Does Distorted Industrial Land Price Lead to Inefficient Industrial Land Use? -- Take the Yangtze River Economic Zone Cities as an Example

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Abstract

This paper uses ML index to measure the industrial land use efficiency of 32 cities in the Yangtze River Economic Belt, and the impacts of industrial land price and its distortion on the environmental efficiency of urban industrial land use are also analyzed using panel data. The results show that: (1) the industrial land environmental efficiency of cities in the Yangtze River Economic Belt has improved significantly, the regional central cities perform better in industrial land environmental efficiency, the ML value of midstream and upstream cities are higher than those of downstream cities; (2) both the regressions without interactive terms and regressions with interactive terms show that industrial land price has a significant positive effect on industrial land environmental efficiency. The coefficients of selection effect and substitution effect are both significantly positive, which means that industrial land price affects the efficiency of industrial land through the mechanism of scale selection and factor substitution. (3) Industrial land price distortion has a significant negative effect on the environmental efficiency of industrial land, while it has a significant positive effect on the general efficiency of industrial land. The findings are useful for determining the rationality of industrial land price in different cities and formulating industrial land price policies.

Keywords: Industrial land price, land price distortion, industrial land, environmental efficiency, Yangtze River economic zone

I. Introduction

Since the reform and opening up, under the development-oriented industrialization and fiscal decentralization system, local governments have adopted preferential measures of tax and fee exemptions to attract industrial investment in order to enhance industrial competitiveness, and competed to attract investment through low land price strategies. Under the traditional industrialization model, the advantage of low land price and other factors is an important source of industrial efficiency, but along with it, the negative environmental effects of this sloppy industrial development model are increasingly prominent. In 2006, the government issued the "National Minimum Price Standard for Industrial Land" to prevent local governments from competing for low land prices or even offering industrial land at zero land price in attracting investment. In 2013, the central government points out the need to establish an effective regulatory mechanism for keeping reasonable price ratio between industrial land and residential land. The report of the 19th CPC National Congress emphasizes the need to adhere to the priority of efficiency, promote quality change and efficiency change in economic development. In recent years, local governments have begun to assess industrial efficiency using industrial production divided by area on input land, which is regarded as a good indicator to reflect the efficiency of land use, concise and easy to obtain data. However, the index, which cannot comprehensively take into account the changes in inputs such as labor and capital as well as the negative effects of environmental pollution, etc. The ML index based on DEA method overcomes these shortcomings and is gradually being widely used in industrial land efficiency assessment.

The Yangtze River Economic Zone is an important zone for industrial development in China, and the improvement of industrial development level and efficiency of the Yangtze River Economic Zone is of great significance for the

overall improvement of industrial competitiveness in China. In particular, what is the efficiency of industrial land in the cities of Yangtze River Economic Zone and its changing trend after considering the negative effects of environmental pollution? Do low land prices lead to low efficiency? This paper first measures the green productivity of industrial land (ML index), and then further analyzes the impact of industrial land price and its possible distortion factors on industrial land productivity, and draws some analytical conclusions and insights.

II. Literature Review

2.1 Theoretical analysis

Efficiency belongs to the category of input-output relationship, and the efficiency of industrial land reflects the correlation between industrial land input and output. Input refers to land area, quality, etc., while output mainly refers to industrial output value, industrial profit tax, etc. Some studies use principal component analysis, entropy method or other comprehensive evaluation methods to evaluate the efficiency of industrial land. In recent years, many scholars have started to use DEA methods to construct linear programming models by averaging input and output per Mu, and then measure the efficiency of industrial land, which is actually the concept of total factor productivity.

In general, total factor productivity is an indicator of output growth that takes into account both labor and capital inputs. It was first measured by the Solow residual method, and after the linearization of the Cobb Douglas production function, total factor productivity is expressed by the constant A, which actually reflects the growth contribution of output growth net of the contribution of labor and capital growth. Total factor productivity is generally considered to reflect the efficiency gains brought about by factors such as technological progress. The land factor is not considered in the general industry productivity analysis. When considering land use efficiency, there are two ways of thinking, one is to take land as the third input factor and measure total factor productivity, and the other is to divide both labor and capital by the area of industrial land to get the average labor and capital input, and then measure total factor productivity, which reflects the total factor productivity of industry based on the perspective of land input. This paper measures industrial land efficiency following the latter method. However, it is important to note that the Malmquist Index or Malmquist-Luenburger Index measured by DEA is an incremental concept, i.e., it is the growth efficiency in year t+1 relative to year t, rather than a simple input-output ratio relationship in a single year. In other words, a city's high industrial efficiency is a relative concept, not in the absolute sense of how much value added per unit of input is brought.

Land is an important input factor for industrial production, and the cost of industrial land acquisition, as one of the components of enterprise production costs, is a fixed cost, and non-variable costs do not directly affect the annual input-output ratio relationship of enterprises, and thus do not directly affect industrial efficiency. However, the change of industrial land price will affect the efficiency of enterprises or industries from the following two aspects. One is the substitution effect. Industrial land price changes are likely to drive enterprises to change the scale of land purchase and use. When the price is low, it tends to increase land use and lead to a decline in land efficiency, and vice versa. The other is the selection effect. High industrial land prices make relatively inefficient enterprises choose not to enter, while low industrial land prices make some relatively inefficient enterprises willing to enter. The two effects are in the same direction, so logically, assuming that firms are rational, low industrial land prices will lead to lower industrial land efficiency.

