of GLUE between cities. The neglect of such spillover effect may lead to biased estimation of land finance's coefficient on GLUE.

In order to make up for the shortcomings of the above literatures, this paper analyzes the impact of land finance on the GLUE and its components in the YRD by using the SAR model. The rest of this article is structured as follows: The second part describes the data and methods. The third part carries on the empirical analysis. The fourth part summarizes the empirical results and policy recommendations.

2 Data and Methodology

2.1 Global Malmquist–Luenberger Index

GML index is defined as follows:

$$\begin{aligned}
&GML^{t,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + D_G^T\left(x^t, y^t, b^t\right)}{1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \\
&= \frac{1 + D_G^t\left(x^t, y^t, b^t\right)}{1 + D_G^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \times \left[\frac{1 + D_G^T\left(x^t, y^t, b^t\right)/1 + D_C^T\left(x^t, y^t, b^t\right)}{1 + D_G^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)/1 + D_C^T\left(x^{t+1}, y^{t+1}, b^{t+1}\right)}\right] \\
&= \frac{TE^{t+1}}{TE^t} \times \frac{BPG_{t+1}^{t+1}}{BPG_t^{t+1}} = BG_t^{t+1} \times BPG_t^{t+1}
\end{aligned} \tag{1}$$

$GMLt, t+1 > 1$ means higher productivity. $GMLt, t+1 < 1$ means lower productivity. Where TE and EC represent technical efficiency and efficiency change respectively. $BPCt, t+1$ mainly measures the change of the "best practitioners gap" in the two periods (technological change).

2.2 Spatial Autoregressive Model

According to the first law of geography, all things are related to other things, but things that are closer are more related than things that are farther away [13]. Therefore, we choose the spatial autoregressive model (SAR). The SAR model mainly reflects the direct interaction of the explained variable by setting the lag term of the explained variable [14], and its expression is as follows:

$$GLUEit = \delta \sum_j WijGLUEit + \alpha i \ln LFit + \theta iXit + \mu it + \varepsilon it \tag{2}$$

where ε is the disturbance term; i represents space and t represents time; W is the spatial weight matrix; δ is the spatial autoregressive coefficient. α is the land finance coefficient; θ is the coefficient of control variable; GLUE is the explained variable; lnLF is the explanatory variables; X are the other control variables.

2.3 Variable Selection

About the GLUE, The GML index is used to measure the GLUE of 26 cities in the YRD. About input indicators, we mainly choose the land inputs M, capital inputs K and labor inputs L as input indicators. And using the fixed asset investment price index, the nominal fixed asset. The investment value is converted into actual fixed asset investment at a comparable price, and the capital stock of each city over the years is calculated. Regarding output indicators, We choose the added value of the secondary and tertiary industries as the expected output. Industrial waste water discharge, sulfur dioxide discharge and smoke (powder) dust discharge are selected as undesired outputs. About the Land finance (LF), Since the cost of land transfer is not easy to measure, considering that at this stage local governments still mainly use land to obtain land transfer fees to increase local government revenue, this paper uses land transfer revenue as a decision variable to measure local government land transfer behavior. In order to eliminate the influence of dimension, this paper uses per capita land transfer income to measure land finance, and conducts logarithmic processing on it. About the Control variables, we selected industrial structure (EC), science and technology level (TEC), economic development level (GDP), infrastructure level (PAR), financial scale (SOF) as control variables.

2.4 Spatial Weight Matrix

Two kinds of spatial weight matrixes are constructed in this paper. The first matrix is the geographical distance matrix W1. The weight matrix is defined as follows: If $i = j$, $W_{ij} = 0$. If $i \neq j$, $W_{ij} = 1/d_{ij}$. D_{ij} represents the straight-line distance between city i and city j. The second is the economic distance matrix W2. This paper uses per capita GDP to establish the weight matrix of economic distance $W_{ij} = 1/|GDP_i\text{-}GDP_j|$, where GDP_i and GDP_j are the average per capita GDP of city i and city j ($i \neq j$) from 2007 to 2016.

3 Results

3.1 Temporal and Spatial Characteristics of GLUE

Figure 1 shows the dynamic change trend of GLUE values and their components in time and space of cities in the YRD from 2007 to 2016. In terms of time, the value of GLUE in the YRD fluctuates between 0.915 and 1.101, with an average value of about 1, indicating that the GLUE tends to be stable from 2007 to 2016. Among them, the values of GLUE in 2009, 2011, 2012 and 2014 are less than 1, indicating that the GLUE decreases, with a decline of about 4%. At the same time, from the overall trend, SE and TC have opposite trends. In terms of space, there are 9 cities with the mean of scale efficiency (EC) greater than 1 and 23 cities with the mean value of technological progress (TC) greater than 1. This indicates that technological progress is the key to promoting the increase of GLUE.

