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Abstract: In China, local government's "land for development" strategy has led to a large number of urban construction land allocated to the industrial field, which has promoted the rapid development of industry and economy in the short term, but also brought serious environmental quality losses. This paper systematically sets out how land misallocation works on urban air quality and employs the spatial Durbin model (SDM) to conduct an empirical analysis on the panel data of 283 China's cities at or above the prefecture level. The result shows that, stimulated by financial maximization and political promotion, in order to obtain more fiscal revenue and growth performance, local governments prefer to allocate a large number of urban construction land to industry and related fields, which leads to the underestimation of industrial land price and the misallocation of land resources. Land misallocation has exerted significant inhibiting effects on the air quality of local and their surrounding cities through inhibiting the upgrading of industrial structure. Further analysis reveals that the bigger the city, the less the inhibition effects of land misallocation on upgrading of industrial structure and urban air quality, and vice versa. The conclusions of this paper can provide useful reference for local governments to optimize land allocation, promote economic restructuring and environmental quality upgrading.

Keywords: land misallocation; upgrading of industrial structure; urban air quality; spatial Durbin model

JEL Classification: R52; E62; P28

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Highlights

- We explore the effects of land misallocation on urban air quality.
- We estimate spatial spillover effect by spatial Durbin model using the panel data of 283 cities.
- We investigate heterogeneous spatial effects from cities of different grades.
- Land misallocation can reduce the urban air quality of local and surrounding cities.
- Land misallocation lowers urban air quality by inhibiting the upgrading of industrial structure.

1. Introduction

Environmental pollution is an important problem that plagues most developing countries, including China. China's economic and social development have the dual tasks of “stabilizing growth” and “promoting emission reduction.” Over the past three decades, China's economy and urbanization have been growing rapidly at an annual rate of 9.4% and 1.02%, respectively. Additionally, however, the extensive development mode characterized by "high pollution, high energy consumption and high emissions" has taken a heavy toll on China's environmental quality. According to the 2019 Report on the State of the Environment in China published by the Ministry of Environmental Protection of the People's Republic of China, among the 337 cities at and above prefecture-levels, 180 cities had ambient air quality worse than the pollution standard, accounting for 53.4%. To control environmental pollution and improve environmental quality, the Chinese government put forward the concept of green development at the 5th Plenary Session of the 18th Central Committee of the Communist Party of China. All the 2017 - 2019 Report on the Work of the Government established the target of reducing sulfur dioxide and nitrogen oxide emissions by 3% and substantially lowering concentration of PM 2.5 in key areas. The reports of the 19th National Congress of the Communist Party of China also stipulate that, in addition to creating more material and cultural wealth to fulfill individuals' ever-increasing desire to improve their lives, China must also provide more quality ecological goods to fulfill individuals' ever-growing demands for a pristine environment. All these demonstrate that the Chinese government's firm will to reduce air environmental pollution and realize the coordinated development of economic construction and ecological civilization construction.

Regarding this question, researchers have used various perspectives to investigate the impetus for environmental topics and paths to improve air quality. Among these researchers, some have discussed the relationship between economic growth stages and environmental quality by testing the Environmental Kuznets Curve by Grossman and Krueger (1991, 1995) (Jebli and Youssef, 2015; Tiba and Omri, 2017; Dong et al., 2018), and others have probed into the relationship between foreign trade, foreign direct investment (FDI), and air environmental pollution (He, 2006; Cole et al., 2011; Ren et al., 2014; liu et al., 2018). Additionally, still another group of researchers has discussed the path to improve air quality from the perspective of industrial restructuring (Mi et al., 2015; Wang et al., 2018; Chen and

Zhao, 2019), and others have demonstrated how spatial agglomeration of economic activities affects air quality (Cheng, 2016; Han et al., 2018a; Fremstad et al., 2018).

In China, economic factors such as international trade, FDI, industrial restructuring, and industrial agglomeration cannot function without relying on a institutional system, especially the land misallocation strategies in association with investment introduction, urbanization, and rapid economic growth (Li et al., 2013; Jiang, 2014; Fan, 2015). The binary land structure in China featured by urban–rural segmentation has given local governments the special triple identity of owner, supplier, and monopolist of state land (Shao et al., 2016), resulting in the land transfer behavior of local governments. Under the system of political centralization and economic decentralization, for the purpose of political promotion and private economic profits, local government officials use the land disposal right to strategically set prices and the size of land leased in the monopolized land market, and tend to allocate construction land to productive infrastructure and capital-intensive industries. The biased allocation of construction land resources distorts the land market and reduces the efficiency of land use. The process of allocation and reallocation of land, as a basic production factor and the most important economic resource, is the process of realizing and deepening capitalization and the process of economic and social structure adjustment and evolvement. Undoubtedly, this essential factor affects environmental issues in the process of economic development. Cai et al. (2008) posited that current environmental issues in China mainly stem from the existing extensive economic development pattern, which is closely related to the government's acts under Chinese-style power division. Thus, how does the land misallocation affect the quality of urban air environment? What is the influence mechanism?

According to our review of the literature, few literature reviews have directly studied promotion mechanisms of urban air quality from the perspective of land misallocation. Even if some studies have involved land misallocation and air environmental issues (Zhang and Xu, 2017), these researchers have only mentioned a specific aspect of urban environmental quality (e.g. carbon emission), whereas none of them has systematically discussed environmental quality in an overall fashion or let probed into land misallocation's functioning mechanism. In this paper, we attempt to create a spatial econometric model based on an analysis and summary of how land misallocation influences urban air quality, and use the panel data of 283 Chinese cities at or above the prefecture level from 2003 to 2015 the sample to

systematically discusse the intrinsic mechanism and spatial spillover effect of land misallocation on urban air quality.

Compared with the existing literature, the contribution of this paper are as follows. First, we introduce land misallocation into the study of influencing factors of air quality, and systematically probe the mechanism of land misallocation on urban air quality. Second, at present, the literature on the mismatch of land resources in China mostly uses the published data of land transfer agreement and industrial and mining storage land to measure the degree of mismatch of urban construction land, but these two kinds of indicators can not directly reflect the real transaction situation of the land market. This paper uses web crawler technology to collect the actual transaction data of commercial land, residential land and industrial land of 283 prefecture level cities in China from 2006 to 2018 from China land market network. Combined with the production function, this paper uses marginal output method to calculate the misallocation index of industrial land, and directly measures the misallocation degree of current urban construction land. Third, in this paper, $PM_{2.5}$ concentration is used to measure the air quality. The existing literatures mostly use provincial $PM_{2.5}$ data to measure the air quality, but because haze pollution mainly occurs in cities, the provincial data actually cover up the heterogeneity of air quality in different cities. In this paper, by analyzing the satellite monitoring grid data of the global $PM_{2.5}$ annual mean concentration, the $PM_{2.5}$ annual mean concentration of 283 prefecture level cities in China from 2006 to 2018 is obtained, and it can truly reflect the air quality of different cities, which is helpful to further deepen the research. Last, we applied the spatial Durbin model (SDM) to further categorize effects into direct and indirect effects. From the perspective of the heterogeneity of cities at different levels, we analyzed land misallocation's spatial heterogeneous influences on air quality in different cities.

2. Analysis of how land misallocation affects urban air quality

2.1 Land misallocation's inhibition effects on urban environmental quality

Land misallocation in this paper refers to the distortion of resource allocation caused by the biased allocation of urban construction land in the industrial field. Since the reform of the tax distribution system in 1994, the central government has reclaimed financial rights, but power division between the

central government and local governments remains basically unchanged. Local governments' financial resources are becoming increasingly limited. To relieve financial pressure after the implementation of a tax distribution system, on the one hand, local governments seek extra budgetary or governmental fund income through land transfer, land mortgage and financial guarantee; on the other hand, they transfer industrial land at a low price to attract investment and expand the tax base. In addition, under the political promotion stimulation system, local governments may also transfer a large amount of land when motivated by a developing local economy (Li et al., 2013; Zhang and Xu, 2017). This means that the Chinese style financial power division system and the political promotion system jointly stimulate the local government's land mismatch strategy and land transfer behavior (Wang et al., 2014). Many local governments have attempted to increase land requisition and supply by establishing new urban districts, industry zones, and development zones; strategically setting land leasing prices and sizes; and using their monopoly of the land market and land disposal right. All these factors result in excessively rapid urbanization and disordered sprawl of urban space. Disordered sprawl of urban space and the change in land utilization and covering rate not only undermine the vegetation surrounding cities but also damage the landscape and compromise ecological service functions (Wu et al., 2015); moreover, they exacerbate consumption of resources and the environment, causing problems such as environmental pollution and noise. (Wu and Yeh, 1999; Zhang and Xu, 2017) and directly imposing negative effects on urban air quality.