2.2 Review of relevant literature

Studies related to industrial land prices and industrial land efficiency emerges from several perspectives. First, a large number of studies focus on the rationality of industrial land prices, i.e., whether industrial land prices are fully priced reasonably or distorted by governmental intervention. Some studies have analyzed the intrinsic drivers of low industrial land prices through logical empirical evidence. Wang et al (2013) estimates the response equation of industrial land prices based on the land transfer prices at the local and municipal levels, and concludes that there is an

inter-regional "race to bottom" effect of industrial land prices in the regional competition among local governments pursuing economic growth [1]. More studies emphasize the analysis and quantitative measurement from the perspective of price rationality. Sun and Gou (2014) compares the ratios of industrial and residential land prices using land price monitoring data of major Chinese cities and sample data of land transactions in Yangzhou, Suzhou, and Hangzhou, and find that both economically developed and less developed regions have low industrial land concession prices and unreasonable ratios to residential land prices [2]. Based on the panel data of 35 large and medium-sized cities in China from 2003 to 2012, Cao and Wang (2014) estimate the reasonable ratio of industrial land to residential land in China's cities, and find that from 2003 to 2012, China's urban ratio of industrial land to residential land is 0.17, while the reasonable ratio is 0.43. Overall, the industrial land price in China is mainly underestimated [3]. Hu, Jin and Wu (2016) analyzes the ratio of industrial land to residential land for the center, suburban, and distant suburban areas within the city of Nanjing, and points out that the ratio is low, but the difference diminishes as the location moves away from the center [4]. Other studies, while acknowledging the existence of low industrial land prices, argues that low industrial land prices are actually a rational behavior of local governments, because they attract industrial enterprises and provide tax sources and employment opportunities.

Peng et al. (2015) empirically analyzes the inner logic of the fiscal incentives of local governments' low-priced industrial land transfer using panel data causality tests and regression analysis, points out that industrial land transfer have a significant positive effect on the growth of local government tax revenue and commercial and residential land transfers, and that investment introduction will lead to the growth of local government's fiscal revenue [5]. Wu et al (2018) argue that the price comparison between industrial land and residential land should be used as the basis to examine the ratio relationship in terms of long-term comprehensive benefits such as tax and employment generated by land use, and they find that the one-time revenue from industrial land transfer is not high, but long-term benefits such as industrial tax and labor compensation account for a higher percentage of total revenue [6]. Chu, Xu and Liu (2014) holds a similar view that the long-term benefits of industrial land are as much as tens of times of the land transfer revenue, and the comprehensive benefits coming from industrial land are as much as twice of the comprehensive benefits of residential land, and local governments have insufficient incentives to increase the land price of industrial land and reduce the supply of industrial land [7].

Second, focusing on the issue of industrial land efficiency, some recent studies have analyzed industrial land efficiency using productivity indices that include land factor. Zhu et al (2018) evaluates the land use efficiency of mining cities in China using the Mamquist-Luenburger (ML) index based on the directional distance function, and show that the industrial land use efficiency of mining cities are at a moderate efficiency level with a downward trend, and the factors influencing the industrial land use efficiency of mining cities of different size classes differed [8]. Wang and Xiao (2016) analyzes the differences in industrial land efficiency in Beijing, Tianjin and Hebei under environmental constraints [9]. Luo and Peng (2016) measure the efficiency of industrial land in China using the Solow residual value method based on the C-D production function, and analyze and test the mechanism of the role of factors such as local government competition on industrial land efficiency. Some studies also analyze the relationship between industrial land price and industrial land efficiency from the perspective of industrial land price [10]. Based on Chinese provincial panel data from 2007-2013, Zhao, Ma and Qu (2016) empirically examine the impact of industrial land market reform on industrial land use efficiency and its regional heterogeneity, and show that industrial land market reform significantly improves industrial land use efficiency in China, and this effect is more prominent in central and western regions [11]. Xi and Mei (2019) measure industrial efficiency using the DEA method and analyze the impact of industrial land prices on land use efficiency, they illustrate that industrial land prices have an enhancement effect on industrial efficiency, and this enhancement effect come from the selection effect that high land prices reduce the proportion of inefficient enterprises entry [12].

III. Research Methodology and Data Description

3.1 Research methodology

The traditional Malmquist index does not consider the negative environmental output, which cannot reflect the negative environmental impact brought by the rapid industrial development in recent years, and thus cannot evaluate the compatibility characteristics of industrial development and ecological civilization, making it difficult to accurately assess the industrial land use efficiency. In this paper, based on the traditional Malmquist index, we further use the DEA method based on the directional distance function to add the negative environmental output constraint in the solution of the linear programming problem, and measure the Malmquist-Luenburger index with green features considering environmental factors, which is measured as follows.

