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Assessing the effects of land transfer marketization on green total factor productivity from the perspective of resource allocation: Evidence from China

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Exploring the determinants of green total factor productivity (green TFP) is of great importance to economic performance and ecological sustainability. Based on the data of 30 provincial units in China from 2004 to 2016, this study first analyzes the mechanism of land transfer marketization (LTM) affecting green TFP through resource allocation, then the regional resource allocation level is measured using the indicator of factor market distortion, and regional green TFP is estimated by the slack-based measure (SBM) directional distance function and Malmquist–Luenberger (ML) index. On the basis of that, a panel threshold regression model is used to empirically examine the theoretical mechanism of LTM affecting green TFP through the intermediate variable of resource allocation. We find that there is one single-threshold effect between LTM, resource allocation, and green TFP taking resource allocation as the threshold variable. Specifically, while the degree of resource mismatch is lower than 0.1371, the coefficient of LTM on green TFP is 0.1553; otherwise, the coefficient changes to −0.2776. This study concludes that LTM would significantly increase green TFP when the degree of regional resource mismatch is below the threshold; otherwise, it would have an inhibitory effect on the development of green TFP. In addition, the economic development level, R&D investment, and infrastructure level can, to a certain extent, contribute to the improvement of green TFP. The findings have three important policy implications for the land transfer policy of local governments, investment strategies of enterprises, and differentiated policy services.

KEYWORDS

land use, land transfer marketization, resource allocation, green total factor productivity, panel threshold regression model

1 Introduction

Resource allocation status always plays a critical role in achieving high-quality economic growth and other related aspects such as ecological sustainability in the usual sense (Levine, 1997; Godwin et al., 2017). Since the reform and opening-up in 1978, China's economy has grown by leaps and bounds over a long period. However, the traditional economic growth mode characterized by high energy consumption, high pollution, and high emissions has also caused excessive consumption of natural resource reserves and continuous deterioration of the ecological environment, posing significant threats and challenges to the sustainable development of the economy and ecosystem (Marr and Howley, 2018; Chen and Lin, 2020). Taking the industrial sector as an example, since 1978, China's industrial GDP growth rate has maintained an average annual rate of 11.5% over a very long period, but at the same time, the average annual growth rates of industrial energy consumption and carbon dioxide emissions are 6% and 6.3%, respectively (Chen, 2009). In other words, China's economic growth in the past decades has come at the cost of ecological destruction and excessive energy consumption to some extent, attracting lots of people's attention from various communities (Sun and Wang, 2021). Therefore, achieving high-quality economic growth, reducing the pollution of the ecological environment from production activities, and improving green TFP in the current stage have become urgent issues in China's economic system reform. To shed light on these meaningful questions and enhance green TFP, it is supposed to rely on scientific innovation and technological progress on the one hand, and the optimal combination and allocation of resource factors on the other (O'Donnell, 2012; Rose et al., 2013; Crafts, 2016). In this study, we are going to focus on the latter and explore its potential mechanism on green TFP that is driven by the change in land transfer conditions.

Typically, resources that are useful to human beings can usually be divided into several types of production factors such as land, capital, and labor, according to their economic attributes (Thompson, 1921; Fisher, 1953; Palmquist, 1989). Land resources are the primary resources for industrial production and social life, and their allocation status is expected to have an impact on the allocation of capital and labor factors in a certain region (Zheng et al., 2019; Huang et al., 2022), which in turn potentially influences green TFP. Taking this into account, China's government began paying more attention to the value of land resources and their role in regulating macroeconomics and ecology in recent years; meanwhile, land use policies and regulations in China have been updated and reformed in a series of rounds in response to development needs and social realities. Since 1980, China has gradually established an urban land grant system based on agreement, bidding, auction, and listing, which has played a central—if not the central position—in the optimal allocation of urban land resources (Liu et al., 2016; Lian et al., 2019; Lu et al., 2020). In general, local governments are always allowed to transfer urban land by the market-oriented method including biding, auction, and listing conventions of the land systems; however, the discretion to use the agreement transfer method is still retained by them in the process of land supply, which potentially increases the uncertainty of original intentions of these weakly enforced policies. As far as the facts of land transfer are concerned, local governments often have a tendency to choose the agreement method to attract foreign investment in order to develop their local economy, which has objectively distorted the allocation of land resources to a certain degree (Zhang et al., 2016; Zhou et al., 2019). According to the data in 2016, the number of parcels transferred by agreement still accounted for 33.26% of the total number of land transfer parcels, while when it is measured by the land area, the area of agreement transfer also made it by 7.97% considerably.

In this regard, the 19th Congress Report of the Communist Party of China proposed that the reform of China's economic system should take the market-based allocation of production factors as one of the priorities and promote the construction and improvement of the factor market system to achieve the goals that land prices could be determined by the market mechanism and land resources could freely flow between land users be allocated efficiently. Correspondingly, the allocation of urban land resources through market-oriented methods has been reconfirmed as a central objective of land system reform for local governments in each city. Therefore, from the perspective of market-oriented reform of the urban land transfer system, it is of great theoretical and realistic significance to investigate how the adjustment in land transfer marketization drives the allocation status of capital and labor factors, and the further impact that it generates on green TFP, which can help clarify the effects and specific paths of the optimal allocation of land resources on green economy and improve the relevance of macro-control policies. Hereby, this study is aiming at unraveling these policy and economic mysteries to fully serve the land system reform in China and other developing countries with similar institutional backgrounds.

In view of this, this study takes the panel data of 30 provincial districts of China from 2004 to 2016 as research samples and establishes the theoretical mechanism of LTM on green TFP through resource allocation at first. After measuring the allocation conditions of capital and labor factors, a panel threshold regression model is adopted to verify the theoretical association between LTM, resource allocation, and green TFP, which is supposed to provide empirical evidence and supporting reference for high-quality and sustainable development of China's economy from the perspective of the reform of marketization allocation of production factors.

Compared with prior research, the potentially marginal contributions of this study are mainly reflected in the following three points: 1) LTM, resource allocation, and green TFP have been integrated into a unified research framework for the first time, which can provide a piece of evidence and a possible explanation for green growth from the approach of land use policy. Evidently, this study is conducive to revealing the sources of the growth of green TFP from land transfer policies and the indirect process from the perspective of resource allocation. 2) Resource allocation has been explored as the intermediary mechanism between LTM and green TFP, and scientific measurement has also been adopted to indicate the allocation status of capital and labor factors accurately, making it competent to identify the mechanism between the three aspects and how it works. 3) Differing from the models based on the linear relationship, multi-stage effects that LTM affects green TFP from the perspective of resource allocation have been noticed in this study, which can help policymakers and researchers understand land transfer policy and its specific impact under different circumstances comprehensively.