Under the political performance assessment system and financial taxation maximization stimulation, local governments strongly prefer the development of capital-intensive industry. The majority of construction land flows to the field of productive infrastructure and capital-intensive industry, resulting in overdevelopment of capital-intensive industries and heavy industry, exacerbation of resource consumption and allocation distortion, and an undermining of urban environmental quality. Leasing of industrial land involves economic growth and political performance. Under race-to-the-bottom pattern, despite the race-to-the-bottom price of land leasing having severely limited leasing revenue from industrial land, local economic growth is spurred by introducing industrial capital and attracting enterprises, which increases the local tax base and, eventually, tax revenue. To this end, local government adopts various industrial land preferential policies, infrastructure construction subsidies, and

so forth to compete for external industrial capital and launch a fierce business and capital tendering race.

Notably, the capital and tax attraction mechanism, from leasing industrial land under race-to-the-bottom pattern, are not necessarily effective for all industrial sectors. Only by introducing specific types of enterprises will this mechanism work. Lu and Ou (2011) reckoned that, driven by the pressure of economic growth competition and the motivation of maximization of tax revenue, local governments are tempted to develop capital-intensive industries or heavy industry that increases tax revenue for the following three reasons: (1) under the same conditions, capital-intensive enterprises can contribute more revenue tax compared with other enterprises; (2) compared with other enterprises, the tax base of the industrial income tax of capital-intensive enterprise and heavy industry is bigger, and to increase the return from income tax from superior governments, local governments must continue to prioritize capital-intensive industries in business and capital tendering; and (3) compared with small enterprises, the unit tax cost of large enterprises is lower. In tax collection, a scale economy prompts local governments to be more biased toward large enterprises in business and capital tendering. Notably. capital intensity in large enterprises is normally higher. Although an increase in capital-intensive industries and heavy industry may result in rapid economic growth and tax revenue in the short term, these industries consume an excessive amount of energy resources, imposing negative effects on urban airenvironmental quality.

In the process of attracting investment, within a limited term of office, what local governments were most concerned with is not the future benefits from by the official operation of these industrial projects, but the economic growth directly driven by the investment of fixed assets pertinent to industrial projects that the government cares about. In other words, the governments prioritize the scale, instead of the quality, of investment attraction. Thus, in the process of industrial land leasing, in addition to expanding land requisition and leasing scale, lowering the leasing price, the governments also compromise investment attraction quality. Such an extensive economic development pattern is the main reason for the environmental problems in today's China (Cai et al., 2008). Additionally, as a means adopted by local governments to compete for economic growth, the biased allocation of land resources in the industrial field has the characteristics of strategic interaction of competition imitation among different regions (Li et al., 2013), which forces rapidly growing industries to surrender their respective resource endowment

advantage and leading to homogeneity of industrial structure, resulting in resources waste and allocation distortion and exacerbation of environmental pollution.

Although land misallocation leads to urban space expansion and land supply increase, land allocation normally biases toward capital intensive industry, and the lands reserved for real estate and service industries are limited and expensive (The Joint Team of World Bank and the Development Research Center of the State Council, 2014), which not only directly leads to housing price increases and insufficient development of modern service industry but also increases production and operation costs of the service industry, which obstructs upgrading industrial structure. Li and Wang (2015) asserted that although land misallocation helps increase the speed of the process of industrialization, it has significant inhibitory effects on the servitization of industrial structure. Local government's land supply strategies such as leasing industrial land at excessively low prices and transferring commercial and residential land at restrictively high prices have strengthened industrial structure rigidity dominated by low-end and middle-end manufacturing industries. Land misallocation's inhibition effects on upgrading industrial structure will hamper the improvement of urban air quality.

Based on the aforementioned analysis, we propose hypothesis as follows:

Hypothesis 1. Under financial maximization and political promotion incentives, land misallocation not only directly causes the disordered sprawl of urban space but also damages landscaping, leads to environmental pollution. In addition, the bias toward urban infrastructure construction and development of capital-intensive industries is counterproductive to urban air quality improvement.

Hypothesis 2. Land misallocation lowers urban air quality by inhibiting the upgrading of industrial structure.

2.2. Land misallocation's spatial spillover effect on air quality

In addition to affecting air quality of local city, land misallocation has an obvious spatial spillover effect. First, urban air quality is featured by evident externalities. Normally, environmental pollution has inter-regional diffusion effect, thus local governments may “hitchhike” regarding stipulation of environmental standards to gain more opportunities for economic growth, driven by a political promotion incentive; namely, efforts made by one region to improve environmental quality may enable other regions to reduce their efforts to improve energy utilization efficiency and reduce air

environmental pollution. Second, actions made by one region to improve environmental quality may prompt another local government to surrender to the pressure of public opinion and political performance assessment and adopt similar actions when formulating energy conservation and emission reduction policies. Such a demonstration effect creates the scenario of "one good example will make others follow suit" regarding urban environmental quality (Han et al., 2018b). Third, growth competition among regions in China will be indirectly reflected in the competition of pollution emissions standards. Driven by growth competition and political promotion pressure, the action of one region to attract enterprise investment and growth advantages by lowering environmental standards induces other local governments to do the same; then, *one bad apple spoils the whole bunch*. (Ulph, 2000; Fredriksson et al., 2003). Finally, affected by economic mechanisms such as industrial transfer, industrial agglomeration, and development of transportation and communication facilities, air quality also demonstrates the feature of positive spatial spillover. Han et al. (2018a) asserted that, affected by industrial space layout and urban agglomeration economy, environmental pollution is characterized by evident spatial spillover. Thus, the existence of "hitchhiking" and "demonstration effect" affects local regions and influences surrounding regions through air quality's spatial spillover effect.

Hypothesis 3. Land misallocation exerts a spatial spillover effect on air quality of surrounding cities.

3. Model design

3.1. Specification of the econometric model

On the basis of an analysis of influencing mechanisms, the paper created the theoretical framework and econometric model of how land misallocation has influenced urban environmental quality. Assume production factors are capital and labor force; in city i, the production function of a representative manufacturing firm is

$$Q_i = aL_i^{\alpha} K_i^{\beta} \tag{1}$$

In which, Q_i is a manufacturer's output; L is the number of employees employed by the manufacturer; K is a manufacturer's capital stock; α *and* β are the labor force and capital output's elasticity coefficient, respectively; and $0<\alpha<1$, $0<\beta<1$, a *is* a constant. Assume a representative

manufacturer only produces one capital-intensive product Z, and in the production process, air pollutant P is produced. Because air pollution is caused in production, λ proportion of resources is put in to control air environmental pollution, and $0 \le \lambda < 1$. λ=0 means manufacturer does not treat pollution at all, and its output is Z=Q. If 0<λ<1, a manufacturer has allocated λ proportion of resources to control air pollution. Then, the output of Z is

$$Z = (1-\lambda) a L_i^{\alpha} K_i^{\beta} \tag{2}$$

Manufacturer's air pollution emission volume is

$$P = \psi(\lambda) a L_i^{\alpha} K_i^{\beta} \tag{3}$$

In which, $\psi(\lambda)$ is the pollution emission function, and $\psi'(\lambda) < 0$. According to Copeland and Taylor (1994), the formula can be specified as follows:

$$\psi(\lambda) = \frac{1}{A}(1-\lambda)^{\frac{1}{\delta}} \tag{4}$$

In which, 0<δ<1, and A *is* total factor productivity, representing production technology. Combine equation (2), (3), and (4):

$$Z = (AP)^{\delta} \left(a L_i^{\alpha} K_i^{\beta}\right)^{1-\delta} \tag{5}$$

Combine equation (2) and (5):

$$P = a A^{-1} L_i^{\alpha} K_i^{\beta} (1-\lambda)^{\frac{1}{\delta}} \tag{6}$$

Air quality improvement is negatively correlated with air environmental pollution degree. Then, equation (6) can be used to reflect the determination equation of air quality. Use $\kappa = 1-\lambda$ to represent the proportion of the resources not devoted to improving air quality. Take the log of both sides of equation (6) and rewrite the matrix form as follows:

$$\mathbf{P} = \mathbf{\Phi} - \mathbf{A} + \alpha \mathbf{L} + \beta \mathbf{K} + \frac{1}{\sigma} \boldsymbol{\kappa} \tag{7}$$

In which, $\mathbf{\Phi}$ is the N×1 vector of the log of the constant; **A is the** N×1 vector of the log of production technology or total factor productivity; **L, K,** and $\boldsymbol{\kappa}$ are the N×1 vectors of the logs of labor force, capital, and proportion of none-pollution control resource, respectively.