3.1.1 Directional distance function

Industrial production processes produce useful material products, called "good output" and emit pollutants such as waste gas and wastewater, called "bad output". The distance function used in traditional linear programming of productivity measures only takes into account the increase of "good output" and ignores the decrease of "bad output". The basic idea of the directional distance function is to consider both the increase of good products (economic growth) and the decrease of bad products (emission reduction) achieved by environmental protection. This function is a generalization of Shephard's output distance function. The directional distance function can be expressed by the following equation.

$$\vec{D}_{a}(x, y, b; g) = \sup\{\beta : (y, b) + \beta g \in P(x)\}$$
(1)

Where g = (gy, gb) is the output expansion direction vector. Depending on the technically strong and weak disposability of the bad output, the directional distance function can be chosen with different directional vectors. In particular, consider two cases: (1) the directional vector is g = (y, 0) and the bad output is ignored in the construction of the production technology. In this case, the measured productivity index is the traditional Malmquist index. (2) When the direction vector is g = (y, -b) and the bad output is technically weakly disposable. In this case, it means that the good output increases while the bad output decreases, which is basically consistent with the current environmental control requirements.

Using DEA to solve the directional distance function, the following linear program is solved.

$$\vec{D}_{o}^{t}(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}) = \operatorname{Max}\beta$$

s.t.
$$\sum_{k=1}^{K} z_{k}^{t} y_{km}^{t} \ge (1+\beta) y_{km}^{t}, m = 1, \cdots, M$$

$$\sum_{k=1}^{K} z_{k}^{t} b_{ki}^{t} = (1-\beta) b_{ki}^{t}, i = 1, \cdots, I$$

$$\sum_{k=1}^{K} z_{k}^{t} x_{kn}^{t} \le x_{km}^{t}, n = 1, \cdots, N$$

$$z_{k}^{t} \ge 0, k = 1, \cdots, K$$
(2)

The value of the directional distance function, if equal to zero, indicates that this country's production is technically efficient at the production availability frontier, otherwise it indicates technical inefficiency. On this basis, it is possible to construct the Malmquist-Luenberger productivity index considering the bad output reduction condition.

3.1.2 Malmquist-Luenberger index

According to Chung et al. (1997), the productivity index based on the output Malmquist-Luenberger (ML) between periods t and t+1 is

1

$$ML_{t}^{t+1} = \left\{ \frac{\left[1 + \vec{D}_{o}^{t}(x^{t}, y^{t}, b^{t}; g^{t})\right]}{\left[1 + \vec{D}_{o}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}]\right]} \times \frac{\left[1 + \vec{D}_{o}^{t+1}(x^{t}, y^{t}, b^{t}; g^{t})\right]}{\left[1 + \vec{D}_{o}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]} \right\}^{\frac{1}{2}}$$
(3)

The ML index can be decomposed into the efficiency change (EFFCH) and the technological progress index (TECH).

$$ML = EFFCH \times TECH \tag{4}$$

$$EFFCH_{t}^{t+1} = \frac{1 + \vec{D}_{o}^{t}(x^{t}, y^{t}, b^{t}; g^{t})}{1 + \vec{D}_{o}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$
(5)

$$TECH_{t}^{t+1} = \left\{ \frac{[1 + \vec{D}_{o}^{t+1}(x^{t}, y^{t}, b^{t}; g^{t})]}{[1 + \vec{D}_{o}^{t}(x^{t}, y^{t}, b^{t}; g^{t})]} \times \frac{[1 + \vec{D}_{o}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})]}{[1 + \vec{D}_{o}^{t}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}]} \right\}^{\frac{1}{2}}$$
(6)

Similar to the Malmquist index, ML, EFFCH and TECH are greater (or less) than 1 indicating productivity increase (decrease), efficiency increase (decrease), and technological progress (regression), respectively. A simple transformation is made in equation (1) to solve the ordinary Sheppard distance function without considering pollution emissions, which in turn can be solved for the traditional Malmquist index without considering pollution emissions.

3.2 Data sources

The research is directed for industrial data of 32 cities in Yangtze River Economic Zone from 2009 to 2017. To measure the productivity of industrial land, the positive output variables are selected from the added value of industrial enterprises with a scale larger than a million dollars, the input variables consider the number of employees, the total value of fixed assets of industrial enterprises above the scale, the area of industrial land, and the negative environmental output variables including industrial wastewater emissions and industrial sulfur dioxide emissions. All output value or tax data are current year prices, adjusted to 2009 constant prices according to the ex-factory price index of industrial products. The total value of fixed assets of industrial enterprises is also uniformly adjusted to 2009 constant prices according to the fixed asset investment price index. In the measurement, all positive output or negative output variable data are divided by the industrial land area to obtain the average input and output data, in order to measure the average level of industrial productivity considering land factor inputs. All the data are used in the citywide caliber. The area of industrial land is obtained from the China Urban Construction Statistical Yearbook, which is only for the municipal districts, and is adjusted to the area of industrial land in the city according to the ratio of output value. All other data are from the China City Statistical Yearbook.