To elucidate these important questions and provide accessible implications, prior studies relating to our concerns have been reviewed in Section 2. After reviewing other valuable and helpful studies, some supporting theories and theoretical hypotheses have been offered to get an intriguing glimpse of the analytical framework of LTM, resource allocation, and green TFP in Section 3. The identification strategy and methodological issues are defined to perform our empirical analysis in Section 4. In Section 5, we draw detailed attention to illustrating how LTM drives resource allocation and its effects on green TFP, and Section 6 concludes the paper.

2 Literature review

Existing studies, either in theoretical or practical aspects, on the relationship between land transfer and the quality of economic development have concentrated on the following three aspects. First, the effects of land transfer, together with its structural components such as the scale, price, and structure, on macroeconomic performance have been explored using qualitative and quantitative methods (Nichols, 1970; Liu et al., 2019; Zhang et al., 2019; Zhang and Yu, 2019). For example, Liu et al. (2013) adopted a DSGE model to verify the co-movements between land prices and business investment. Zhang et al. (2019) analyzed the impact that industrial land prices have on the total factor productivity of enterprises using historical data from industrial enterprise databases and land price monitoring networks. Evidently, the price of land, its scale, and the structure of land types can influence economic growth through different kinds of mechanisms. The critical role of land resources in economic growth has been confirmed in these studies, even though the mechanisms still remain indistinct. Second, from the perspective of land factor allocation, many scholars evaluated the allocative efficiency of land resources in the process of land transfer and revealed the possible consequences on production efficiency (Li et al., 2016; Li and Luo, 2017). Using the level of city-industry data, Li et al. (2016) evaluated how land resource mismatch affected productivity differences among Chinese industrial firms formed by land transfer with low-price agreements. Specifically, Talen et al. (2016) studied a mismatch pattern between single-family residential land use and found that the mismatch tends to be connected with the communities that are of lower socioeconomic status. In this way, the attention to land transfer has been increased, and the perspective has also been expanded substantially. Based on these two aspects, the third research dimension of land transfer and macroeconomics is expanded to investigate the influence and mechanism of market-based allocation of land resources on green economic growth (Filatova et al., 2011; Li et al., 2017). In fact, the market-based allocation has been interpreted as one of the major means to realize the optimal allocation of land resources in these studies. Following this, it has been found that urban land transfer through a market-based approach could correct the mismatch of land resources to a large extent (Cheng et al., 2019; Fan et al., 2020), which in turn affected the regional green economic performance. However, land resources are always closely related to capital and labor factors, and changes in the allocation condition of land factors can also alter the allocation of capital and labor factors in the region (Sirmans and Redman, 1979; Helpman, 1998; Foley, 2003). In other words, the effects that LTM has on green economic growth not only manifest in the correction of land resource mismatch but also in the allocation condition of capital and labor factors (Chen, 2017). As proposed by Smiley (1997), land rights and how they flow can bring up changes in demography, technology, and economic transitions.

The literature to date shows that many scholars have conducted rich studies on the relationship between land transfer and economic growth; however, there are still several shortcomings to be further supplemented and improved as follows. First, most of the prior literature focused on land transfer in terms of land size, price, and the structure of land supply, while little attention has been paid to how the marketization of land resources affects green TFP from the dimension of market-based allocation. Qian and Mou (2013) and Xu et al. (2018) have conducted some studies on the impact of land marketization on economic performance from dimensions such as urbanization and income inequality, but unfortunately, they lack the inspection of energy constraints and environmental pollution in measuring economic growth. Second, the existing studies are more likely to test the direct correlation between land resource mismatch and economic performance; for example, Lu et al. (2020) evaluated the effects of LTM on green TFP and its mechanism from the perspective of the industrial structure, while they were not aware of the indirect effect that efficient allocation of land resources affects the allocation in capital and labor factors and then generates a promising impact on economic performance. In fact, the indirect effects should not be neglected for their profound policy implications in the reform of land transfer policies, and it is worthwhile to explore further how LTM drives the indirect effects and its features under certain conditions.

3 Background and conceptual framework

As far as China's land system is concerned, the property rights over urban land pertain to all the people and are managed by local governments, which is defined by the constitution and gives local governments a monopoly over the land market. Generally speaking, there are four methods available to transfer urban land rights to land users which contain agreement, bidding, auction, and listing under the existing institutional constraints. Specifically, the method of agreement is always privately carried out between the government and the specified individual, causing lots of problems such as official corruption and the waste of natural resources. While the methods of bidding, auction, and listing allowing competition among potential land buyers, have always been recognized as market-oriented land transfer methods (Lu et al., 2020). For a long time, as the monopoly supplier in the urban land market, local governments in China have substantially provided essential conditions for the increase of local taxation and employment through strategic policies that attract investment by providing industrial enterprises with low-priced land intentionally which is transferred by agreement method, forming a "land for development" growth model (Liu, 2012; Lian et al., 2019). As for commercial and residential land, local governments usually tend to transfer them by market-oriented methods, so land resources can be traded at a normal price, much higher than the price of industrial land to make up local government finance. However, the distortion of land transaction prices has led to the deviation of land allocation from its optimal equilibrium state, objectively causing inefficient use and mismatch of the transferred land (Gorddard, 2013; Nathan and Sarkar, 2015). In terms of the condition that matched with other factors, the enterprises introduced by low-land prices as preferential conditions are often crude industries, which are characterized by worn equipment and obsolete technology because they cannot burden normal prices in the land market but can quickly benefit the local economy. The massive gathering of these inefficient industries will crowd out the space of high-tech industries and block the path of local industrial upgrading (Watson, 1990), which is not eventually conducive to the improvement of green TFP (Farrell, 1957; Afriat, 1972; Anandalingam and Kulatilaka, 1987; Färe et al., 1994). Therefore, the impact of local government intervention in the land market on resource allocation is not only reflected in the allocation of land resources but also its impact on the allocation of capital and labor factors cannot be ignored. Undoubtedly, existing studies suggested that there are other determinants that can also play a decisive role in the growth of TFP such as foreign investment (Mankiw et al., 1992; Umar, 2017), the input in funds for scientific and technological endeavors (Zhou et al., 2019), and government intervention (Sahminan et al., 2017). The policy of LTM is still one of the important factors shaping the green TFP through multiple channels, especially its impacts on the status of resource allocation.

