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The Regional Effect of Land Transfer on Green Total Factor Productivity in the Yangtze River Delta: A Spatial Econometric Investigation

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Abstract: This paper investigates the spatial mechanisms and impacts of land transfer on green total factor productivity (GTFP) in the economically dynamic Yangtze River Delta region of China. Using urban-level panel data from 2007 to 2020 and applying spatial econometric models, the study examines the relationship between land transfer and GTFP. The results of the spatial econometric analysis show that land transfer in the overall Yangtze River Delta region contributes positively to the improvement of GTFP. The mediating mechanism of industrial restructuring and upgrading shows statistically significant effects. Further investigation reveals differences in the spatial interdependence of land transfer on the GTFP among cities in different regions. Land transfer in the core area has significant indirect effects on the GTFP of neighboring cities, while the impact of land transfer in peripheral cities on the GTFP of surrounding cities is less discernible. This suggests that there is still a need for further deepening and development of integration in peripheral cities, as factor integration is still insufficient. The findings of this study provide useful insights for local governments in optimizing land transfer practices and promoting industrial transformation, upgrading, and sustainable green development.

Keywords: land transfer; green total factor productivity; Yangtze River Delta; spatial heterogeneity effects

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Citation: Yan, W.; Yan, D. The Regional Effect of Land Transfer on Green Total Factor Productivity in the Yangtze River Delta: A Spatial Econometric Investigation. *Land* **2023**, *12*, 1794. https://doi.org/10.3390/land12091794

Academic Editor: Hossein Azadi

Received: 12 August 2023
Revised: 2 September 2023
Accepted: 13 September 2023
Published: 15 September 2023

1. Introduction

Economic sustainability is a crucial issue for most developing countries, including China. In the years since the launch of China's reform and opening-up policies, its economy has achieved sustained and rapid growth. However, this growth has also brought negative impacts, such as overconsumption of resources and premature depletion of environmental capacity. By promoting green transformation in the economic sector, both the goals of energy conservation and emission reduction and sustainable green development can be achieved [1,2]. In the process of industrial structure adjustment and regional economic development, land use plays a crucial role [3]. As an important component of the land system, land transfer activities can allocate land resources to different industries through land transfer prices and scale and can affect the adjustment and upgrading of industrial structure, thereby affecting macroeconomic sustainable development [4]. Therefore, this study will focus on how land transfer activities affect sustainable green development and provide theoretical support for promoting the dual goals of stable economic development and energy conservation and emission reduction.

Previous research on this topic can be broadly divided into three aspects. The first aspect is land allocation and productivity, which shows that there is a close relationship between land resource allocation and productivity. Optimizing the allocation of agricultural land resources is of great importance in improving agricultural production and productivity [5–8]. In urban industrial production, misallocation of urban construction land resources will significantly reduce urban technological innovation and production efficiency [9]. The second aspect is the study of green total factor productivity. With changes in the stage of economic growth, traditional total factor productivity no longer meets the needs of economic research. It only takes into account the input constraints of factors such as labor and capital while ignoring resource and environmental constraints. This can lead to distortions in the assessment of changes in social welfare and in the evaluation of economic performance, thereby leading to misleading policy proposals [10]. Many scholars have tried to incorporate environmental factors into the efficiency and productivity analysis framework to empirically study the situation of the Chinese economy [11]. With the gradual increase of resource and environmental constraints, scholars have begun to shift their focus to green total factor productivity, which has a "green" connotation [12–14]. The third aspect concerns the impact of land allocation on the sustainable development of the green economy. Optimal land allocation in the industrial sector promotes technological progress and industrial diffusion [2,15,16]. Innovations and improvements in production techniques are conducive to the convergence of human capital in technologically advanced industrial sectors [17]. As a result, a reorganization of the industrial layout can be achieved [18], leading to a reduction in pollutant emissions and the preservation of the ecological environment while promoting sustainable development [19,20].