According to the mechanism analysis of this paper, land misallocation not only affects total factor productivity of a city but also imposes a spatial spillover effect on that of surrounding cities. Furthermore, production technology or total factor productivity is not only reliant on the characteristic variable and production factor of a city but is also affected by technical progress in other cities (all other cities j in the economy system). Assume the interdependence of technical progress among cities works through spatial externalities, and technological externalities can breakthrough a city's boundary and reach other cities. However, under various frictional influences resulting from geographical distance and differences among society, the economy, and systems, the boundary effects among cities gradually reduce the strength of spatial externalities. Thus, production technology or total factor productivity(A_i) can be specified as follows:

$$A_i = A_0 G_i^{-\eta} \prod_{j \neq i}^{N} G_j^{-\vartheta w_{ij}} A_j^{\delta w_{ij}} \tag{8}$$

In which, A_0 is the mutual exogenous technical progress of all cities; G is land misallocation; and η is the elasticity coefficient of land misallocation and η>0. $G_j^{-\vartheta w_{ij}}$ and $A_j^{\delta w_{ij}}$ are geographically weighted averages of land misallocation, and technical progress of neighboring city j. ϑ and δ denote interdependence of land misallocation and technical progress among cities. We used exogenous friction term w_{ij} (j=1, …, N and $j \neq i$) to represent the correlation degree between city i and its neighboring city j. The higher the correlation degree between cities, the bigger the w_{ij}.

Take the log of equation (8), and put it into the matrix form as follows:

$$\mathbf{A} = \mathbf{A_0} - \eta \mathbf{G} - \vartheta \mathbf{WG} + \delta \mathbf{WA} \tag{9}$$

In which, **G** are the N×1 matrix of land misallocation, respectively, and **W** is an N×N dimension matrix containing spatial friction term w_{ij}. If $\delta \neq 0$ and $1/\delta$ is not matrix **W's** characteristic root, equation (9) can be rewritten as follows:

$$\mathbf{A} = \left(I - \delta \mathbf{W}\right)^{-1} \mathbf{A_0} - \eta \left(I - \delta \mathbf{W}\right)^{-1} \mathbf{G} - \vartheta \left(I - \delta \mathbf{W}\right)^{-1} \mathbf{WG} \tag{10}$$

Substitute equation (10) into (7) and multiply $\left(I - \delta \mathbf{W}\right)$ both sides as follows:

$$\begin{aligned} \mathbf{P} = \delta \mathbf{WP} + \Omega + \eta \mathbf{G} + \alpha \mathbf{L} + \beta \mathbf{K} + \theta \boldsymbol{\kappa} \\ + \vartheta \mathbf{WG} - \vartheta_1 \mathbf{WL} - \vartheta_2 \mathbf{WK} - \vartheta_3 \mathbf{W}\boldsymbol{\kappa} \end{aligned} \tag{11}$$

In which, $\Omega = \left(I - \delta \mathbf{W}\right)\mathbf{\Phi} - \mathbf{A_0}$, $\theta = \frac{1}{\sigma}$, $\vartheta_1 = \alpha\delta$, $\vartheta_2 = \beta\delta$, and $\vartheta_3 = \frac{\delta}{\sigma}$. Based on equation (11), labor force, capital, and proportion of resources not devoted to pollution control all inhibit the air quality (promote the air pollution) of a city. However, those variables of surrounding cities have improved air quality of cities; thus, an increase in the labor force, capital, and proportion of resources not devoted to pollution control of surrounding cities has transferred the polluting enterprise of cities, improving air quality. Land misallocation reduces the environmental quality of local and surrounding cities. Rewrite the matrix form of equation (11) to the general form; then, the equation of environmental quality of city *i* can be as follows:

$$\begin{aligned} \ln P_i = {} & \theta_0 + \delta \sum_{j \neq i}^{N} w_{ij} P_j + \eta \ln G_i + \alpha \ln L_i + \beta \ln K_i + \theta \ln \kappa_i \\ & + \vartheta \sum_{j \neq i}^{N} w_{ij} \ln G_j - \vartheta_1 \sum_{j \neq i}^{N} w_{ij} \ln L_j - \vartheta_2 \sum_{j \neq i}^{N} w_{ij} \ln K_j + \vartheta_3 \sum_{j \neq i}^{N} w_{ij} \ln \kappa_j \end{aligned} \tag{12}$$

In which, $\theta_0 = \ln \Phi - \delta \sum_{j \neq i}^{N} w_{ij} \ln \Phi - \ln A_0$.

In addition to the aforementioned variables, other variables affecting urban environmental quality may include, for example, foreign direct investment (*FDI*) and urbanization level (*URB*). Liu et al. (2018) asserted that FDI has an obvious effect on lowering regional pollution emission level. Urbanization is also a key factor affecting energy consumption and pollution emission(Poumanyvong and Kaneko, 2010). Based on equation (12), the paper further introduces the control variables, as aforementioned, to obtain equation (13) as follows:

$$\begin{aligned} \ln P_i = {} & \theta_0 + \delta \sum_{j \neq i}^{N} w_{ij} P_j + \eta \ln G_i + \alpha \ln L_i + \beta \ln K_i + \theta \ln \kappa_i + \varphi_1 \ln FDI_{it} \\ & + \varphi_2 \ln URB_{it} + \vartheta \sum_{j \neq i}^{N} w_{ij} \ln G_j - \vartheta_1 \sum_{j \neq i}^{N} w_{ij} \ln L_j - \vartheta_2 \sum_{j \neq i}^{N} w_{ij} \ln K_j \\ & + \vartheta_3 \sum_{j \neq i}^{N} w_{ij} \ln \kappa_j + \vartheta_4 \sum_{j \neq i}^{N} w_{ij} \ln FDI_{jt} + \vartheta_5 \sum_{j \neq i}^{N} w_{ij} \ln URB_{jt} + \varepsilon_{it} \end{aligned} \tag{13}$$

In which, φ_1 and φ_2 are the influence elasticities of FDI and urbanization on urban air quality (air pollution), respectively, and ϑ_4 and ϑ_5 are elasticity coefficients of its lagged spatial variables. Because equation (13) contains both a lagged explained variable and explanatory variable but not a spatial interaction term of an error term, such a spatial econometric model is called a SDM (Vega and Elhorst,

2015).

3.2. Variables, indicators and data source

The sample was the panel data of 283 cities at or above the prefecture level nationwide from 2006 to 2018. To maintain the consistency and steadiness of the panel data, the data of six cities, namely, Lhasa, Sansha, Haidong, Chaohu, Longnan, and Zhongwei was excluded. The data was mainly from the China City Statistical Yearbook, China Land and Resources Statistical Yearbook, and China land market network[①]. Due to the lack of data for city-level price indicators, the paper adopts price indicators at the provincial level to adjust city data. Price indicators at the provincial level are from the China Statistical Yearbook. The concrete specification of the definition and measurement of the relevant variables and indicators is as follows.