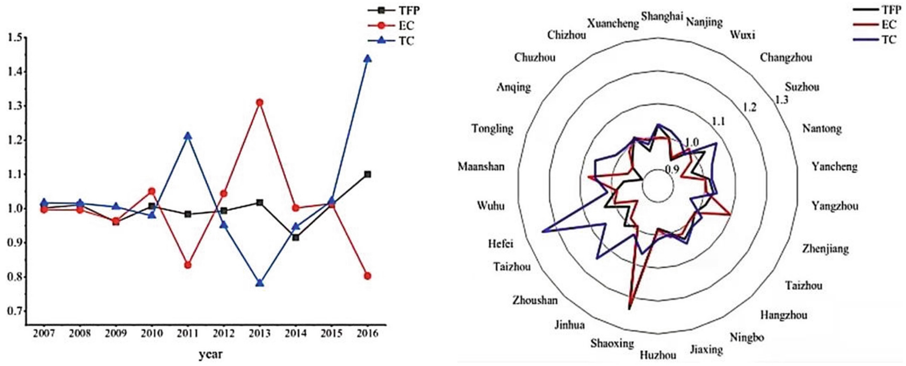

Fig. 1. Spatial and temporal distribution of GLUE in the Yangtze River Delta from 2007 to 2016. (Note: This is self drawing)

Table 1. The Estimation Results of Benchmark Regression

	OLS	FE	RE
lnLF	−0.0145	−0.100***	−0.0448*
	(−0.49)	(−2.81)	(−1.72)
Control Variable	Yes	Yes	yes
N	260	260	260
R^2	0.1286	0.2702	0.2197
F test		5.41***	61.13***
LM test			234.76***
Hausman test		12.29*	12.12*

t statistics in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

3.2 Benchmark Regression Analysis

We select mixed OLS, fixed effect and random effect three non-spatial models to analyze the impact of land finance on GLUE (Table 1). According to the F test, LM test and Hausman test results, we choose the fixed-effect model to explain the estimated results. The coefficient of land finance is significantly negative.

3.3 Empirical Results of Spatial Econometric Models

We use the SAR model to further analyze the impact of land finance on land green use efficiency in the YRD. As shown in Table 2, the column (1), (2), (3), (4), (5) and (6) represents the results of the impact of land finance on GLUE, technical progress (TC) and scale efficiency (SE) under spatial weight matrix W1 and W2, respectively. As shown in Table 2, the column (1), (2) and (3) represents the results of the impact of

Table 2. The estimation results of SAR model

		W1			W2	
	(1)	(2)	(3)	(4)	(5)	(6)
lnLF	−0.105***	−0.114***	0.0107	−0.107***	−0.120***	0.0133
	(−3.25)	(−2.77)	(0.45)	(−3.34)	(−2.85)	(0.55)
EC	−0.0386**	−0.0525**	−0.0162	−0.0338**	−0.0439	−0.0162
	(−2.21)	(−2.34)	(−1.28)	(−1.97)	(−1.95)	(−1.24)
lnGDP	0.283***	0.345***	0.0395	0.250***	0.288**	0.0325
	(2.91)	(2.77)	(0.55)	(2.59)	(2.27)	(0.45)
TEC	−0.0255	−0.0550***	0.0138	−0.0206	−0.0479**	0.0166
	(−1.66)	(−2.83)	(1.25)	(−1.39)	(−2.47)	(1.47)
PAR	−0.0183***	−0.0169***	−0.00401	−0.0174***	−0.0166**	−0.00426
	(−3.60)	(−2.59)	(−1.08)	(−3.46)	(−2.51)	(−1.12)
SOF	0.394	0.146	−0.0407	0.353	0.0829	−0.0544
	(1.76)	(0.51)	(−0.25)	(1.59)	(0.29)	(−0.32)
Spatial	−0.547**	−0.959***	−0.713*	−0.393***	−0.386***	−0.0859
Rho	(−2.11)	(−3.48)	(−2.54)	(−2.89)	(−3.42)	(−0.76)
N	260	260	260	260	260	260
Time control effects	yes	yes	yes	yes	yes	yes
Region control effects	yes	yes	yes	yes	yes	yes
R^2	0.2087	0.1081	0.0223	0.2131	0.1059	0.0216
Hausman test	34.65***	74.82***	111.29	34.70***	37.58***	151.80