The impact of LTM on resource allocation is mainly through the reconfiguration effect, which reflects in the optimal allocation of land resources reversing the mismatch of other production factors. The fundamental role of land resources in production and social living determines that they must be combined with labor, capital, and other production factors so that their potential function can be achieved (Nichols, 1970). Under the policy of LTM, the reconfiguration effect can be mainly interpreted in the following two aspects. The first aspect stresses the screening effect, which has a promoting effect on green TFP theoretically. Specifically, LTM would reduce some manual intervention in land prices in the transfer process of the agreement method, raise the price threshold for enterprise entry, and force some inefficient enterprises with backward production technology to move to suburban areas or exit the local market, while some high value-added industries can afford higher land prices and enter correspondingly. In the process of this adjustment, there are apparent differences in the production efficiency, pollution emission intensity, and pollution control strategies of these industries (Gross and Solymossy, 2016; Zhang et al., 2022). The transition from traditional inefficient industries to capital- and technology-intensive industries can not only improve the use of resources, but also contribute to the preservation of the ecological environment (Crotty, 2002; Jensen and Mina, 2019). From the provincial level, the industry changes in the jurisdiction can be manifested as the increase of green TFP in total. In fact, from the process of China's current industrial transformation, the old inefficient production enterprises are usually some industries with excessive pollution emissions and negative ecological effects, while most of the new high-tech industries are in line with immigrant areas in the standards of energy conservation, emission reduction, and ecological indicators (Han et al., 2016). Therefore, the screening effect of LTM on resource allocation is mainly shown as a beneficial influence on green TFP.

The second explanation can be summarized as the substitution effect of internal factors in local enterprises. For new high-efficiency enterprises that entered, although the rise in land price does not necessarily determine their production places and location selection, it is undeniable that the cost of their internal land resources and employee living will rise, and the input scale of other factors in these enterprises will be crowded out to some points, thus causing a certain degree of resource mismatch within the industry (Wang and Rong, 2014). In a more extreme case, due to a sharp rise in housing prices, some firms alter the capital that is originally invested for production to the real

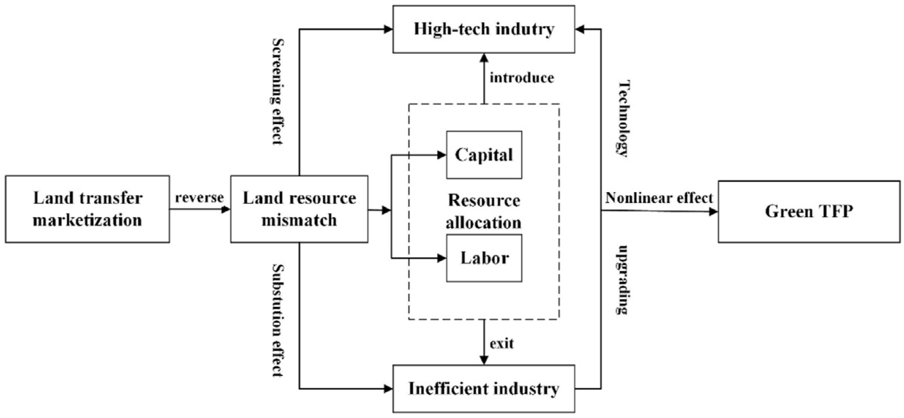

FIGURE 1
Theoretical model of LTM, resource allocation, and green TFP.

estate sector for arbitrage and seek quick short-term profits, thus decreasing the scale of investment in technological innovation (Yu and Zhang, 2017). For the labor resources, the rise of housing prices lowers the relative utility of labor and reduces the potential inflow scale of top talent, which in turn inhibits the level of labor resource concentration in the province (Henning and Henningsen, 2007; Farnham et al., 2011; Chen et al., 2018). Therefore, in terms of internal factor allocation of new entrants, if LTM leads to a rapid rise in land prices, it will aggravate the provincial resource mismatch, which is detrimental to the provincial concentration of high-quality production factors such as capital and labor resources, thus reducing the scope for improving green TFP.

From the two heterogeneous effects of the process of LTM on resource allocation that has been analyzed before, its impact on green TFP seems to be uncertain and notoriously hard to predict, and whether it performs positively or negatively depends on the development stage of LTM and the status of resource allocation. In other words, if it is at a relatively low stage, the industrial structure is dominated by traditional industries in the region, and the effect on resource allocation is mainly manifested as the screening effect, which enhances the provincial green TFP. If it is higher than a certain level and leads to a significant increase in the industrial, commercial, and residential overall land prices, it may aggravate the mismatch of the enterprises' internal resources, thus forming an inhibitory effect on the provincial green TFP. In summary, the direction of the impact on resource allocation is not consistent at different stages, and LTM may generate totally different performances on green TFP as its status changes. The theoretical model of LTM, resource allocation, and green TFP is shown as follows (Figure 1). Hereby, we propose three hypotheses according to the aforementioned theoretical analysis.

Hypothesis 1: LTM drives the status change of resource allocation and shows different effects on green TFP depending on their stages.

Hypothesis 2: When LTM drives resource allocation in the screening effect, the provincial green TFP would relatively increase.

Hypothesis 3: When LTM drives resource allocation in the substitution effect, the provincial green TFP would relatively decrease.

4 Methods and data

4.1 Model setting

In order to test the possible "threshold features" in the effect of LTM on resource allocation, and further on green TFP through the potential mechanism, this study adopted the non-dynamic panel threshold regression model proposed by Hansen (1999). Combined with the theoretical analysis among LTM, resource allocation, and green TFP before, a panel threshold regression model is constructed as shown in Eq. 1.

$$\begin{aligned} \ln Gtfp_{i,t} = {} & \alpha_0 + \beta_1 \ln Lm_{i,t} \cdot I\left(Misa_{i,t} \le \lambda_1\right) + \beta_2 \ln Lm_{i,t} \cdot I\left(\lambda_1 < Misa_{i,t} \le \lambda_2\right) + \ldots + \\ & \beta_n \ln Lm_{i,t} \cdot I\left(\lambda_{n-1} < Misa_{i,t} \le \lambda_n\right) + \beta_{n+1} \ln Lm_{i,t} \cdot I\left(Misa_{i,t} > \lambda_n\right) + \alpha_1 \sum_{i=1}^{n} X_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where i and t represent the province and year in the samples, respectively; $Gtfp_{i,t}$ represents green TFP of province i in the year t; $Lm_{i,t}$ is LTM in province i in the year t; $Misa_{i,t}$ is the threshold variable in this study and denotes the resource allocation indicator contained capital and labor factors; I (*) is a schematic function which could be 0 or 1, and depending on

TABLE 1 Descriptive statistics of all the variables in this study.