Among them, the cities in study are limited to those of which Industrial land prices are available in China Statistical Yearbook of Land Resources. Considering the geographical distance factor, cities in Guizhou, Yunnan and other provinces are not considered.

IV. Analysis of Industrial Land Efficiency for Cities in Yangtze River Economic Zone

Based on the above method, the industrial land efficiency (M-index and ML-index) between seven years from 2009-2017 can be measured, and the average productivity growth between all years is calculated using the geometric mean method. Examining first the industrial land efficiency index (M index) without considering the negative environmental output, the mean value of the geometric mean of the industrial Malmquist index for all 32 cities is

1.029, which means that the industrial land efficiency of the cities in the Yangtze River Economic Zone grew at an average annual rate of 2.9% the growth of efficiency comes mainly from the improvement of technical progress the mean value of the geometric mean of technical efficiency of 32 cities' industries for all years is 0.999, with an overall growth rate of -0.1%, and the mean value of the geometric mean of technical progress efficiency of 32 cities' industries for all years is 1.03, with an overall growth rate of 3.0%. Correspondingly, we analyze the industrial land efficiency index (ML index) considering the negative environmental output, and the geometric mean value of the ML index for all 32 cities is 1.039, i.e., the industrial environmental land efficiency of the cities in the Yangtze River Economic Zone grows by 3.9% per year, which is significantly higher than the measured traditional efficiency growth, and the growth mainly comes from the contribution of technological progress. The geometric mean value of technical efficiency is 0.998, while the geometric mean value of technical progress efficiency of industry in 32 cities is 1.042.

Table 1 presents the geometric mean of industrial land efficiency of 32 cities in the Yangtze River economic belt during 2009-2017, which can better reflect the change of efficiency in each city in the sample years. Firstly, from the sub-belt, urban industrial land efficiency shows a significant increasing trend along the lower, middle and upper reaches of the Yangtze River. The downstream 16 cities have an average of 1.025 and 1.014 for the two types of industrial land efficiency index, respectively; the midstream 12 cities have an average of 1.037 and 1.06 higher than the downstream cities for the two types of industrial land efficiency, respectively; the upstream 4 cities also have higher efficiency than the downstream cities for the two types of industrial land efficiency, respectively; the upstream 4 cities perform best overall, but not much higher than upstream and downstream cities; as for industrial environmental efficiency ML index, downstream cities has the weakest growth, midstream and upstream cities have more significant growth, among which the average growth rate of four upstream cities reaches 7.5%. This indicates that without considering the negative environmental impact, the industrial land efficiency of midstream and upstream cities is slightly higher than that of downstream cities is significantly higher than that of downstream cities perform the best.

The comparison of ordinary efficiency and environmental efficiency of industrial land is examined. The environmental efficiency of land use is greater than the ordinary efficiency of a total of 16 cities, exactly half, indicating that in recent years measures taken for environmental protection have achieved certain results. There are five cities where the general efficiency index of industrial land is 0.05 higher than the environmental efficiency index of industrial land, namely Shanghai, Suzhou, Yangzhou, Bengbu and Yichang, and there are four cities where the environmental efficiency index of industrial land is 0.05 higher than the general efficiency index, namely Nantong, Hefei, Nanchang, Wuhan and Changsha. The top three cities in terms of traditional efficiency of industrial land are Yichang (1.124), Huabei (1.077), and Wuhan (1.071), and the next three are Hefei (0.971), Nantong (0.990), and Nanchong (0.984); the top seven cities in terms of environmental efficiency of industrial land are Changsha (1.232), Chengdu (1.206), Wuhan (1.186), Nantong (1.112), Jiaxing (1.107), Nanchang (1.084), and Hefei (1.083). Interestingly, five of the seven cities are provincial capitals in the middle and upper reaches of the river, indicating that provincial capitals play an important role in the coordinated development of the Yangtze River Economic Belt region, and better carry out the coordination between industrial land.

| Table 1 | Average tra | ditional | efficiency | index (| MI) | and env | vironment | al effici | ency i | index (| (ML) | by city | over | the p | period |
|---------|-------------|----------|------------|---------|-----|---------|-----------|-----------|--------|---------|------|---------|------|-------|--------|
| | | | | | | 2000 | 2017 | | | | | | | | |

| 2009-2017 | | | | | | | | | | |
|-----------|----------|-------|-------|--------|----------|----------|-------|-------|--------|--|
| Sub-belt | City | MI | ML | Differ | Sub-belt | City | MI | ML | Differ | |
| | Shanghai | 1.046 | 0.932 | -0.114 | | Nanchang | 1.000 | 1.084 | 0.084 | |
| | Nanjing | 1.026 | 1.055 | 0.029 | | Jiujiang | 1.059 | 1.051 | -0.008 | |
| | Wuxi | 1.001 | 0.956 | -0.045 | | Wuhan | 1.071 | 1.186 | 0.115 | |
| | Xuzhou | 1.045 | 1.041 | -0.004 | | Huangshi | 1.002 | 0.960 | -0.042 | |