However, based on a comprehensive review of existing research, there is still a lack of literature exploring the impact of land allocation on GTFP, particularly in terms of analyzing 'spatial spillovers' and delving into the 'heterogeneity effects' of the regions studied. The current literature does not take into account the asymmetric nature of spatial spillovers of economic factors in different regions, nor does it provide an in-depth exploration of the mechanism of the role of land concessions on GTFP on this basis. In response to the above questions, this study uses data from 41 cities at or above the prefecture level in the Yangtze River Delta region of China from 2007 to 2020. First, it explores the mechanisms between GTFP measured by the SBM-DDF model and land transfer behavior, as well as industrial transformation and upgrading. It then empirically tests the spatial effects and heterogeneity of land transfer on GTFP. The aim is to provide policy recommendations for local governments in China on land transfer behavior and improving GTFP.

Compared to related studies, the marginal contributions of this study can be summarized as follows: (1) Integrating land transfer, industrial upgrading, and GTFP into a theoretical framework, exploring the underlying mechanisms of land transfer on GTFP, and conducting mediation effect tests. From the perspective of spatial spillovers, it provides a systematic approach to analyzing the relationships between them and the potential of developing existing theories in land use for green economic growth; (2) Considering the asymmetry of the spatial effects of different regional economic factors in reality, the traditional spatial weight matrices can no longer meet the real economic and social activity connections in the Yangtze River Delta region with the development of synergy. This study adopts a new asymmetric geographic economic weight matrix as a spatial matrix to test the spatial mechanism and impact of land transfer on GTFP. This contributes to the investigation of the mechanism between land transfer and GTFP from a methodological perspective; and (3) In order to comprehensively study the relationship between land transfer activities and GTFP, this paper examines the regional development disparities in the Yangtze River Delta region by dividing it into core and peripheral areas. This allows the regional heterogeneity characteristics of different areas to be examined separately, revealing the insufficient factor flow driven by urban integration in peripheral areas and the need to further deepen synergy development. These studies contribute to improving and enriching the existing literature.

2. Analysis of How Land Transfer Affects GTFP: Theoretical Considerations

Local governments in China have long adopted a land supply strategy of low-price agreements for industrial land and high-price agreements for residential and commercial land to promote rapid local economic development. This model has played a crucial role in increasing local tax revenues and employment opportunities. By attracting industrial enterprises through land supply conditions of zero or even negative land prices, it has driven sustained economic growth and made significant contributions to the stability and development of the local economy [21]. However, the country should not only take into account the increase in production value in the process of economic development but also pay more attention to environmental factors, which is in line with the actual economic production process but also reflects the concept of green development. We are committed to better understanding the economic forces driving these changes [22]. In the long-term "development-oriented land use" model implemented in China, large-scale investment attraction has shown mixed results. If land resources are allocated to production sectors with low value-added and low environmental standards, it leads to inefficiency in land resource allocation [23–25]. The extent of optimization of land allocation factors, which further drives the optimization of other production factor resources and affects regional GTFP [26,27]. Based on these considerations, this study proposes research Hypothesis 1.

Hypothesis 1. *Land transfer activities affect the green total factor productivity of a region.*

The rational allocation of land resources often relies on market-based and competitive pricing, which forces selected land transferees to adjust the factor structure of production inputs according to the principles of comparative advantage. This helps to increase the marginal production value of input factors and maximize cost compensation [28,29]. Overall, this promotes the transformation and upgrading of industrial structures [30–32]. From a specific perspective, on the one hand, the creation of barriers for foreign companies prevents traditional industries with low intensity and low value added from entering the market. On the other hand, this directly increases the production costs of enterprises [33,34], which in turn forces enterprises to upgrade their technology and transform their industries to adapt to higher production costs. Firms that fail to upgrade may choose to relocate from their current locations because they are unable to bear the increased costs, leading to regional shifts and spatial re-planning [16,35].

From the perspective of the overall regional industrial structure, the rational allocation of land transfers plays an important role in the selection of relevant industries within the region, thereby facilitating the increase in the concentration of high-value-added industries in this geographical area. In addition, this process will promote the upgrading and transformation of the regional industrial structure [17,36]. At the same time, the effects of industrial agglomeration, land allocation, and adjustment of industrial structure, among other economic factors, are closely related to the foundation of institutional systems [37]. By optimizing allocation and other methods, these factors influence the output of regional firms and hence GTFP. Based on the above analysis, this study proposes research Hypothesis 2.