(1) Urban air quality (*P*). The paper uses the data of $PM_{2.5}$ to measure urban air quality. PM2.5 is an important source of urban air pollution. However, China only started PM2.5 monitoring in 2012 in Beijing, Tianjin, Hebei, Yangtze River Delta, Pearl River Delta and other key regions, as well as municipalities and provincial capitals. In 2013, PM2.5 monitoring was carried out in 113 key environmental protection cities and environmental protection model cities. Until 2015, PM2.5 monitoring was carried out in all cities above prefecture level. In order to solve the problem of missing historical data of PM2.5 concentration, according to the study of van Donkelaar et al.(2015)， we use the grid data of global PM2.5 concentration annual mean based on satellite monitoring published by the center for social and economic data and application of Columbia University, and used ArcGIS software to analyze it into the specific annual PM2.5 concentration values of 283 prefecture level cities in China from 2006 to 2018, so as to measure the urban air quality. The larger the index is, the lower the air quality is.

(2) Land misallocation (*G*). In this paper, the marginal output method is used to measure the misallocation of land resources. Classical microeconomics theory points out that factors can achieve the optimal and most efficient allocation under the full competition of the market mechanism. At this time, the marginal output of factors is consistent with the marginal cost and factor price. Therefore, under the condition of complete market competition, the marginal output of land elements can be regarded as the

① https://www.landchina.com/.

price when the land resources reach the optimal allocation, and the deviation of the actual price from the optimal price in the real world reflects the degree of land market distortion or land resources misallocation. This paper uses Cobb Douglas production function to measure the marginal output of land. The production function can be expressed as:

$$\ln \bar{Y}_{it} = \sum_{k} \rho_{i,k} U_{it}^{k} + \eta_{i,1} \ln \bar{L}_{it} + \eta_{i,2} \ln \bar{K}_{it} + \eta_{i,3} \ln S_{it} + \xi_{it} \tag{14}$$

Where, U_{it} is an indicator reflecting the technological progress at the city level, which can control the impact of different production efficiency on urban output, measured by the proportion of employees in urban information transmission, computer service and software industry, scientific research and technical service industry in the total employees. $\bar{L}_{it}$ is the added value of urban industry, expressed as the GDP of the secondary industry; $\bar{L}_{it}$ is the number of labor force in the industrial sector, expressed as the number of employees of the secondary industry in the city; $\bar{K}_{it}$ is the capital stock of the urban industrial sector, calculated by the annual fixed asset investment and formula of $\bar{K}_{it} = (1-\psi)\bar{K}_{i,t-1} + I_t / w_{i,t}$, where, ψ is the annual depreciation rate, set as 5%; I_t is the investment in fixed assets; $\omega_{i,t}$ is the cumulative capital price index of each city; according to the practice of Han and Ke (2016), the industrial capital stock at the beginning of the period is estimated by the net value of current assets and fixed assets of Industrial Enterprises above the quota in each city. S is the area of urban industrial land, and the data is taken from China Urban Construction Statistical Yearbook. η_1~η_3 are elastic coefficients and $\eta_{i,1} + \eta_{i,2} + \eta_{i,3} = 1$; ξ is the random disturbance terms. The econometric equation used to estimate the elastic coefficients of each element can be obtained by changing equation (14) appropriately. That is,

$$\ln \frac{\bar{Y}_{it}}{\bar{L}_{it}} = \rho_i U_{it} + \eta_{i,2} \ln \frac{\bar{K}_{it}}{\bar{L}_{it}} + \eta_{i,3} \ln \frac{S_{it}}{\bar{L}_{it}} + \xi_{it} \tag{15}$$

The estimation value $\hat{\eta}_{i,1}$、$\hat{\eta}_{i,2}$、$\hat{\eta}_{i,3}$ of $\eta_{i,1}$、$\eta_{i,2}$、$\eta_{i,3}$ can be obtained by estimating equation (15).

Then the marginal output of industrial land in each city can be calculated as follows:

$$MP_S = \hat{\eta}_{i,3} \frac{\bar{Y}}{S} \tag{16}$$

In which, MP_S is the marginal output of industrial land. If r is the price of urban industrial land, the

degree of land resource misallocation can be expressed as the ratio of marginal output of industrial land to its real price. That is,

$$G = \frac{MP_S}{r} \tag{17}$$

Where, G equal to 1 means that there is no misallocation of industrial land; G greater than 1 means that the due value of industrial land is greater than the actual price (that is, the actual price is undervalued), and land resources present reverse misallocation; G less than 1 means that the due value of industrial land is less than its actual price (that is, the actual price is overvalued), and land resources present positive misallocation.

The calculation of industrial land price r is complicated. Due to the fact that there is no complete price information of land for different types of use in cities at prefecture level or above, this paper uses web crawler technology to collect transaction data of commercial land, residential land and industrial land for 283 prefecture level cities in China from China land market network during August 1, 2006 to December 31, 2018 The information of land transaction includes the object of land supply, the location of the plot, the area of land supply, the transaction price, the mode of land supply, the type of land use and so on. According to the type of land use, this paper sums up the land transfer area and price of each project whose land supply mode is bidding, auction and listing according to the land use, and calculates the ratio of transaction price and land transfer area to get the average land price (10000 yuan/km2) of commercial land, residential land and industrial land in prefecture level cities every year. Finally, this paper calculates 282 land resource misallocation indicators of prefecture level cities by substituting the average annual industrial land price into equation (17). Table 1 reports the average value and change trend of the degree of misallocation of land resources in China and cities of different grades.

Insert Table 1

The results show that the total average value of land resource misallocation in China is 1.8383, and the average value of each year is above 1, which indicates that there is an obvious reverse misallocation problem in China's land resource allocation. For cities of different grades, the total mean value of land resource misallocation of type I and above cities is 1.0158, which is the lowest value among all types of cities, and the degree of land resource misallocation from the year 2014 - 2018 is less than 1, which

indicates that the land resource allocation of type I and above cities is close to the optimal allocation state in the market, which is consistent with the current situation of land resource allocation of China's most mega cities. The larger the scale of a city and the higher the level of economic development, the more perfect its market mechanism will be, and the higher the allocation efficiency of land resources under the market effect will be. The total mean value of land resource misallocation in type II large cities and medium-sized cities is 1.4625 and 1.4706 respectively, which indicates that the real price of industrial land in these two types of cities is obviously undervalued. The total mean value of land resource misallocation in small cities is 3.3155, which is significantly higher than the national average level, indicating that there is a serious reverse misallocation in the allocation of land resources in small cities in China, and the real price of industrial land is seriously underestimated. Generally speaking, the degree of land resource misallocation in China is gradually decreasing with the continuous expansion of urban scale.

(3) Other variables. The number of employees in all industries is collected from the number of employees in units, as stated in the China City Statistical Yearbook (10,000 people). The paper uses the total of the number of employees in units and individual employees in an urban district to represent non-agricultural employment (10,000 people). Capital stock of a city is calculated by the annual fixed assets investment in an urban district and equation $K_{i,t}= (1-\delta)K_{i,t-1}+I_t/\omega_{i,t}$. In the equation, $K_{i,t}$ is domestic capital stock, and δ is yearly depreciation rate, which is specified as 5%. I_t is fixed assets investment. $\omega_{i,t}$ is the accumulated capital price indicator of all cities. The paper refers to Han and Ke's (2016) perpetual inventory method for calculating FDI stock, and the depreciation rate is specified as 5%. Input of pollution governance (λ) reflects urban pollution treatment strength. Generally, the greater the treatment input, the greater the treatment and utilization capacity, and the better the environmental quality, and vice versa. The paper uses output value of products made from waste gas, water, and solid wastes in an urban district to represent a city's treatment input (RMB 10,000). because the products made from waste gas, water, and solid wastes reported in the China City Statistical Yearbook are the data of the whole city, the paper assumes that treatment input is in direct proportion to the economic scale of a city. Thus, multiply the output value of products made from three wastes of the whole city by the proportion of urban district's GDP in the total GDP to represent the treatment input level of an urban

district. Given that the data of the output value of products made from the three wastes in the Yearbook has been provided only up to 2010, the paper makes up the input indicators of the subsequent years by using an exponential smoothing method (because time series data of such indicators of most cities are evidently increasing, the smoothing coefficient is specified as 0.7).[①] This paper uses the proportion of the non-agricultural population in the total population of an urban district to represent urbanization level (*URB*) of the cities at or above the prefecture level. Because such statistics in the China City Statistical Yearbook have been provided only up to 2010, the data of the non-agricultural population in subsequent years are made up according to China Population and Employment Statistics Yearbook. All data regarding monetary value is adjusted with 2003 as a base period. Table 2 shows the sample statistics of land misallocation, environmental quality, and other variables of cities at or above the prefecture level in China.