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| | Changzhou | 0.004 | 1 001 | 0.007 | | Vieheng | 1 1 2 4 | 1 072 | 0.052 |
|--------|-----------|-------|-------|--------|--------|-----------|---------|-------|--------|
| | Changzhou | 0.994 | 1.001 | 0.007 | | Tichang | 1.124 | 1.072 | -0.032 |
| Down | Suzhou | 1.000 | 0.937 | -0.063 | Middle | Xiangyang | 1.005 | 0.990 | -0.015 |
| Stream | Nantong | 0.990 | 1.112 | 0.122 | Stream | Jingzhou | 1.033 | 1.056 | 0.023 |
| Reach | Yangzhou | 0.994 | 0.837 | -0.157 | Reach | Changsha | 1.062 | 1.232 | 0.17 |
| | Hangzhou | 1.039 | 1.045 | 0.006 | | Zhuzhou | 1.004 | 1.031 | 0.027 |
| | Jiaxing | 1.060 | 1.107 | 0.047 | | Xiangtan | 1.069 | 1.039 | -0.03 |
| | Huzhou | 1.025 | 1.019 | -0.006 | | Hengyang | 0.996 | 1.038 | 0.042 |
| | Hefei | 0.971 | 1.083 | 0.112 | | Yueyang | 1.013 | 0.981 | -0.032 |
| | Wuhu | 1.039 | 1.046 | 0.007 | | Average | 1.037 | 1.06 | |
| | Bengbu | 1.058 | 1.006 | -0.052 | Upper | Chongqing | 1.016 | 1.075 | 0.059 |
| | Huainan | 1.034 | 1.006 | -0.028 | Stream | Chengdu | 1.067 | 1.206 | 0.139 |
| | Huaibei | 1.077 | 1.048 | -0.029 | Reach | Nanchong | 0.984 | 0.995 | 0.011 |
| | | | | | | Yibin | 1.012 | 1.024 | 0.012 |
| | Average | 1.025 | 1.014 | | | Average | 1.02 | 1.075 | |

The data were measured and compiled from the author.

V. Regression results

5.1 Variables and data description

The explanatory variables are industrial land prices (LDPRIC) in each city, and the data are obtained from China Land and Resources Statistical Yearbook in previous years. The control variables includes: (1) Scale characteristics of industrial enterprises above the scale of each city (SCALE), which is expressed by the total fixed assets of industrial enterprises divided by the number of enterprises, i.e., the average scale reflects the scale level of enterprises, and the total fixed assets are deflated by the fixed asset investment price index. (2) Foreign direct investment (FDI), which is expressed as the ratio of industrial added value of FDI enterprises to the added value of all industrial enterprises. (3) Science and technology expenditure (SCIEXP), being expressed as the amount of science expenditure or science and technology expenditure in each city's fiscal expenditure. In addition, some exogenous variables such as the supply of land for construction in each city, the distance of each city from Shanghai, and the distance of the regional center city are also introduced as the corresponding instrumental variables. The distance value of the Shanghai city itself is taken as 10 km, which is convenient to take logarithm. (4) The interaction term between land price and enterprise size (LNLDPRIC*LNSCALE), expressed as the product of log industrial land price and log enterprise size, reflects the selection effect of land price. (5) The interaction term between land price and log of industrial land price and the log of industrial land price and the log of industrial land average capital, reflecting the substitution effect of land price.

5.2 Relationship between environmental efficiency and urban industrial land prices

Table 2 presents the regression results of the environmental efficiency of industrial land and the technological progress index on the variables such as land price, with all variables taken as natural logarithms. Regressions 1, 3, 5, and 7 do not include two interaction terms and are regressed on the ML index and the ML decomposition term technical progress efficiency index, respectively. Regression 1 and regression 5 are fixed-effect regressions, and random-effects regressions have also been done followed by Hausman tests, which rejects the hypothesis of indifference between fixed effect regressions and random effect regressions, so fixed-effect regressions are adopted. Regressions 3 and 7 are two-stage least squares regressions. The results of the fixed-effects regression show that the price of industrial land has a significant positive effect on both the environmental efficiency of industrial land and the technological progress index, which is significant at the 5% level. Among the control variables, enterprise size and foreign direct investment both have significant effects on the environmental efficiency of industrial land as well as the technological progress index. The regression coefficients of the enterprise size are 0.209 and 0.162, which are significant at the 5% levels, respectively. It indicates that the increase of enterprise size and 0.166, which are significant at the 1% and 5% levels, respectively. It indicates that the increase of enterprise size and

the utilization of foreign investment are generally conducive to enhancing the ability of coordinated development of industry and environment and promoting the construction of ecological civilization.

The two-stage least squares regression are conducted with two exogenous variables, urban construction land supply and urban location, as instrumental variables, both of which pass the instrumental variable test and over-identification test, indicating that the instrumental variables better solve the endogeneity problem. The results show that with the elimination of endogeneity due to demand factors, the change in land price caused by industrial land supply factors has a weaker impact on the environmental efficiency of industrial land, with the coefficient decreasing from 0.239 to 0.147 and the significance decreasing from 5% to 10%. And the effect of industrial land price on the index of technical progress of industrial land under instrumental variables becomes insignificant. Overall, considering the endogeneity in the regression, land price still has a positive effect on the environmental efficiency of industrial land, indicating that an increase in land price does drive enterprises to choose environmentally friendly production methods.