Attribute	Variable	Description	Observations	Mean	Std. dev	Min	Max
Explained variable	Green TFP	Measured by the SBM model and ML index	390	1.2211	0.5149	0.2647	4.3666
Explanatory variable	Land transfer marketization (*Lm*)	Measured by the price weight method	390	0.8183	0.2152	0.1759	1.0000
Threshold variable	Regional resource mismatch (*Misa*)	Estimated by the capital and labor misallocation	390	0.1114	0.0122	0.0838	0.1444
Control variables	Economic development level (*ecl*)	Logarithmic forms of GDP per capita	390	9.9168	0.5741	8.2792	11.1752
	Structure of the ownership (*sow*)	Ratio of the number of employees of state-owned enterprises to the total urban employees	390	30.5546	11.9646	8.3000	57.3317
	Degree of openness (*fdi*)	Proportion of foreign direct investment in GDP	390	2.3947	1.8587	0.0386	8.1914
	Level of R&D (*rdp*)	Proportion of R&D input in GDP	390	1.3685	1.0500	0.1776	6.0137
	Human capital (*hmc*)	$hmc = \frac{6PS_{it}+9JS_{it}+12SS_{it}+15JC_{it}+16HE_{it}+19PG_{it}}{P_{it}}$, where PS_{it}, JS_{it}, $SSit$, SC_{it}, HE_{it}, and PG_{it} are the number of employees with the education of primary school, junior high school, high school, college, undergraduate, graduate and above, and P_{it} is the total number of employees	390	6.8067	0.1250	6.4660	7.2034
	Infrastructure level (*inf*)	Ratio of the mileage of railway and highway to the area of urban built-up areas	390	120.4026	95.0070	10.2573	562.6430
	Government intervention (*gov*)	Proportion of government fiscal expenditure in GDP	390	20.8986	9.3036	7.9176	62.6863

whether the condition is true, $\lambda_1, \lambda_2, \ldots, \lambda_n$ is the threshold value to be estimated; $X_{i,t}$ is a set of control variables; α_1 represents their elasticities; β_1, β_2, β_n, and β_{n+1} are the coefficients of LTM in different stages, reflecting its elasticity on green TFP; α_0 is the constant term in this model; and μ_i, γ_t, and $\varepsilon_{i,t}$ represent the individual, time effect, and error term, respectively.

4.2 Variable selection and data description

According to our theoretical framework and methodological strategies, different kinds of variables are selected and introduced in detail correspondingly. After that, all the variables in this study are calculated and presented in Table 1.

4.2.1 Explained variable: Green total factor productivity

Based on the improvement of the traditional radial DEA method by Tone (2001), green TFP is measured by the SBM directional distance function and the Malmquist–Luenberger index. Specifically, assuming that the green TFP of 2003 is one, we multiply the growth rates of green TFP, which are calculated by the SBM model and ML index cumulatively, and obtain the green TFP of each year (Chung et al., 1997; Qiu et al., 2008). It needs to be stressed that since the ML index only calculates the growth rate of green TFP, the input data should include the year 2003 considering the fact that the research period is from 2004 to 2016. In this study, we select the input indicators from the following four aspects: capital, labor, land, and energy. Generally, the capital input is captured by the capital stock of each province, which is estimated by the "perpetual inventory method," with the base year of 1996, depreciation rate of 9.6% (Young, 2003; Zhang et al., 2004), and conversion to the constant prices of 2004. The total number of employees in secondary and tertiary industries, the built-up area, and the total energy consumption in standard coal are used as indicators for labor, land, and energy inputs, respectively. For output indicators, the desirable output is measured by the added value of secondary and tertiary industries that have also been converted to constant prices of 2004, while the undesirable output is measured by these discharged pollutants including industrial wastewater discharge, waste gas emissions, and solid waste. The detailed calculation process and the results of green TFP are shown in the Supplementary Appendix. Moreover, the data are obtained from the China Statistical Yearbook and the China Urban Statistical Yearbook during the period from 2003 to 2016.

4.2.2 Explanatory variable: Land transfer marketization

Most of the available literature on the measurement of LTM uses the price weight method (Xu et al., 2018), which is calculated as follows:

$$Lm_{int} = \sum_{n=1}^{N} X_{int} w_n \Big/ X_{int}, \tag{2}$$

where Lm_{int} denotes the level of LTM of the province i in the year t, X_{int} is the total scale of land transfer, W_n indicates the weight of the transfer method n, and N represents the total number of all the land transfer methods; here, $N = 4$ because the present framework of the current urban land system in China provides four land transfer methods, namely, agreement, bidding, auction, and listing, that have been introduced in Section 3. One thing that needs extra attention is that these four transfer methods are only applicable to urban land, which is quite different from rural land. According to the actual situation of land transfer in various regions, local governments usually choose the listing method to transfer urban land, and the proportions of bidding and auction methods are relatively small (Lu et al., 2020); therefore, the average price of bidding, auction, and listing is directly used as the normal price to take place of the listing price because of the data availability, and the ratio of the price of other land transfer methods to the normal price is taken as their price weight. The data for calculating the level of LTM are obtained from the China Statistical Yearbook of Land and Resources from 2004 to 2016.

4.2.3 Threshold variables: Regional resource mismatch

In this study, resource allocation, which contains the allocation status of capital and labor factors, is measured by the degree of regional resource mismatch. Assuming that, under the condition of a perfect competition market, the ratio of the marginal output value to the actual output value of the firm's capital and labor inputs can reflect the degree of resource misallocation. Accordingly, the Cobb–Douglas production function is constructed with the output of the final product market at the first step.

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta}, \tag{3}$$

where Y_{it} is the output and A_{it}, K_{it}, and L_{it} indicate the technology, capital, and labor input, respectively. The parameters α and β denote the output elasticities of capital and labor, respectively, and assume that $\alpha + \beta = 1$, which means that the returns to scale of the production function are constantly unchanged.