Insert Table 2

4. Spatial econometric test and result analysis

4.1 Spatial weight matrix and the spatial correlation of urban environmental quality

Building a proper spatial weight matrix is the key to accurately measuring a spatial interactive effect among individuals. This paper constructs spatial weight matrices including a geographical distance spatial weight matrix (W_d), economic distance spatial weight matrix(W_e) and nested spatial matrix of geographical and economic distance (W_{de}). Details are as follows:

(1) Geographical distance matrix. Geographical distance among cities is a notable factor affecting spatial distribution of industries and population. W_d can be specified as follows:

$$W_d = 1/d_{ij}, \quad i \neq j \tag{18}$$

In which, d_{ij} is the distance between cities calculated using latitude and longitude data, and when $i \neq j$, $i=j$, it is 0.

(2) Economic distance matrix. This paper uses per capita GDP to create W_e:

[①]As time series data of such indicators of most cities are evidently increasing, the paper adopts 0.6, 0.7, and 0.8 as smoothing coefficients for calculation. By comparing predicted standard errors under different smoothing coefficient values, the paper chooses 0.7, whose error is the smallest, as the treatment input's smoothing coefficient value.

$$W_e = 1 \Big/ \left| \bar{Q}_i - \bar{Q}_j \right|, \quad i \neq j \tag{19}$$

In which, $\bar{Q}_i$ is the per capita GDP of city j from 2003 to 2015. W_e measures the relative positions of cities in economic development. The closer the economic development levels of the two cities, the more similar their economic operation modes.

(3) Nested spatial matrix of geographical and economic distance. Geographic proximity and economic connection are key factors affecting spatial layout of economic activities. A geographical distance matrix and an economic distance matrix, based on relative geographical location and economic operation model, respectively, reflect mutual relations among spatial individuals. Nevertheless, in reality, a correlation effect among cities may not be merely from similarity regarding geographical location or economic development. Such effects may subject to the combined influence of geographical proximity and economic operation model. The spatial weight matrix, integrating a variety of factors of spatial individuals such as their geographical location and economic characteristics, can better reflect a dataset's distribution characteristics and spatial correlation in space. Thus, the nested spatial matrix of geographical and economic distance can be constructed as follows:

$$W_{de} = \kappa W_d + (1-\kappa) W_e \tag{20}$$

In which, $0<\kappa<1$ is the weight of a geographical distance matrix representing the relative importance of geographic proximity in the spatial interaction. To find the optimal value of φ, we estimate the model for different values of φ, say 0, 0.1, 0.2, …, 0.9 and 1 and use the parameter value that provides the best performance. We also standardize the matrix, and the elements of each row are equal to 1.

The paper mainly uses nested spatial matrix of geographical and economic distance to carry out spatial econometric estimation on equation (13). By calculating Moran's I, the paper conducts spatial auto-correlation test of urban air quality[①]. Meanwhile, in order to calculate Moran's I under various weight matrices, the paper follows the method of Shao et al. (2016) and temporarily specifies κ *as* 0.5. If

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① The exponential formula is as follows:

$$Moran's\ \ I = \frac{n}{\sum_{j=1}^{n}\sum_{v=1}^{n} W_{jv}} \times \frac{\sum_{j=1}^{n}\sum_{v=1}^{n} W_{jv}\left(X_j - \bar{X}\right)\left(X_v - \bar{X}\right)}{\sum_{j=1}^{n}\left(X_j - \bar{X}\right)^2}$$

In which, X_i is the observed value of region i. W_{ij} is spatial weight matrix.

the Moran's I under W_{de} passes significance test, the paper will further discuss the accurate value of κ when estimating spatial econometric model.

Insert Table 3

Based on various spatial weight matrices, the paper calculates urban air quality's panel Moran's I value. Table 3 shows that, Moran's I values in W_d, W_e and W_{de} are respectively 0.0993, 0.0920 and 0.1065, their concomitant probabilities are all 0.0000. After Moran's I controls explanatory variable, spatial correlation is significantly positive, indicating city with relatively high air quality must be surrounded by cluster of cities with high air quality.

4.2. Estimation of spatial econometric model

According to Elhorst (2014), we use the methods of Lagrange multiplier (LM), likelihood ratio (LR) and Wald statistics to test the spatial econometric model. The results show that, this study should adopt the spatial Durbin model with spatial and time-period fixed effects. For details, see Appendix A.

As in a SDM, the spatial lagged variable of urban air quality is an endogenous variable, we applies the method of maximum likelihood estimation to acquire consistent parameter estimation. To accurately confirm the value of κ in W_{de}, and to better compare and test the robustness of parameter estimation of various variables, the paper calculates spatial weight matrices, when κ is 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1, respectively. Additionally, the paper uses SDM to conduct estimations. Table4 shows the corresponding results of panel spatial econometric estimation.

Insert Table 4

According to Anselin et al. (2008), statistics including goodness of fit and log-likelihood are integrated to judge and select the optimal spatial econometric models in Table 4 and confirm the value of κ. The result in Table 4 shows that when κ=0.4, goodness of fit of SDM (R^2=0.8932) and log-likelihood = -1973.884 are optimal in various spatial models. Therefore, in the geographical and economic distance embedding matrix, κ=0.4 is the optimal weight for the geographical distance spatial weight matrix, and its corresponding SDM is the optimal model in the empirical study in the paper. κ=0.4 means that in the spatial interactions among cities, the spillover effect of environment relies on the joint function of

geographical distance and economic connection of spatial individuals. Among cities, proximity in economy is more important than proximity in geographical distance.

In Table 4, most spatial auto-regressive coefficients ρ are significantly positive, implying that after the exogenous space interaction effect between explanatory variables and air quality is controlled, spatial economic connection and geographic proximity jointly prompt air quality to exert an endogenous spatial interaction effect on cities. When there is a spatial spillover effect, change in a certain explanatory variable causes air quality to vary along with it; notably, such a variation influences air quality of surrounding cities and leads to a series of changes through cyclic feedback (Shao et al., 2016).

In the SDM where overall effect is specified, parameter estimation value of a variable and its significance can only represent influential direction and effect of various vectors, not the marginal effect on urban air quality. As asserted by LeSage and Pace (2009), judging whether there is spatial spillover effect when using point estimation (ρ or θ) by one or more spatial regression models may lead to wrong conclusions. However, they also asserted that, for different spatial model specifications, interpretation of the partial differential of changes of a variable can better test whether there is a spatial spillover effect. Thus, merely by SDM's point estimation result in Table 4, we cannot compare and analyze the effects of land misallocation and other explanatory variables and cannot assess whether land misallocation and other variables have a significant spatial spillover effect.

Thus, the paper refers to the method adopted by LeSage and Pace(2009). Based on the parameter estimation result when κ=0.4 is in Table 4, the paper further estimates the direct and indirect effects of land misallocation and other control variables on urban air quality in corresponding SDM; in which, direct effects show explanatory variables including land misallocation's influence on air quality of local city, including the spatial feedback effect. In other words, the change in an influence factor of a city affects the air quality of surrounding cities, which affects the air quality of local city. Indirect effects show the spatial influence on air quality by land misallocation of surrounding cities (or land misallocation's influence on the environment of surrounding cities), which reflects the spatial spillover effect.