t statistics in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

land finance on GLUE, technical progress (TC) and scale efficiency (SE), respectively. The spatial rho coefficient is significantly negative at the level of 5%, indicating that there is a negative spatial spillover effect on the GLUE. The land finance coefficient is significantly negative at the 1% level, indicating that land finance and urban GLUE present obvious negative correlation. On one hand, local governments tend to take low or even zero price for industrial land selling strategy, which rely on low cost for land transfer and the development of extensive development model may lead to the low efficiency of technical equipment backward enterprises to enter. On the other hand, selling commercial land at a high price will push up house prices. The excessively high housing price significantly increases the living cost of consumers, leads to a large outflow of labor force, thus inhibiting the improvement of GLUE. As for the control variables, the influence of industrial structure on GLUE is significantly negative, because the development of modern service industry and emerging industry in China is relatively backward. The improvement of economic development level is helpful to improve the GLUE. The possible reason is that the continuous improvement of level of economic development will expand the demand for land, which will increase its value. The estimated coefficient of road infrastructure level is significantly negative at the 1% level, which may be because the exessive loss of road and maintenance cost increase the transportation cost. The technological level does not show its due promoting effect, because the proportion of scientific and technological expenditure is relatively low, which is insufficient to promote the full utilization of factors. Column (2) and (3) report the impact of land finance on TC and scale efficiency SE, respectively. It can be seen that the scale expansion of land finance has a inhibiting effect on TC, and the significant level is 1%, while the promoting effect on SE is not significant, which indicates that the influencing ways of land finance on the GLUE are mainly reflected in the significant hindering of technological progress. Under a high level of land finance, the real estate market intervention of local government lead to higher land prices. The innovative talents are beginning to shift to other industry sectors, limiting the ability of technological innovation.

3.4 Robustness Test

The robustness test is carried out by replacing the spatial weight matrix, and the nested matrix W3 (W3 = 0.5W1 + 0.5W2) of geographical and economic distance is used as the spatial weight matrix for regression. Meanwhile, the SAC model is also used to estimate the results. It can be found that the sign and significance of the major variables did not change significantly, which basically verified the robustness of the empirical results in this paper.

4 Conclusion and Policy Recommendations

This paper uses the Global Malmquist-Luenberger (GML) index to measure the GLUE of 26 cities in the Yangtze River Delta (YRD), and analyzes the influence of land finance on the GLUE and its action mechanism by using the panel data regression model and spatial autoregressive model. The following conclusions are as follows: Firstly, the GLUE in the YRD presents a stable development trend, and there is a spatial agglomeration feature. Secondly, land finance has a statistically significant negative impact on GLUE. Thirdly, the mechanism test found that the negative impact of land finance on the GLUE is mainly realized by inhibiting technological progress. Based on the above conclusions, the paper puts forward some policy suggestions to improve GLUE in the YRD.

Firstly, Local governments should actively seek other sources of financial funds to avoid the misallocation of land resources and distortion of land structure caused by excessive land fiscal scale. Secondly, the central government should undertake more regional and universal spending on people's livelihood, and gradually reducing the pressure on local government's expenditures. Finally, the local government should give full play to the decisive role of market mechanism in allocation of land elements.

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References

1. Kuang B et al (2020) Provincial cultivated land use efficiency in China: empirical analysis based on the SBM-DEA model with carbon emissions considered. Technol Forecast Soc Chang 151:119874
2. Chen W et al (2018) The effect of industrial relocation on industrial land use efficiency in China: a spatial econometrics approach. J Clean Prod 205:525–535
3. Wu C et al (2017) Economic transition, spatial development and urban land use efficiency in the Yangtze River Delta, China. Habitat Int 63:67–78
4. Han W et al (2019) Does urban industrial agglomeration lead to the improvement of land use efficiency in China? An empirical study from a spatial perspective. Sustainability 11(4):986
5. Chen M et al (2016) Challenges and the way forward in China's new-type urbanization. Land Use Policy 55:334–339
6. Lu X et al (2018) Regional difference decomposition and policy implications of China's urban land use efficiency under the environmental restriction. Habitat Int 77:32–39
7. Liu S et al (2020) Urban land use efficiency and improvement potential in China: a stochastic frontier analysis. Land Use Policy 99:105046
8. Xie H et al (2018) Spatial-temporal disparities, saving potential and influential factors of industrial land use efficiency: a case study in urban agglomeration in the middle reaches of the Yangtze River. Land Use Policy 75:518–529
9. Yu J et al (2019) Land use efficiency and influencing factors of urban agglomerations in China. Land Use Policy 88:104143
10. Wang P et al (2020) The impact of land finance on urban land use efficiency: a panel threshold model for Chinese provinces. Growth Chang 52:310–331
11. Liu Y et al (2018) Impacts of land finance on urban sprawl in China: the case of Chongqing. Land Use Policy 72:420–432
12. Du JF, Thill JC, Peiser RB (2016) Land pricing and its impact on land use efficiency in post-land-reform China: a case study of Beijing. Cities 50:68–74
13. Tobler WR (1970) A computer movie simulating urban growth in the Detroit region. Econ Geogr 46:234–240
14. Zhang L et al (2018) How does foreign trade influence China's carbon productivity? Based on panel spatial lag model analysis. Struct Change Econ Dyn 47:171–179