Hypothesis 2. *Land transfer activities influence green total factor productivity by promoting the transformation and upgrading of industrial structures.*

The contribution of land and other factors of production to economic development varies across regions and shows spatial concentration phenomena [38]. Due to the existence of communication and interaction, local government actions such as land transfers can affect the development of neighboring cities. On the one hand, there are strong economic linkages between cities, including knowledge and technology diffusion and industrial synergies [39,40]. When a city implements a policy, it not only affects local economic development but also influences the economic efficiency and sustainable development of the surrounding areas through radiation-driven effects and spatial optimization [41,42]. On the other hand, the implementation of specific policies or measures in a region can affect the distribution of spatial resources. Central cities can attract resources from surrounding areas, leading to a so-called 'siphoning effect' on the development of neighboring cities [43]. This could potentially lead to behaviors that are detrimental to specialization and effective competition, such as seeking privileged treatment, thereby preventing neighboring cities from achieving an increase in green total factor productivity [44]. Therefore, based on the above analysis, this study proposes research Hypothesis 3.

Hypothesis 3. *Land transfer activities indirectly affect the GTFP of neighboring areas through spatial spillovers.*

According to the above theory analysis, we advance the following mechanism of land transfer affecting green total factor productivity (Figure 1):

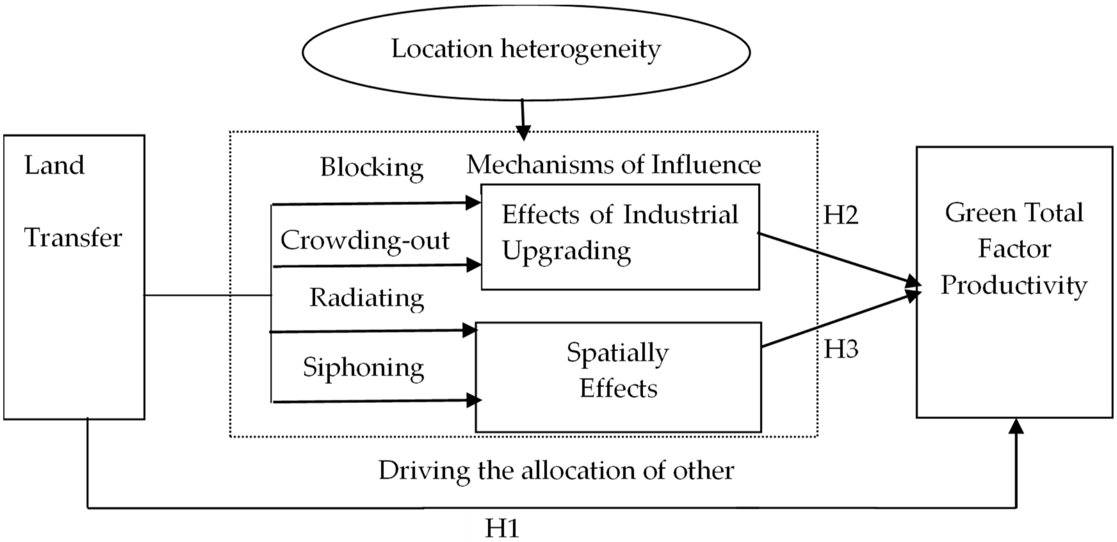

Figure 1. The mechanism of land transfer affecting green total factor productivity.

3. Empirical Analysis

3.1. Spatial Measurement Modeling

In the previous theoretical and mechanistic analyses, it was clear that within the process of land transfer influence on GTFP, there are intricate economic production relationships between regions that inevitably involve spatial correlations. To obtain estimates that are relatively accurate and reflective of reality, it is imperative to use a spatial econometric model, through which this study will analyze the impact effects of land transfer on the evolution of GTFP. The specific spatial econometric model used is as follows:

$$\mathrm{GTFP}_{it} = \alpha + \beta X_{it} + \rho \sum_{j=1, j \neq i}^{N} w_{ij} \mathrm{LAND}_{jt} + \theta \sum_{j=1}^{N} w_{ij} X_{ijt} + \mu_i + \nu_t + \varepsilon_{it}, \tag{1}$$

$$\varepsilon_{it} = \psi \sum_{j=1, j \neq i}^{N} w_{ij} \varepsilon_{jt} + \mu_{it}, \tag{2}$$

where ρ quantifies the indirect effects on GTFP. X represents a collection of explanatory and control variables, including land transfer. β measures the contribution of each explanatory variable to GTFP. θ, on the other hand, it quantifies the indirect effects of explanatory variables from neighboring cities on GTFP. It also takes into account temporal and regional effects. Equation (1) represents the most general form of a nested spatial model, known as the GNS model, which includes all types of interaction effects. Since this study focuses primarily on the spatial effects of land transfer on GTFP, four spatial econometric models are used for the analysis: the spatial autoregressive model (SAR), the spatial error model (SEM), the spatial Durbin model (SDM), and the spatial lag model (SLX). The optimal spatial econometric model will be determined through appropriate testing methods.