Additionally, with the continuous optimization of the shift of local governments' assessment standards, the competition among local governments is likely to shift from "competing for growth" to

"competing for welfare" (Li et al., 2013). This assertion means that local governments may devote the profits from land allocation to pollution treatment, increasing treatment input. A multi-collinearity for land allocation and pollution treatment in the equation may exist. Based on equation (13), the paper introduces the variables of land misallocation and pollution treatment respectively and adopts stepwise regression method to identify and control the multi-collinearity between the two variables. Table 5 shows the direct and indirect effects of the SDM of W_{de} when κ=0.4.

Insert Table 5

First, we analyze the influence of land misallocation (ln$G$). When pollution treatment(lnλ) is uncontrolled, direct and indirect effects of land misallocation in Model 5.1 are all significantly positive. When land misallocation are uncontrolled, direct effects of pollution treatment in Model 5.2 are obviously negative, and indirect effects have not undergone the significance test. When conducting estimations by putting both of the variables into one econometric equation in Model 5.3, direct and indirect effects of both land misallocation and pollution treatment have not fundamentally change, suggesting no obvious co-linearity between them, that is, a local government has not devoted most of the profits from land allocation to pollution treatment and air environmental improvement despite its competition for welfare. Even if part of the land allocation profits is devoted, no obvious effect is achieved. Parameter estimation of land misallocation (ln$G$) exerts significant inhibiting effects on the air quality of local and surrounding cities (promoting effects on $PM_{2.5}$ of local and surrounding cities), which is consistent with hypothesis 1 and suggests that driven by financial taxation maximization and political promotion incentive, land misallocation's inhibition on air quality has outstripped the environmental quality improvement effect resulting from a local government "competing for welfare." Thus, a local government's effort to gain more extra-budgetary revenue and economic growth performance through land misallocation has worsened overall air quality. Additionally, under the strategic interaction of competition and imitation among local governments, the impact of land misallocation also has an obvious spatial spillover effect on surrounding cities.

Next, the paper analyzes the parameter estimation of the control variables. In all models, an increase in labor force supply (ln$L$) has a significant promoting effect on $PM_{2.5}$ of local and surrounding cities, indicating that the increase in the labor force prompts local governments to request enterprises in

the jurisdiction to implement development strategies more conducive to employment and that government has eased their regulations on high energy consumption, high pollution, and high emission enterprises and lifted restrictions on the negative externality of enterprises, lowering environmental quality. Such influence, under the strategic interaction of political promotion among all local governments, sprawls in space through the demonstration effect, causing an increase in labor force supply to exert a spatial spillover effect on the air quality of surrounding cities. Domestic capital (ln$K$) exerted a significant inhibiting effect on the air quality of local and surrounding cities, showing that various regional capital investments remain biased toward high-pollution fields such as infrastructure construction and heavy industry. Additionally, capital investment imposes a significant demonstration-imitation effect, causing environmental pollution to continuously spread among cities. Increases in pollution treatment (lnλ) help improve the air quality of local city but have no significant effect on surrounding cities, indicating that the improvement effects from the pollution treatment are localized and do not cause similar behavior of surrounding cities. Environment treatments in different regions are not significantly synergistic. FDI (lnFDI) helps improve the air quality of the local and surrounding cities, suggesting that foreign enterprises introduced by regions are at the medium or high end of industrial structure, and their technological spillover effects help improve labor productivity, reduce environmental pollution locally, and exert a positive spatial spillover effect on surrounding cities. Urbanization (lnURB) helps improve the air quality of local city but imposes negative effects on surrounding cities. Normally, urbanization development has both negative and positive effects on air quality. On the one hand, cities with a high urbanization level normally have substantial demand for houses, home appliances, and vehicles and traffic jams, which lower air quality. On the other hand, urbanization level improvement and population expansion may produce scale economy effect and lower environmental pollution by enhancing the public transportation sharing rate and resource utilization rate and sharing emission reduction facilities. Based on the analysis presented in this paper, through the scale economy effect, urbanization obviously improved the air quality of local cities, and improvement in the urbanization level caused the population of surrounding cities to migrate to local cities, weakening the scale economy effect on emissions reduction by the expansion of the population in surrounding regions.

5. Robustness test

5.1. Difference in air quality indicator: measurement based on pollution level

In this part, we replace the $PM_{2.5}$ indicator that measures the urban air quality with Industrial NOx emissions, industrial SO_2 emissions, and industrial dust emissions, to assess the robustness of land misallocation's influential mechanism on urban air environment quality. Direct and indirect effects in the SDM are presented in Table 6.

Insert Table 6

Table 6 shows that, direct and indirect effect of land misallocation are all significantly positive, suggesting land misallocation has not only significantly increased pollution emission in local city, but also hampered the improvement of air quality in surrounding cities. Based on land misallocation's influence on urban environmental pollution, the results are consistent with Table 5.

5.2. Difference in land misallocation indicator: measurement based on per capita land leasing revenue and land misallocation dependence

This paper also constructs two other indicators of land resource mismatch for robustness test. First, under the condition that the city's annual land supply index is set, the biased allocation of construction land in the industrial field will inevitably lead to less index of commercial land, resulting in the price of commercial land far higher than that of industrial land. This paper further constructs the index of deviation degree of industrial land price to measure the degree of land resource misallocation, and tests the robustness of the index estimation result of equation (13). The calculation formula of industrial land price deviation is:

$$\vartheta = \frac{r_B - r_M}{r_B} \tag{21}$$

Where, ϑ is the deviation degree of industrial land price, measuring the degree of misallocation of land resources; r_B is the price of urban commercial land; r_M is the price of urban industrial land. Second, according to Li et al.(2016), This paper constructs the proportion of industrial and mining storage land supply area in the total transfer area of construction land to measure the degree of land resource misallocation. The results of robustness tests are presented in Table 7.

590 *Insert Table 7*

591 After replacing land misallocation with industrial land price deviation and the proportion of
592 industrial and mining storage land supply area in the total transfer area of construction land, Table 7
593 shows that land misallocation has greatly inhibited air quality of local and surrounding cities. The result
594 shows strong robustness.

595 **5.3. Difference in estimation method: empirical test based on spatial lagged explanatory variable**

596 LeSage and Pace (2009) asserted that the direct motivation for the creation of an SDM is that it can
597 solve the problem of missing variables and its resulting endogenous problems. Nevertheless, an SDM
598 cannot solve the simultaneous endogenous problem caused by the interaction between the explanatory
599 variable and explained variable. Notably, Not only land misallocation can affect urban air quality, but
600 also the quality of urban air environment will change the land allocation mode of local government
601 under the pressure of public opinion. For example, to overcome the environmental problems caused by
602 disordered urban sprawl, a local government may strategically lower its reliance on land biased
603 allocation. Given that there might be simultaneous endogeneity between land misallocation and urban air
604 quality, the paper uses the spatial model of lagged explanatory variables (SLX) by Vega and Elhorst
605 (2015) and the method of two stage least squares (2SLS) to estimate the econometric model. The scale
606 and price of industrial land transfer are related to the terrain and altitude of the city. The larger the terrain
607 gradient and the higher the altitude, the smaller the scale of industrial land transfer may be, because even
608 if the local government lowers the price or zero land price to transfer industrial land, enterprises will not
609 invest and set up factories in the higher or steeper terrain for the consideration of land development and
610 transportation costs; and the terrain gradient and altitude, as the natural geographical conditions, will not
611 directly affect the urban air environment quality, so they meet the requirements of instrumental variable
612 selection. Because the samples used in this paper are panel data, the simple use of urban surface slope
613 and average altitude which do not change with time as instrumental variables will be automatically
614 eliminated in the fixed effect estimation due to the fixed effect. In order to solve this problem, this paper
615 uses the idea of Nunn and Qian (2014) to set instrumental variables, and uses the interaction terms of
616 average surface slope, average altitude (related to individual change) and the value of land resource

mismatch at the national level (related to time change) as instrumental variables of urban land resource misallocation. The degree of land resource misallocation at the level of a single city will not affect the overall land resource allocation of the whole country, and the air environment quality at the level of the city is difficult to produce a feedback mechanism for the land resource misallocation at the level of the whole country. Therefore, the interaction term can be used as good instrumental variables for urban land resource misallocation. The results are shown in Table 8.