The marginal production of the capital and labor can be obtained by taking the derivative of both sides in Eq. 3; we therefore get Eqs. 4, 5 respectively:

$$MP_{K_{it}} = \frac{\alpha Y_{it}}{K_{it}}, \tag{4}$$

$$MP_{L_{it}} = \frac{\beta Y_{it}}{L_{it}}. \tag{5}$$

Then, we assume that the real prices of capital and labor in each province are denoted as r and w; the ratio of their marginal production to price, as shown in Eq. 6 and Eq. 7, can be used to capture the degree of resource misallocation of capital and labor. Specifically, when the ratio equals 1, it indicates that there is no resource misallocation of capital and labor in economic activities.

$$Misa_{K_{it}} = \frac{MP_{K_{it}}}{r_{it}} = \frac{\alpha Y_{it}}{r_{it} K_{it}}, \tag{6}$$

$$Misa_{L_{it}} = \frac{MP_{L_{it}}}{w_{it}} = \frac{\beta Y_{it}}{w_{it} L_{it}}. \tag{7}$$

On the basis of Eq. 6 and Eq. 7, the indicator of the degree of resource mismatch containing capital and labor is constructed as shown in Eq. 8:

$$Misa_{it} = \frac{\left(\rho Misa_{K_{it}} + \vartheta Misa_{L_{it}}\right)}{\rho + \vartheta}, \tag{8}$$

where $Misa_{it}$ is the degree of resource mismatch in province i in year t; ρ and ϑ represent the relative importance of capital and labor inputs, respectively; and both of them are assigned with one for their essential roles in the production process.

The data measuring resource mismatch involves total regional output, labor input, capital stock, and the real rates of the returns of labor and capital. Among them, the real rate of the return on labor is observed by the annual average wage of urban employees in each province, and the real rate of capital, return capital, is measured by the benchmark loan interest rate published by the People's Bank of China. All the data in this part are obtained from the China Statistical Yearbook, the China Labor Statistical Yearbook, and the Table of Benchmark Interest Rates for RMB Loans to Financial Institutions that is published by the Monetary Policy Department of the People's Bank of China.

4.2.4 Control variables

Referring to existing studies (Grossman and Krueger, 1995; Audretsch and Feldman, 1996; Black and Lynch, 1996; Knowles and Garces-Ozanne, 2003; Seyoum et al., 2015), we select the following variables to control other economic factors that potentially influence green TFP, including economic development level and its quadratic term, structure of ownership, degree of openness, R&D, human capital, infrastructure level, and government intervention.

5 Empirical results and analysis

5.1 Threshold effect test

Before estimating the model, there are two steps required to make our empirical strategies more rigorous. First, the stationarity test of the main variables is supposed to check whether LTM, resource allocation, and green TFP in this study are stationary. In this respect, we take the logarithms of these three variables and their first-order difference primarily, then adopt the unit root test method for panel data including

TABLE 2 Stationary test of the main variables.

Method	D.ln*Lm*	*p*-value	D.ln*Misa*	*p*-value	D.ln*Gtfp*	*p*-value
LLC	−10.0369	0.0006	−3.2505	0.0006	−1.8527	0.0000
Breitung	−6.2950	0.0000	−13.0811	0.0000	−4.0166	0.0000
IPS	−8.4445	0.0000	−1.5116	0.0653	−4.1736	0.0000
Fisher-ADF	18.7377	0.0000	14.1905	0.0000	7.3726	0.0000
Fisher-PP	46.3891	0.0000	20.5574	0.0000	37.3172	0.0000

Note: D.ln*Lm*, D.ln*Misa*, and D.ln*Gtfp* represent the first-order difference of LTM, resource allocation, and green TFP, respectively.

TABLE 3 Results of the threshold effect test.

Model	F statistics	*p*-value	Bootstrap times	Critical values of different significance levels		
				10%	5%	1%
Single threshold	23.42**	0.0167	1000	15.8849	19.2660	25.0498
Double threshold	2.89	0.9100	1000	15.6167	22.0091	46.4768
Triple threshold	7.79	0.5733	1000	22.2744	27.2292	41.0570

Note: *, **, and *** indicate that the results are significant at the level of 10%, 5%, and 1% respectively.

TABLE 4 Single threshold estimation results.

Model	Threshold	Confidence interval of 95%
Single threshold	0.1371	(0.1363, 0.1376)

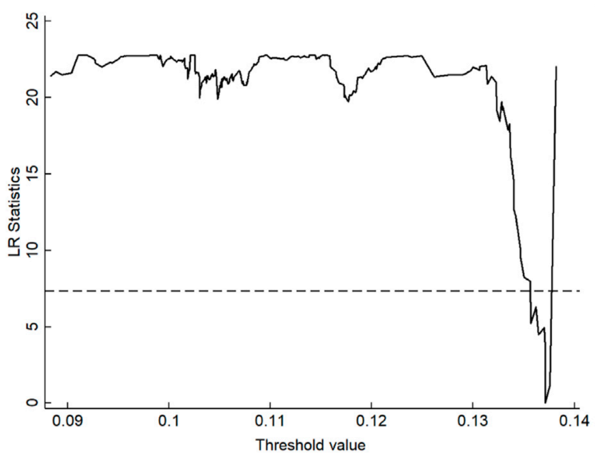

FIGURE 2
Confidence intervals for the single-threshold model.

LLC, Breitung, IPS, Fisher-ADF, and Fisher-PP. Table 2 shows the results of the stationarity test for these variables in the first-order difference form, which indicates that the main variables in this study are stationary and can be used for regression analysis.

Second, we need to test the threshold effect of Eq. 1 to determine the number of threshold values and the specific form of the threshold model as well. According to Hansen (1999), this study takes the degree of regional resource mismatch as the threshold variable of the model, and first assumes that there are one, two, and three thresholds in turn, and tests them, respectively. The number of thresholds can be determined according to the F value and *p*-value of the results shown in Table 3. Specifically, the *p*-value of the F statistic in the single threshold model is 0.0167 and significant at the statistical level of 5%, while the F statistics corresponding to double and triple thresholds have not passed the significance test, which indicates that the model rejects the original hypothesis and has been confirmed with one single threshold after the threshold effect test. Thus, Hypothesis 1 has been tested positively to a certain extent.

On this basis, the threshold value of the single threshold model is identified, and Table 4 reports the single threshold estimates and their corresponding 95% confidence intervals. It can be found that the threshold value corresponds to a narrow range of values for the 95% confidence interval, and when the threshold value is in this interval, the likelihood ratio values are all less than the 5% significance level. In order to show the estimation of the threshold value and the range of the confidence interval, a plot of the likelihood ratio function is given as Figure 2. We can easily obtain the threshold value of 0.1371 when the likelihood ratio function $LR(\lambda) = 0$, and the

TABLE 5 Sample grouping based on threshold values (2016).

Grouping with threshold	Province	Sub-sample size
λ ≤ 0.1371	Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang	25
λ > 0.1371	Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong	5

TABLE 6 Panel threshold model and linear model estimation results.