3.2. Explanation of Variables and Data Sources

This article uses panel data from the Yangtze River Delta region from 2007 to 2020 as the study sample. Given the incompleteness of the data and for the sake of consistency, this paper selects panel data from 41 cities at the prefecture level and above in the Yangtze River Delta region. Smoothing or averaging methods are used to fill in the missing city data. Data are obtained from various sources, including the "Regional Statistical Yearbook" (2008–2021), the "China Urban Statistical Yearbook" the "China Energy Yearbook" the "China Environmental Yearbook" the "National Land and Resources Statistical Yearbook", land market websites, and provincial and municipal statistical yearbooks. Further details on the relevant variables are provided in the following explanations, while basic descriptions of the variables can be found in Table 1.

Table 1. Descriptive statistics of the regression variables.

Variable	Meaning	Number of Observations	Average Value	Standard Deviation	Minimum Value	Maximum Value
Green Total Factor Productivity	GTFP	574	0.9922	0.0463	0.8824	1.4314
Land Transfer	LAND	574	1.9378	1.4200	0.0801	10.5079
Industrial Structure Upgrading	STRU	574	6.6317	0.3234	5.8465	7.5180
Economic Openness	OPEN	574	0.0182	0.0156	0.0001	0.1581
Education	EDU	574	398.2487	291.8996	14.2114	1704.2800
Technological Development	SCI	574	0.0068	0.0135	0.0003	0.1627
Financial Development	FIN	574	1.5931	1.0479	0.4469	6.2709
Infrastructure	INFR	574	13.6756	5.9451	2.4330	37.5701
Per Capita Land Premium	PLAND	574	14,778.1700	13,950.7400	432.6385	86,302.7600

3.2.1. Core Variables

Green total factor productivity (GTFP), the main explanatory variable in this text, is a measure of productivity that incorporates environmental considerations. The traditional directional distance function, which is a radial and directional approach, can overestimate efficiency in the presence of slack variables and cannot simultaneously account for changes in input and output efficiency in a nonproportional manner [45]. Tone (2001) proposed a non-radial, nondirectional SBM model based on slack variables, which effectively addresses the issue of overestimated production efficiency [46]. Fukuyama and Weber (2009) introduced a non-radial, nondirectional SBM-DD on slack measures, combining the SBM model with directional distance functions. This approach allows the simultaneous nonproportional measurement of input and output efficiency factors [47]. Therefore, we use the superefficient SBM-DDF method for calculation purposes.

The indicators for measuring green total factor productivity (GTFP) are as follows:

(1) Input-side indicators: These include labor input, capital input, land input, and energy input. Labor input is measured by the number of employees in each urban jurisdiction. Capital inputs and land inputs are measured by the capital stock and the built-up area of the city jurisdictions, respectively, with the urban capital stock measured using the perpetual inventory method and deflated to the base year 2006 [48].

The energy input is measured by "fitting energy consumption data to global stable nighttime lighting values". The nighttime lighting remote sensing data are now widely used in research work in many fields, such as energy consumption [49]. It is a more reliable international practice to fit energy consumption to the global stable night lighting values [50–52]. The correlation between total energy consumption and total lighting is strong, and the night lighting data can reflect the spatial and temporal dynamics of energy consumption more reliably [53];

(2) Output-side indicators: These include expected output and unexpected output. Expected output is measured by the actual GDP of each city in the Yangtze River Delta region, deflated to the base year of 2006. Unexpected output is measured by the emissions

of three pollutants: industrial wastewater, carbon dioxide emissions, and particulate matter emissions. The number of raw data observations for measuring the GTFP input–output indicator is 4363, and the number of observations used for estimation in this paper is 4592 after filling the gaps using either the smoothing method or the mean method.