Insert Table 8

According to Vega and Elhorst (2015) and Pace and LeSage (2009), spatial spillover effect is defined as the influence exerted by change in the explanatory variable of a specific spatial unit *j* on the explained variable of other spatial unit *v*.[①] Thus, when measuring the spatial spillover effect using SAR and SDM, on the basis of the estimation result by using an SAR and SDM, the explanatory variable's direct and indirect effects on explained variable (spillover effect) shall also be measured. The research by Vega and Elhorst (2015) shows that, because of the conciseness of SLX, various measuring methods can be used flexibly to conduct empirical analysis. In the model, the coefficient of a lagged explanatory variable reflects the spatial spillover effect. When using SLX to conduct estimation, measuring direct and indirect effects is not required. Additionally, a spatial spillover effect directly measured by SLX is basically consistent with the indirect effects measured by SDM. Thus, SLX is a handy tool to test the robustness of the estimation result from the SDM. The test result of F in Table 8 shows that the instrumental variable is highly correlated with the endogenous variable. Sargan's test statistics accept all the instrumental variable's effective null hypotheses. Thus, the instrumental variable the paper uses is rational, and its estimation result is viable.

When the explained variable is air quality ($PM_{2.5}$) and explanatory variables are industrial land price deviation and the proportion of industrial and mining storage land supply area, parameters of direct and indirect effects of land misallocation are significantly positive in local and surrounding cities, which is basically consistent with Table 5. When explained variables are industrial NOx emissions, industrial SO_2 emission and industrial dust emission, the sign of parametres of land misallocation are opposite to Table 5 when the explained variable is $PM_{2.5}$, but the same as Table 6, further testifying to the robustness of the

① Specific unit depends on the characteristics of study object and can be, for example, a manufacturer, city, or region.

result.

6. Mechanism test

The conclusion of the paper shows that land misallocation significantly hinders the improvement of air quality. And the theoretical analysis shows that this effect is likely to be realized by the misallocation of land resources affecting the adjustment of industrial structure. To verify such a mechanism, this paper takes the proportion of the output value of secondary industry in the regional added value and the proportion of the output value of tertiary industry in the regional added value as the mediator variables of land misallocation, respectively, and refers to the method of Hayes (2018) to assess the transmission mechanism of how land misallocation affects urban air quality. The mediation model can be set as follows:

$$\ln P_{it} = \Phi_0 + \eta \ln G_{it} + \delta_j \sum_{j=1}^{n} \ln Z_{jit} + \zeta_{it} \tag{22}$$

$$\ln T_{it} = \gamma_0 + \gamma_1 \ln G_{it} + \delta_j \sum_{j=1}^{n} \ln Z_{jit} + \varepsilon_{it} \tag{23}$$

$$\ln P_{it} = \Phi_0 + \eta_1 \ln G_{it} + \eta_2 \ln T_{it} + \delta_j \sum_{j=1}^{n} \ln Z_{jit} + \zeta_{it} \tag{24}$$

In which, T represents mediator variable, it is the proportion of the output value of secondary industry in the regional value added (*ECBZ*) or the proportion of the output value of tertiary industry in the regional value added (*SCBZ*); Z represents control variables; δ is its elasticity coefficient; and ε and ζ are random errors. First, test equation (22) and verify whether land misallocation has exerted a significant positive effect on air quality ($PM_{2.5}$). Second, regress equation (23) and equation (24), and test whether land misallocation has significant effects on the mediator variables and the mediator variables have significant effects on air quality. If they are both significant, it means that the misallocation of land resources has obvious indirect effects on air quality. Third , test equation (24). If coefficients η_1 is significant, it is considered that the direct effect of land resource misallocation on air quality is significant. Finally, comparing the symbols of the product of γ_1 and η_2 with that of η_1, if they have the same sign, the indirect effects belong to partial mediation effects; if they have different signs, the indirect effects belong to masking effects. Table 9 shows these estimation results.

Insert Table 9

First, let's look at the test results when the intermediary variable is *ECBZ*. In equation (22), the parameter estimation of land misallocation's direct effect and indirect effect are all significantly positive, meaning that land misallocation is not conducive to the improvement of air quality. Parameter estimation of equation (23) shows that land misallocation's direct and indirect effect are all significantly positive, suggesting that land misallocation apparently improved the proportion of capital intensive industries in total value added. Parameter estimation of equation (24) shows that the direct and indirect effects of the proportion of output value of the secondary industry are significantly positive, which means that the indirect effect of land resource misallocation on air pollution is significant by increasing the proportion of secondary industry output value (mainly capital intensive industries).The direct and indirect effects of land misallocation (ln*G*) also have significant positive parameter estimation, which shows that land resource misallocation has a direct impact on air quality. Furthermore, the sign of the product of the direct and indirect effects of the proportion of output value of the secondary industry in equation (24) and the direct and indirect effects coefficient of land resource misallocation in equation (23) is consistent with that of the direct and indirect effects coefficient of land resource misallocation in equation (24). It mens that the proportion of secondary industry output value has a partial mediation effect in the process of land resource misallocation affecting air quality.

When the intermediary variable is *SCBZ*, the estimation of the direct and indirect effects of land resource misallocation in equation (23) is significantly negative, which indicates that the biased allocation of land resources in the industrial field significantly reduces the proportion of the output value of the tertiary industry in the total output value, and inhibits the upgrading of industrial structure. In equation (24), the direct effect and indirect effect parameters of the proportion of the output value of the tertiary industry are significantly negative, indicating that the upgrading of industrial structure (servitization of industrial structure) is helpful to reduce the air pollution of the city and its surrounding cities, and improve the environmental quality of the city and its surrounding cities. At the same time, it also shows that the indirect effect of land resource misallocation on air quality exists by reducing the proportion of the output value of the tertiary industry (inhibiting the upgrading of industrial structure). Furthermore, in equation (23) an (24), the parameter sign of the product of γ_1 and η_2 is consistent

with that of η_1, which means that the proportion of the output value of the tertiary industry has a partial mediation effect in the process of land resource mismatch affecting air quality. The results of the above two mediation effect tests fully confirm the mechanism of land resource misallocation affecting air quality through industrial structure adjustment.

7. Further analysis based on a sample of cities at different levels

Land misallocation may demonstrate obvious heterogeneity as city size varies. To reveal land misallocation's influence on environmental quality in cities at different levels, the paper further builds up the nested matrix of geographical distance and economic distance to conduct spatial econometric analysis on the samples of different levels of cities. Categorization of city sizes in the paper refers to the Notice of the State Council on Adjusting the Standards for Categorizing City Sizes adopted by the State Council on November 21, 2014. According to the permanent population in the jurisdiction, cities in China are categorized into four types: large cities of type I and above (population above 3 million), typeIIlarge cities (population 1~3 million), medium-sized cities (population 0.5~1 million), and small cities (population below 0.5 million). TypeIlarge cities and megacities are in one type because there are only a few such cities nationwide and the roles they play in a city cluster or certain region are basically the same. Table 10 shows the estimation results of direct and indirect effects of cities at different levels.

Insert Table 10

The results in Table 10 show that in type I big cities, land misallocation has no apparent impact on air quality of local and surrounding cities. In type II big cities, land misallocation's influence on a city and surrounding cities are all negative and have failed the significance test. In medium-sized cities and small cities, land misallocation greatly inhibits air quality of local and surrounding cities.

Regarding the parameter estimation of land misallocation in cities at each level, the bigger the city, the less land misallocation's influence on air quality is, and vice versa. A possible explanation is that the cities with a bigger size and a more developed economy always have a larger economy scale and higher industrial agglomeration level. The larger the economy scale, the greater the tax base of fiscal revenue and the less the government relies on land misallocation. Additionally, the higher the regional economic density, the more the region's land plan is limited, and the smaller the land supply elasticity. Thus, the

room for local government to rely on land misallocation to acquire extra-budgetary revenue and economic growth will be smaller[①], and the less will land misallocation reduce the air quality. Otherwise, the smaller the city size, the lower the economic growth rate and the smaller the tax base of a local government's fiscal revenue, causing governments to be more reliant on land misallocation, which exerts a greater inhibiting effect on air quality.