Regressions 2, 4, 6, and 8 are added with two interaction terms of land price and firm size, land price and land-average capital, respectively. The fixed-effect and random-effect regressions are done separately, and Hausman's test rejects the null hypothesis that there is no significant difference between the coefficients of fixed-effect and random-effect regressions, so fixed-effect regressions are used, and regressions 2 and 6 are the results of fixed-effect regressions. The fixed-effects regression results show that land price still has some significant positive effect on environmental productivity and its technical progress index, and industrial land price has a more significant positive effect on both environmental efficiency and technical progress index of industrial land, which is significant at the 10% level. Among the control variables, firm size and foreign direct investment, have significant effects on the environmental efficiency of industrial land and its technical progress index. The regression coefficients of firm size are 0.154 and 0.115, both significant at the 5% level, and the regression coefficients of the FDI variable are 0.136 and 0.171, significant at the 5% level. It indicates that the increase of firm size and FDI are generally conducive to enhancing the ability of coordinated development of industry and environment and promoting the construction of ecological civilization. The coefficients of the interaction term between land price and scale reflecting the selection effect are 0.168 and 0.103, which are significant at the 5% and 10% levels, respectively. It indicates that the effect of land price on environmental efficiency or technological progress of industrial land is influenced by the factor of firm size. The selection effect of increasing land price leads to the expansion of scale, which leads to the improvement of environmental efficiency of industrial land. The coefficients of the interaction terms of land price and land-average capital reflecting the substitution effect are 0.159 and 0.155, respectively, both significant at the 5% level. It indicates that industrial land price also affects the level of land-average capital through the substitution effect, which in turn positively affects the environmental efficiency or technical progress of industrial land.

Similarly, two-stage least squares regressions are done for regressions 4 and 8, respectively. Two exogenous variables, urban construction land supply and urban location, used as instrumental variables, and both the weak instrumental variable test and over-identification test passed, indicating that the instrumental variables resolve the endogeneity problem better. Compared with regressions 2 and 6, the effects of industrial land price, scale effect, and FDI on environmental efficiency of industrial land, etc. are weakened, but the overall effect on environmental efficiency of industrial land remains unchanged. The coefficients of the interaction term of land price and scale reflecting the selection effect are still positive and significant at the 5% or 1% level. Both are significant at the 5% level. It indicates that the regressions eliminating endogeneity also suggest that industrial land price also positively affects the environmental efficiency or technological progress of industrial land through both the selection effect and the substitution effect.

Considering the endogenous regressions, land price still has a positive effect on the environmental efficiency of industrial land, suggesting that rising land prices do drive firms to choose environmentally friendly production

methods.

| Table 2 Regression results of environmental effectercy of industrial land pirce | | | | | | | | | | |
|---|---------------|--------------|--------------|--------------|--------------|--------------|---------------|---------------|--|--|
| Variables | Regressi | Regressi | Regressi | Regressi | Regressi | Regressi | Regressi | Regressi | | |
| | on 1 | on 2 | on 3 | on 4 | on 5 | on 6 | on 7 | on 8 | | |
| | ML(FE) | ML(FE) | ML(2SL | ML(2SL | MLTC(F | MLTC(F | MLTC | MLTC | | |
| | | | S) | S) | E) | E) | (2SLS) | (2SLS) | | |
| LNLDPRIC | 0.239** | 0.112^{*} | 0.147^{*} | 0.103* | 0.121** | 0.086^{*} | 0.083 | 0.043 | | |
| | (0.122) | (0.066) | (0.081) | (0.056) | (0.061) | (0.050) | (0.062) | (0.032) | | |
| LNSCALE | 0.209^{**} | 0.154^{**} | 0.094^{**} | 0.068^{**} | 0.162^{*} | 0.115^{**} | 0.144^{***} | 0.105^{**} | | |
| | (0.116) | (0.066) | (0.045) | (0.035) | (0.106) | (0.047) | (0.051) | (0.044) | | |
| LNFDI | 0.258^{***} | 0.136** | 0.129** | 0.101^{**} | 0.166^{**} | 0.171^{**} | 0.142^{***} | 0.094^{***} | | |
| | (0.073) | (0.065) | (0.056) | (0.054) | (0.069) | (0.073) | (0.038) | (0.035) | | |
| LNSCIEXP | -0.078 | -0.055 | 0.041 | 0.035 | 0.093^{*} | 0.074 | 0.046 | 0.037 | | |
| | (0.056) | (0.041) | (0.028) | (0.022) | (0.054) | (0.061) | (0.039) | (0.028) | | |
| LNLDPRIC*LNSC | | 0.168^{**} | | 0.075^{**} | | 0.103^{*} | | 0.085^{**} | | |
| ALE | | (0.075) | | (0.036) | | (0.045) | | (0.039) | | |
| LNLDPRIC*LNK | | 0.159^{**} | | 0.133** | | 0.155** | | 0.077^{***} | | |
| | | (0.080) | | (0.061) | | (0.064) | | (0.038) | | |
| Cons | 1.745 | 1.213 | 1.542 | 1.414 | 0.412 | 0.541 | -1.317 | -1.125 | | |
| | (1.272) | (0.084) | (1.059) | (1.021) | (1.206) | (1.015) | (1.308) | (1.244) | | |
| Within R ² | 0.2730 | 0.3021 | | | 0.2562 | 0.0726 | | | | |
| Between R ² | 0.2070 | 0.2532 | | | 0.2021 | 0.2139 | | | | |
| Hausman test | 0.016 | 0.009 | | | 0.008 | 0.015 | | | | |
| Ν | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | | |

Table 2 Regression results of environmental efficiency of industrial land price

Note: Standard errors are in parentheses, and "***", "**", and "*" indicate that the coefficients are significant at the 1%, 5%, and 10% levels, respectively.

5.3 Further analysis of industrial land price distortion

Further analysis and verification are needed to determine whether the "Race to Bottom" competition among local governments leads to distortions in industrial land prices and whether such distortions affect the efficiency of industrial land. The minimum standard of industry land price decreases from 840 yuan / m2 for the 1st grade to 60 yuan / m2 for the 15th grade, and clearly designates the grade of industrial land for each city and its jurisdiction. This minimum price standard not only reflects the basic value of industrial land under current conditions, but also can be used as a criterion for judging whether there is low-priced industrial land for sale [13]. In this paper, we utilize the method of Huang et al. (2015) to measure the land price distortion [14].

$$LPDIST_{i,t} = \frac{LPS_i - LP_{i,t}}{LPS_i}$$
(7)

where i, t denote city and year, respectively. $LPDIST_{i,t}$ denotes the degree of price distortion of industrial land in city i in year t, LPS_i denotes the minimum criterion of industry land price in city i, and $LP_{i,t}$ denotes the price of industrial land in city i in year t, adjusted to 2009 constant prices based on the fixed asset price index for each city for comparison. Due to the rising trend of land price itself and the requirement of rule compliance, the index is generally negative. The smaller the value, the higher the actual land price is compared with the minimum standard of land price, and the distortion is relatively small, and vice versa, there may be some distortion effect.

According to the competition theory, it is expected that the land price of each city may change along the minimum standard line. Table 3 gives the mean value, standard deviation and its rate of change of the land price distortion index of each city, which shows that most of the measured results are negative, indicating that most of the cities have strictly implemented the minimum limit policy according to the policy regulations. The average land price distortion index is -0.433 in the downstream Yangtze River cities, -0.592 in the middle Yangtze River cities, and -0.611 in the

upper stream Yangtze River cities. The overall difference is small and shows a weak decreasing trend from the upper to the lower reach of Yangtze River. Regressions of land prices on time for most cities are done to observe changes in land prices over time. Except for four cities, Wuhan, Jiaxing, Hangzhou, and Chongqing, the significance test of the land price distortion index in most other cities were not significant, indicating that land prices in each city do not show structural changes. Specifically, the cities with an average land price distortion index less than -1 are Changzhou, Bengbu, Jingzhou, Yueyang, and Yibin, indicating that the land prices in these cities are significantly higher than the minimum limit; the five cities with the smallest average absolute values of the land price distortion index are Suzhou, Huzhou, Huainan, Nantong, and Chengdu, which are closer to the minimum limit.

| Sub | city | Mean | Standard | Change | Subbelt | city | Mean | Standard | Change |
|--------|-----------|--------|-----------|--------|---------|-----------|--------|-----------|--------|
| belt | 5 | | Deviation | rate | | 5 | | Deviation | rate |
| | Shanghai | -0.601 | 0.592 | 0.15 | | Nanchang | -0.376 | 0.368 | -0.09 |
| | Nanjing | -0.231 | 0.098 | 0.01 | | Jiujiang | -0.405 | 0.366 | -0.11 |
| | Wuxi | -0.329 | 0.298 | 0.01 | | Wuhan | -0.933 | 1.115 | 0.38 |
| | Xuzhou | -0.406 | 0.242 | 0.05 | | Huangshi | -0.325 | 0.251 | 0.02 |
| | Changzhou | -1.056 | 0.681 | 0 | Middle | Yichang | -0.258 | 0.338 | 0.06 |
| Down | Suzhou | -0.186 | 0.272 | 0.05 | Stream | Xiangyang | -0.376 | 0.261 | 0.01 |
| Stream | Nantong | -0.234 | 0.182 | 0.02 | Reach | Jingzhou | -1.06 | 1.093 | -0.27 |
| Reach | Yangzhou | -0.413 | 0.360 | 0.02 | | Changsha | -0.599 | 1.032 | 0.27 |
| | Hangzhou | -0.444 | 0.194 | -0.08 | | Zhuzhou | -0.330 | 0.276 | 0.06 |
| | Jiaxing | -0.669 | 0.713 | 0.29 | | Xiangtan | -0.328 | 0.376 | -0.08 |
| | Huzhou | -0.213 | 0.223 | 0.05 | | Hengyang | -0.430 | 0.229 | -0.02 |
| | Hefei | -0.26 | 0.315 | -0.03 | | Yueyang | -1.681 | 1.524 | 0.39 |
| | Wuhu | -0.339 | 0.239 | 0.04 | | Average | -0.592 | | |
| | Bengbu | -1.093 | 0.878 | 0.16 | Upper | Chongqing | -0.475 | 0.344 | -0.12 |
| | Huainan | -0.217 | 0.303 | 0.01 | Stream | Chengdu | -0.177 | 0.183 | -0.01 |
| | Huaibei | -0.238 | 0.229 | 0.02 | Reach | Nanchong | -0.415 | 0.373 | 0.04 |
| | | | | | | Yibin | -1.376 | 1.579 | 0.5 |
| | Average | -0.433 | | | | Average | -0.611 | | |