The variables of land transfer (LAND) and intermediate variables (STRU) are the main explanatory variables of this paper. Given the availability of data in the Yangtze River Delta region and the need for data consistency, this study examines the impact of land transfer on GTFP. In the economically prosperous Yangtze River Delta region, where the population continues to migrate and the land market is active, land transfer revenue accounts for a relatively high proportion of local comprehensive financial resources. Therefore, the ratio of total land transfer transaction value to general budget revenue is used as an indicator of land transfer. In addition, in a robustness analysis, we use per capita land premiums (PLAND) to investigate the mechanism of the impact of land transfer on GTFP.

The intermediate variable of industrial structure upgrading (STRU) is an important dimension in the process of industrial structural transformation and upgrading. It reflects the dynamic development of industrial structure from a lower level to a higher level in accordance with the historical and logical sequence of economic development. The measurement of industrial structure upgrading can generally be undertaken through indicators such as the coefficient of industrial structure hierarchy, Moore's structural change index, and the proportion of high-tech industries. We can consider the proportion of each industry in GDP as a component of a spatial vector and then combine them into a three-dimensional vector. Then, we can calculate the angles between these three-dimensional vectors and each industry vector separately [54].

$$\theta_j = \arccos\left(\frac{\sum_{i=1}^{3}(x_i, j \times x_i, 0)}{\left(\sum_{i=1}^{3}\left(x_i, j^2\right)^{1/2}\right) \times \left(\sum_{i=1}^{3}(x_i, 0^2)^{1/2}\right)}\right) \quad j = 1, 2, 3, \tag{3}$$

$$\text{STRU} = \sum_{k=1}^{3}\sum_{j=1}^{k}\theta_j, \tag{4}$$

in the formula, STRU indicates the upgrading of industrial structure, and its higher value indicates a higher level of advanced industrial structure.

3.2.2. Other Control Variables

The control variables selected for this study are as follows: the degree of openness (OPEN) is measured using the method commonly used in the literature, which consists of expressing the actual amount of foreign investment (converted at the average annual exchange rate) as a ratio of GDP. The level of education (EDU) is measured by the ratio of the number of students enrolled in higher education to the total population at the end of the year. The level of technological development (SCI) is measured by the ratio of scientific expenditure to regional GDP. The level of financial development (FIN) is represented by the ratio of the sum of deposits and loans in financial institutions to GDP. Infrastructure (INFR) is assessed by measuring the area of roads per capita.

3.3. Spatial Distribution Patterns Test

We use ArcGIS11.0 to visually depict the spatial distribution of GTFP and land transfer in the 41 cities at the sub-provincial level or above in the Yangtze River Delta (Figure 2). Representative years are selected for a preliminary examination of their spatial and temporal evolutionary features. Figure 2 shows that the spatial stratification of GTFP and land transfer has become more pronounced over time. The areas with high GTFP in each year are concentrated in Shanghai, Changzhou, Nanjing, Hangzhou, and Ningbo, among others, while the areas with high land transfer are concentrated in Jinhua, Lishui, Shaoxing, Bozhou, and Suzhou, and the surrounding cities show significant diffusion. This indicates the potential spatial dependence between GTF and land transfer in the Yangtze River Delta region, suggesting the need to further consider the spatial effects of both variables in empirical analysis.