8. Conclusions and policy suggestions

This paper systematically discusses the effects of land misallocation on urban air quality. The result shows that stimulated by financial maximization and political promotion incentive, local governments tend to allocate construction land to industry and related fields, which leads to the distortion of industrial land price and the misallocation of land resources. The misallocation of land resources not only directly leads to the expansion of urban space, and then reduces the quality of urban air environment quality, but also reduces the quality of urban air environment by inhibiting the upgrading of industrial structure of cities and their surrounding cities. Further analysis reveals that the bigger the city, the less the land misallocation inhibits air quality. Otherwise, the tax base of fiscal revenue and economic growth performance of local government will be less, making the government more reliant on land misallocation and exerting greater inhibitions on air quality.

The following policy suggestions are made based on the conclusions of the paper. (1) Land misallocation not only directly reduces urban air quality but also significantly inhibits the improvement of air quality of neighboring cities. Thus, a suggestion is that a local government's land supply behavior should be further regulated and supervised to make the scale and speed of land supply consistent with urban industry and the size and rate of population growth. Land supply type shall fulfill the development demand of local industries with comparative advantages to prevent disordered sprawl of urban space. How a local government uses land misallocation should also be regulated and supervised. More construction land should be devoted to the development of local industries with comparative advantages based on market rule. A local government's disruptive actions of aimlessly advancing the development

[①] Although regions with high density and more plan restrictions normally have a higher house price, a high house price may prompt a local government to acquire more extra-budgetary revenue through land misallocation. Nevertheless, as the central government continuously strengthens its effort to regulate and control housing prices, the room for price increases becomes increasingly smaller, a the room for a local government to gain land misallocation revenue from high prices decreases.

of capital-intensive industries through land misallocation should be corrected, making land allocation contribute more to the development of advantageous industries and environmental protection.

(2) Land misallocation has significantly inhibited upgrading of industrial structure and urban air quality. To reduce a local government's reliance on such a pattern, the solution should begin with the root cause of land misallocation. First, deepen financial and taxation system reform, facilitate the division of fiscal power and administrative authority between central and local governments, leave local government room for fiscal revenue, and reduce local governments' reliance on land misallocation. In addition, a local government's performance and promotion assessment standard or requirement should be reformed. Change local governments' solely taking GDP growth as an assessment indicator and further include industrial structure upgrading and environmental quality improvement in local governments' performance assessment. Establish a growth quality indicator comprehensively reflecting structural adjustment, transformation of development mode and ecological environment protection as local governments' assessment criteria to reverse the scenario of biasing toward capital-intensive industries through land misallocation, and facilitate upgrades to industrial structure and lift ecological environment pressure.

(3) As difference in city size significantly affects the effect of land misallocation on urban air quality, cities at each level shall refer to their own industrial structure, characteristics, and endowments to properly develop their advantageous industries, based on which, they shall create an economic foundation to eliminate the reliance on land misallocation and improve urban air quality. Type I and above cities should further strengthen industrial structure upgrading, continuously adapt to and lead in cutting-edge technologies and industrial restructuring, propel the development of advanced manufacturing industries, and provide full play to industrial structure upgrades to improve environmental quality. For type II cities, medium-sized cities, and small cities, land misallocation has significantly inhibited the effect of industrial structure upgrade and air quality. These cities should further consolidate the industrial foundation, promote industrial agglomeration, and improve the economic scale and economic development level, according to their scale characteristics and comparative advantages, so that the local government can reduce the possibility of obtaining extra budgetary revenue and growth performance through the biased allocation of land resources, so as to

gradually get rid of the dependence on the biased allocation of industrial land and reduce the inhibition effects of land resources misallocaiton on urban air quality.

Appendix A. Spatial econometric tests:

According to Elhorst (2014), we use the methods of Lagrange multiplier (LM), likelihood ratio (LR) and Wald statistics to test the spatial econometric model. We first estimate the non-spatial model and employ the Lagrange multiplier (LM) tests to choose between the SAR and SEM models. If LM-lag is significant instead of LM-err, we select the SAR model; otherwise, we choose the SEM model. If both LM-lag and LM-err are significant, it is necessary to further compare R-LM-lag and R-LM-err. We select the SAR model if R-LM-lag is significant and the SEM model if R-LM-err is significant. Second, if the non-spatial model is rejected, we estimate the SDM model, and perform LR tests to determine whether a spatial fixed effect or temporal fixed effect exists. Third, we conduct a Hausman test to choose between the fixed effects and random effects model. Finally, we employ the Wald and LR tests to test our hypotheses, H_0^1: $\theta = 0$ and H_0^2: $\theta + \rho\beta = 0$, to determine whether the SDM can be simplified to the SAR or SEM. If both hypotheses are rejected, SDM best describes the data. However, if the first hypothesis could not be rejected and the LM (R-LM) tests also point to SAR, then the SAR best describes the data. On the other hand, if the second hypothesis could not be rejected and the LM (R-LM) tests point to SEM, then SEM is the best model to describe the data. If the LM (R-LM) tests highlight one model and the Wald or LR tests do so for another, then the SDM is more suitable for estimating the spatial panel model because SDM is the general form of spatial autoregressive and error models. Table A1 lists the test results for the spatial econometric model. [①]

Table A1. Spatial econometric tests under different spatial weighted matrices

Contents	Methods	Geographic distance matrix		Economic distance matrix		Nested spatial matrix of geographical and economic distance	
		Statistic value	p-value	Statistic value	p-value	Statistic value	p-value
SAR model and SEM model test	LM-lag test	167.0531	0.0000	90.0561	0.0047	188.4365	0.0000
	R-LM-lag test	327.3158	0.0000	1.8029	0.2013	35.2691	0.0000
	LM-err test	1966.0259	0.0000	137.0296	0.0000	565.2890	0.0000
	R-LM-err test	2018.5131	0.0000	39.9042	0.0000	406.3771	0.0000
The fixed	SFE-LR test	4569.1766	0.0000	4799.5125	0.0000	4598.7102	0.0000

[①] Since table 4 shows that φ=0.4 is the best weight for the geographic distance spatial weight matrix in the nested spatial matrix of geographical and economic distance, we mainly report the test results of land misallocation on urbanization environmental quality under the nested spatial matrix with φ=0.4.

effect test of SDM model	TFE-LR test	36.6306	0.0038	348.3091	0.0000	110.0667	0.0000
	STFE-LR test	3866.9452	0.0000	5240.8208	0.0000	4772.9006	0.0000
Hausman test of SDM model	Hausman test	151.2367	0.0000	2735.4572	0.0000	630.8912	0.0000
Simplified test of SDM model	Wald-lag test	703.8295	0.0000	269.6435	0.0000	366.3512	0.0000
	LR-lag test	695.8451	0.0000	273.4327	0.0000	357.6580	0.0000
	Wald-err test	135.6152	0.0000	163.1849	0.0000	80.3617	0.0000
	LR-err test	166.3582	0.0000	149.5408	0.0000	86.5746	0.0000

The results show that LM-lag, LM-error, and R-LM-err tests are significant at the 1% level under the geographic distance, economic distance, and nested spatial matrix of geographical and economic distance, while R-LM-lag is not significant under the economic distance matrix, indicating that the SEM model is more effective than the SAR model. Second, because the non-spatial model was rejected, we estimate the SDM model and check for fixed effects. The LR test results indicate that we should simultaneously control the spatial and temporal effects in SDM. The Hausman test results for SDM under the three weight matrices support the estimation of the fixed effects spatial econometric model. Finally, the Wald-lag, LR-lag, Wald-err, and LR-err statistics under the three spatial weight matrices are significant at the 5% level, which means that the double fixed effects of the SDM model cannot be simplified to a SAR or SEM model. According to the criteria, this study should adopt the spatial and temporal fixed spatial Durbin model.

Declarations

Ethical Approval: Not applicable

Consent to Participate: Not applicable

Consent to Publish: Not applicable

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