Variable	Single-threshold model	Fixed-effects model	Random-effects model
LnLm·I (Misa ≤ 0.1371)	0.1553* (0.0921)	—	—
LnLm·I (Misa > 0.1371)	−0.2776** (0.1350)	—	—
LnLm	—	0.1832* (0.0946)	−0.1372 (0.0941)
Lnecl	6.6750*** (1.0380)	8.0129*** (1.0266)	8.0012*** (1.0026)
Lnecl_2	−0.3744*** (0.0548)	−0.4416*** (0.0544)	−0.4340*** (0.0529)
Lnsow	−0.2742*** (0.1013)	−0.2278* (0.1037)	−0.0989 (0.0953)
Lnhmc	−0.5923* (0.3028)	−0.3931 (0.3085)	−0.2707 (0.3083)
Lnrdp	0.4970*** (0.0689)	0.4678*** (0.0952)	0.1869** (0.0628)
Lnfdi	0.0185 (0.0305)	0.0155 (0.0314)	−0.0045 (0.0300)
Lninf	0.1686** (0.0689)	0.1735** (0.0709)	0.3152*** (0.0628)
Lngov	−0.8472*** (0.1595)	−0.6783*** (0.1598)	−0.3907*** (0.1160)
Cons	27.3276*** (4.8929)	34.9994*** (4.7421)	35.4041*** (4.7056)
R^2	0.4137	0.3773	0.2646
F-test/Wald-test	24.70	22.64	194.66
Observations	390	390	390

Note: Standard errors are given in parentheses; *, **, and *** indicate that the results are significant at the level of 10%, 5%, and 1%, respectively.

95% confidence interval for λ is below the dashed line in Figure 2.

In addition, based on the aforementioned threshold value estimated, the sample provinces are divided into two groups of regions accordingly, and Table 5 shows the grouping results in 2016. It can be derived that Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong are in the high resource mismatch region, while the other provinces remain in the low resource mismatch region. As analyzed previously, LTM may have driven the regional land price to a higher level, especially in the developed eastern regions; thus, the resource allocation of capital and labor may be distorted to some extent. However, the degree of resource mismatch is not notable at the national level, and its status in most provinces is in a trend of continuous improvement.

5.2 Results analysis

The non-linear effect of the resource allocation mechanism of LTM affecting green TFP is examined while taking resource allocation as a threshold variable, and the estimates are reported in Table 6. As it shows, LTM does generate periodic impacts on green TFP under different conditions of resource allocation. Specifically, while the degree of resource mismatch is lower than 0.1371, LTM can benefit the development of green TFP to a considerable extent of 0.1553 and is significant at the 10% statistical level. While the degree of resource mismatch is higher than 0.1371, the coefficient changes to −0.2776. The seemingly opposite results in the two stages indicate the economic effect that there does exist a significant threshold effect that LTM affects green TFP through the mechanism of resource allocation. When the degree of resource mismatch is below the threshold, LTM would significantly promote green TFP; otherwise, it would mostly have an inhibitory effect on green TFP correspondingly.

According to the theoretical analysis in Section 3, when local governments carry out the measures of LTM, the optimal allocation of production factors does not directly manifest itself as a screening effect on local enterprises at the first stage, but rather the allocation adjustment of production factors within the enterprises. Under the traditional "land for capital" development model, local enterprises are mostly resource- and labor-intensive industries (Zhou et al., 2021). When land prices rise, these enterprises would pay more attention to the current scale of output and reduce the inputs for technological innovation and environmental protection, thus resulting in a decrease in green TFP. Another scenario is that the implementation of LTM can influence enterprises' production decisions from the factor input substantially. In this condition, although the rising land price is not enough to alter the location of production for new entrants, it can still cause an increase in production costs objectively. Consequently, some enterprises will be induced to invest their capital in the real estate sector or some other high-profit industries to obtain short-term profits, which may also reduce the inputs of the capital in production and innovation. On the other hand, the rapid increase of regional housing prices is not conducive to the concentration of regional labor resources and deteriorates the labor resource allocation of local enterprises, thus causing a decrease in regional resource allocation and green TFP (Winter and Whittaker, 1981; Wang et al., 2020). In fact, from the sample grouping based on the threshold value, those provinces with the higher degree of resource mismatch are concentrated in the eastern regions, which are more developed, and the house prices in these regions are significantly higher correspondingly, proving the existence of the phenomenon of resource mismatch to a certain extent. In these two situations, LTM would inhibit the improvement of green TFP in a sense.

While the degree of regional resource allocation is above the threshold, the impact of LTM on resource allocation would manifest itself as a screening effect on local enterprises, and it would significantly promote the development of green TFP at this point. This is due to the fact that the increase in land prices has been sufficient to form a price threshold for some inefficient firms, and in this case, the cost constraint for efficient firms has not yet shown up; LTM thereby mainly exhibits the screening effect on resource allocation, thus promoting the growth of green TFP.

As for the results of control variables, the coefficients of the economic development level and its quadratic term have contrasting effects on green TFP and both of them pass the 1% significance test, indicating that there is an inverted U-shaped relationship between economic development and green TFP, which can further provide the evidence that the "environmental Kuznets curve" is still valid in the sample provinces at the current stage (Grossman and Krueger, 1995). In addition, the coefficients of the structure of ownership, human capital, and government intervention are all significantly negative, indicating that the increase in the proportion of state-owned enterprises, education input, and government spending would significantly inhibit green TFP. Specifically, it should be noted that state-owned enterprises in China always have large scales and relatively sluggish management, and many of them engage in heavy industry such as mining and metallurgy, which is not conducive to the preservation of the ecological environment (Kapopoulos and Lazaretou, 2009; Rhee et al., 2018). Some evidence that government intervention may have negative impacts on green TFP could be found in prior studies (Barro, 1996; Knowles and Garces-Ozanne, 2003), which provide some essential instructions for explaining the negative results. As for the impact of human capital on green TFP, some studies have pointed out that the enrollment policy in universities sharply increases the number of university graduates, and it is matched with the economic growth rate and results in a mismatch in resource capital (Wang and Hu, 2013). While the level of R&D and infrastructure level have significantly positive effects on the development of green TFP, this is due to the fact that the input of R&D investment contributes to innovation and the invention disclosures of new technologies and then provides the essential requirements for the growth of green TFP (Audretsch and Feldman, 1996). On the other hand, the increase in the input of infrastructure has a promoting effect on the improvement of production conditions and capacities, meanwhile reducing the cost of product transportation (Lin and Chen, 2019), which would boost the growth of green TFP. Hence, Hypothesis 2 and Hypothesis 3 have been proven to be positive, and LTM does have different impacts on green TFP, which depends on how it acts on resource allocation.