Table 3 Land price distortion index and changes of cities in Yangtze River Economic Zone

Table 4 shows the results of regressions of the general efficiency of industrial land, environmental efficiency on the industrial land price distortion index for each city. For simplicity, only the fixed effect regressions results are reported, because the random effect regressions and Hausman tests are done and both rejected the null hypothesis, indicating that the fixed effect regressions are more appropriate. The results of regression 9 and regression 10 show that industrial land price distortion has a significant negative impact on the industrial land environmental efficiency, with coefficients significant at the 5% or 1% level. This indicates that lower than normal land prices attract more low-level, less environmentally conscious firms. The results of regression 11 and regression 12 show that industrial land price distortion has a significant positive effect on the general efficiency of industrial land. This is because low land prices reduce the cost of firms not considering negative environmental output, which leads to a relative increase in efficiency. In addition, as analyzed earlier, the two control variables of firm size and FDI have significant positive effects on industrial land general efficiency and environmental efficiency.

| $1 a 0 0 \pm 100000000000000000000000000000$ |
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|--|

| Variable | Regression 9 ML(FE) | Regression10 ML(2SLS) | Regression11 MI(FE) | Regression12 MI(2SLS) |
|----------|------------------------|--------------------------|------------------------|--------------------------|
| LPDIST | -0.186*** | -0.172** | 0.118*** | 0.102** |
| | (0.074) | (0.087) | (0.054) | (0.058) |
| LNSCALE | 0.280^{***} | 0.088^{**} | 0.115^{**} | 0.072^{**} |
| | (0.094) | (0.037) | (0.052) | (0.034) |
| LNFDI | 0.190^{***} | 0.170^{***} | 0.104^{**} | 0.107^{**} |
| | (0.062) | (0.064) | (0.043) | (0.051) |

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LNSCIEXP 0.051 0.023 0.071 -0.062(0.048)(0.051)(0.034)(0.048)Cons 1.314 0.076 0.092 -0.444(0.579)(0.602)(0.405)(0.570)Within R² 0.151 0.166 Between R² 0.132 0.162 Hausman test 0.018 0.038 N 256 256 256 256

VI. Conclusions

The results of industrial land efficiency measurement based on DEA method show that the general efficiency of industrial land is slightly higher in the middle and upper reaches of Yangtze River than in the downstream reach, while the environmental efficiency of industrial land is significantly higher in the middle and upper reaches. With the emphasis on environmental protection, the environmental efficiency of industrial land has achieved more significant growth, especially some provincial capital level regional center cities have performed better in the environmental efficiency of industrial land.

The fixed effect regression results without considering the interaction term show that industrial land price has a significant positive effect on both industrial land environmental efficiency and technical progress index. The two-stage least squares regression results show that land price still has a positive effect on the environmental efficiency of industrial land, indicating that the increase in land price will drive enterprises to choose environmentally friendly production methods. The fixed-effect regression results with the addition of two interaction terms show that land price still has some significant positive effects on environmental productivity and its technological progress index. The coefficient of the interaction term between land price and firm size, which reflects the selection effect, is significant due to the fact that selection effect makes enterprises relatively larger and increase the environmental efficiency of industrial land. The coefficients of the interaction term between land price and land capital reflecting the substitution effect are both significant at the 5% level. In the two-stage least squares regression, the effects of industrial land price, scale effect, and FDI on environmental efficiency of industrial land are weakened, but the overall effects on environmental efficiency of industrial land remains unchanged. The coefficients of selection effect and substitution effect are still positive.

The two variables of firm size and FDI have significant effects on the environmental efficiency of industrial land and the technological progress index, which means that there is also a scale effect on environmental protection and a significant "pollution halo" effect from FDI. Further, industrial land prices in all cities are in line with the land transfer price limit, but land price distortion exists to some extent. The distortion of industrial land price has a significant negative effect on the environmental efficiency of industrial land, while it has a significant positive effect on the general efficiency of industrial land.

This study explores the theoretical and empirical aspects of industrial land price and its influences on industrial land efficiency, and the research results have some implications for the determination of the reasonableness of industrial land price and the formulation of industrial land price policies in different cities.

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