In addition, for comparison, the effects of LTM on green TFP are also estimated by using a fixed-effects model and a random-effects model that are all based on a linear relationship, the results are reported in the last two columns of Table 6. According to the estimates, the coefficient of LTM is significantly positive and its direction remains consistent with the results of the threshold model, while the value is higher than the result of the single-threshold model. This is because the fixed-effects model does not consider the threshold mechanism effect of LTM on green TFP through resource allocation and treats the three core variables as a linear relationship, resulting in some variations of the results in different models.

5.3 Robustness test

In the previous part, we evaluated whether there is a non-linear relationship between LTM, resource allocation, and green TFP. From the estimates of the panel threshold model, it is initially believed that the mediating effect of resource allocation in LTM affecting green TFP has multiple features in line with the specific condition of resource allocation. Specifically, when LTM drives the degree of resource allocation mismatch higher than 0.1371, green TFP will be experienced a considerable decrease, otherwise, it will be beneficial from LTM and production factors dominated by capital and labor in this stage are also reasonably allocated. However, this finding may be biased due to the possibility that there are measurement inaccuracies in our main explanatory variable. Consequently, we use another method to measure LTM as an alternative measurement of the price weight method, which was constructed and adopted in a study by Qian and Mou (2012). In this study, we also adopt the proportion method and take the proportion of the parcels and area of bidding, auction, and listing transfer methods in all transferred land as the alternative indicator. The estimates are reported in columns (1) and (2) of Table 7. Furthermore, it must be considered that the effects of LTM on resource allocation may have a time delay because the

TABLE 7 Results of the robustness test.

Variable	(1)	(2)	(3)	(4)
LnLm·I (Misa≤ λ*)	0.5591* (0.2920)	0.3960** (0.1367)	0.9706*** (0.1247)	0.2472* (0.1432)
LnLm·I (Misa>λ*)	−0.0323* (0.0205)	−0.0740 (0.0882)	−0.4523*** (0.0885)	−0.0513* (0.0624)
Lnecl	6.3409** (2.0052)	6.3630*** (1.0276)	—	7.8301*** (1.1579)
Lnecl_2	−0.3560** (0.1185)	−0.3576*** (0.0543)	—	−0.4191*** (0.0611)
Lnsow	−0.2616 (0.3283)	−0.2632** (0.3052)	—	−0.1773* (0.1052)
Lnhmc	0.5028 (0.5036)	0.5638* (0.3027)	—	0.8076** (0.3281)
Lnrdp	0.4804** (0.2339)	0.4965*** (0.0931)	—	0.3554*** (0.1016)
Lnfdi	0.0121 (0.0335)	0.0160 (0.0697)	—	0.0098 (0.0326)
Lninf	0.1520** (0.0605)	0.1642** (0.0700)	—	0.1397** (0.0796)
Lngov	−0.8716* (0.4295)	−0.8738*** (0.1597)	—	−0.4997** (0.1683)
Cons	26.5311** (8.3401)	26.1517*** (4.8539)	0.8485*** (0.0750)	32.2752*** (5.2937)
R^2	0.4199	0.4124	0.1561	0.3494
F-test/Wald-test	5.45	23.5	38.84	25.93
Observations	390	390	360	360

Note: Standard errors are given in parentheses; *, **, and *** indicate that the results are significant at the level of 10%, 5%, and 1%, respectively. λ^* is the threshold value in different models, it equals 0.1371 in (1) and (2) and 0.1365 in (3) and (4).

adjustment of production factors within local enterprises always needs some time for communication and decisions. Thus, we adopted regional resource mismatch that lagged one period as our threshold variable and re-ran the analyses. The results are in columns (3) and (4) of Table 7, while column (4) results have added control variables based on the former.

Table 7 results indicate that LTM generates different effects on green TFP when resource allocation is above and below the threshold value, which is consistent with the results of our main regressions in Table 6. Specifically, in columns (1) and (2), LTM has estimated positive effects on green TFP when the degree of resource mismatch is below 0.1371; however, when the degree is above 0.1371, the effects are observed as negative on green TFP. Moreover, in columns (3) and (4) results, the threshold value has slightly altered to 0.1365 and the estimates of LTM are coherent with the results before.

5.4 Discussion

In the previous sections, we explored the non-linear relationship between LTM, resource allocation status, and green TFP not only in theoretical ways but also in empirical ways. The results showed that resource allocation had an evident threshold effect when it acted as a mechanism between LTM and green TFP. Further evidence suggests that the threshold exists around 0.1371, which means LTM drives the change in the status of resource allocation, and when resource mismatch is below 0.1371, LTM can promote green TFP; otherwise, LTM would inhibit green TFP. In general, this study broadens the scope of the mechanism between LTM and green TFP from the perspective of resource allocation. By comparison, Lu et al. (2020) discussed that the industrial structure could be taken as the mechanism between LTM and green TFP. Similarly, Liu et al. (2013) presented evidence that land prices move together with macroeconomic variables over business cycles. In fact, a growing number of studies are concerned about the relationship between land resource allocation, along with its prices and economic development or ecosystem conservation; however, the investigation of its mechanism is still absent (Zheng et al., 2019; Jiang et al., 2021).

In addition, we discussed various stages of resource mismatch with LTM changes and their impact on green TFP in the theoretical model and then summarize it as the threshold effect in a quantitative model in empirical strategies, which can present the complicated relationship between these three main variables adequately. When the relationship between land transfer, land price, and economics or its related aspects was mentioned in other studies (Geng et al., 2016; Chen et al., 2018; Nakamura, 2019; Zhang et al., 2022), the linear effect of land transfer or land price on economics has been explored in depth, while the multi-stage effects have still not received much attention. Chen et al. (2022) examined the non-linear effects of developer obligation on property prices from the perspective of land dedication in China's bottom-up urban redevelopment. Even though, there is not enough literature that concentrates on the non-linear effect that LTM affects green TFP through the mechanism of resource allocation. In this respect, we noticed that the non-linear effect of LTM on the status of resource allocation in turn has multiple influences on green TFP that depends on the condition of resource allocation.

Notably, this study has carried out some work in exploring the determinants of green TFP from the perspective of urban land transfer system reform and further investigating the non-linear effect between them,

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which could be one of the most important innovations that are worth mentioning. However, due to data availability and the complexity of the theoretical model, we have to adopt the provincial panel data from 2003 to 2016 as our research sample and describe the general information of the main variables. Owing to the gap between theory and social reality, there is no choice but to simplify reality to a certain extent, which may distort the facts. Nevertheless, we still try to make our simplified theoretical model, i.e., the theoretical association between LTM, resource allocation, and green TFP, conform to reality as much as possible. As it shows, the marginal contributions of this study, especially the theoretical framework and concerns for non-linear effects, are also expected to be a useful guide for other studies that focus on urban land transfer system reform in China and those developing countries. Finally, in terms of the modeling setting, we assume that different provinces in our sample converge to their equilibrium at the same or near the same rate, and they are independent of each other. Based on these assumptions, we set a panel threshold regression model as described by Woo and Kumar (2015) and Eberhardt and Presbitero (2015). While there are so many reasons that may be causing the correlation between different sections (Chudik et al., 2017), these factors may raise the possibility of inefficient estimates. However, limited by the materials and capacity available to the author, the question of how to estimate the panel threshold model with cross-sectional dependency considered remains elusive in this study. Given these practical difficulties, we control the provincial and time effects and the shocks from external policy across the years to minimize those provincial characteristics that are difficult to observe in our model. All in all, this defect can also provide a guide for the analysis of the panel data model in the future and will be regarded as one of the most important methodological issues we focus on in the next step.

6 Conclusion and policy recommendations

6.1 Conclusion

When considering the effects of LTM on green TFP, resource allocation cannot be ignored and it even functions as one of the most important mechanisms between them frequently. However, that various LTM scenarios run the linear effect on green TFP through the mechanism of resource allocation has been proved inadequate to capture the specific features in our theoretical model. Therefore, this study takes resource allocation as the intermediary mechanism and constructs the theoretical mechanism between LTM, resource allocation, and green TFP first, and then the data of China's 30 provincial units from 2003 to 2016 are used to empirically verify it by adopting a panel threshold model. It is found that the linear relationship between LTM, resource allocation, and green TFP does not exist, but a significant single-threshold effect taking account of that resource allocation is introduced as the threshold variable. Specifically, when the degree of regional resource mismatch is below 0.1371, the implementation of LTM will significantly increase green TFP by 0.1553; on the contrary, it will have an inhibitory effect on green TFP by 0.2776 on the other end. In addition, the economic development level, the scale of R&D, and the infrastructure level have significant promoting effects on green TFP to some extent. However, we also find that the structure of the ownership, human capital, and government intervention in this stage may have somewhat negative impacts on green TFP during the research period.

6.2 Policy recommendations

Based on the aforementioned findings, the following three policy recommendations are put forward for policymakers to improve the existing land transfer system and promote the optimal allocation of production factors, and further green economic growth as well.

First, as far as the rising land prices that may be brought by excessive competition are concerned, local governments should be alert to the negative impact of excessively high urban housing prices caused by the rapid proceeding of land transfer market reform and appropriately regulate housing prices by increasing the supply of residential land and affordable housing to curb the excessive rise in land and housing prices in order to reduce the distortion of resource allocation such as the allocation of capital and labor. As a matter of fact, the land transfer policy that is piloted lately in China's representative cities such as the central supply of land can be explained as an effective experiment to reform the existing land transfer model to market-oriented land transfer policies, which decreases the space for backroom deals in land transactions and ensures the effective allocation of urban land resources in a relatively fair way under just conditions. Nevertheless, it is necessary to innovate the land transfer system and increase the proportion of market-oriented transferred land in land transactions, and its impacts that reflect on land prices should be also closely monitored so that resource allocation can coordinate with the measures of market-oriented land transfer.

Second, from the perspective of business operation and management, local commercial enterprises should formulate long-term strategic goals and investment plans in accordance with their own industrial types and development stages so that the rational use of corporate funds could be guaranteed over a longer period, especially when there are large gaps in short-term gains between different sectors. Specifically, more attention should be paid to R&D investment and technological innovation to improve their efficiency by enhancing the technological and capital-added value of their products in the enterprises' operations. According to the long-

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term strategies, short-term investment plans are supposed to prevent the massive flow of capital for production to the industries that particularly stressed short-term profits such as the real estate sector, which may hinder the normal production activities of enterprises, and these are causally estimated to promote the optimal allocation of factors within enterprises. From this point of view, some regulations and supporting policies should also be introduced by the government to cooperate with the long-term strategies of enterprises and enable them to benefit from these visionary development strategies. In fact, some local governments in China, for example, Zhejiang, have taken diverse measures to optimize the allocation of urban land resources. Instead of a full market-based transfer mode, the Zhejiang province is attempting to transfer urban land to enterprises through a comprehensive evaluation including economic and ecological indictors, called "yield first," which has performed strongly at primarily promoting green TFP and has curbed short-term investment of enterprises.

Third, the differences in the status of resource allocation in different regions should be treated objectively, and differentiated supporting policies and strategies for land transfer and green economic growth are supposed to be developed as well. For those regions with relatively reasonable resource allocation, the coordinated relationship between market-oriented land transfer and regional industrial development must be stressed by local governments, and guide regional industrial upgrading and enhance the efficiency of enterprises through market-oriented land transfer policies, thus forming a vigorous and benign development approach. For those regions with relatively poor resource allocation, the situation of resource mismatch should be treated specifically. In those regions where resource allocation is distorted due to the gathering of inefficient and low-tech industries, these enterprises should be forced by the method of market-oriented land transfer such as bidding, auction, listing, and environmental regulations to improve their productivity and promote the optimization of factor allocation within the enterprises, thus enhancing the improvement of regional resource allocation to step over the threshold of resource allocation. In those regions where the rapid proceeding of LTM has deteriorated the status of resource allocation, it is necessary for local governments to regulate housing prices within an appropriate range and adopt comprehensive measures, for instance, increasing housing supply from multiple sources and strengthening the support and institutional protection for advanced manufacturing, especially for the modern productive services and strategic emerging industries. Moreover, the government should play its due role of supervision and regulation for the market and industries to avoid the massive inflow of social capital into the real estate sector and the phenomenon of labor dispersion which may lead to the decline of resource allocation and harm the green and high-quality development of the economy (Wu, 2008).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

XJ: conceptualization, data, writing—original draft, methodology, and formal analysis; XL: conceptualization, supervision, project administration, and writing—review and editing; MG: methodology, visualization, and conceptualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer CL declared a shared affiliation with the author XL to the handling editor at the time of review.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.975282/full#supplementary-material

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