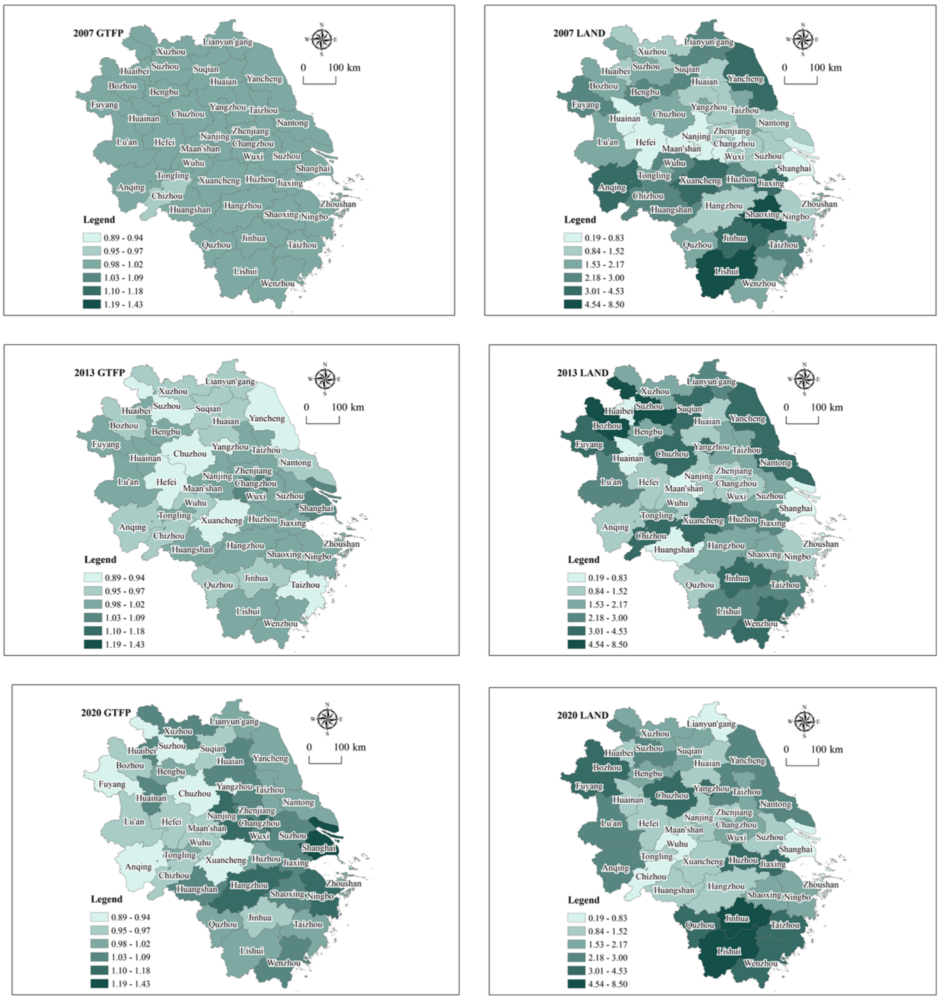

Figure 2. Spatial distribution patterns of GTFP and land transfer in the Yangtze River Delta region in 2007, 2013, and 2020.

3.4. Spatial Weight Matrix and Spatial Correlation Test

The spatial weight matrix represents the degree of connectivity between two cities. This study constructs two types of spatial weight matrices, namely, the traditional symmetric geographic distance weight matrix (W_d) and the novel asymmetric geographic economic weight matrix ($W_{d\text{-}e}$).

First, the geographical distance weight matrix calculates the geographical distances between cities based on the latitude and longitude of their administrative centers and takes the reciprocal of these distances. The form is given as follows: $W_d = 1/d_{ij}, i \neq j$.

Before conducting spatial econometric analysis using panel data, it is necessary to perform a spatial correlation test. In this study, Moran's I index is mainly used to measure spatial correlation, with values between -1 and 1. A Moran's index greater than 0 at a certain level of significance indicates a positive spatial correlation. The formula for calculating Moran's I index is as follows:

$$\text{Moran's I} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{n}(X_i - \overline{X})^2}. \quad (5)$$

Second, to realistically account for the asymmetry of spatial spillovers of different regional economic factors, we constructed a more realistic asymmetric spatial weight matrix for a more accurate spatial econometric analysis. Following Shao et al. (2020), we developed an asymmetric geographical–economic weight matrix that considers geographical distance and spatial economic linkages [55]. The new asymmetric geographical–economic weight matrix shows that economically prosperous regions have a greater impact on relatively underdeveloped regions, thereby highlighting the spatial weight. The matrix is calculated as follows:

$$W_{d-e} = \frac{1 perGDP_j}{d_{ij} perGDP_i}, i \neq j. \quad (6)$$

According to Table 2, the panel global Moran's I values for GTFP are positive under both weight matrices, indicating the presence of positive spatial autocorrelation. The estimation results of the panel global Moran's I index in this study are consistent, and the Moran's I index for GTFP passes the 1% significance test with values of 0.1668 and 0.1606. Based on the above analysis, it is necessary to consider the spatial correlation between cities in the Yangtze River Delta when studying GTFP. The impact of land transfers on GTFP should be analyzed using a spatial econometric model.

Table 2. Global Moran's I value for green total factor productivity.

	Geographic Distance Matrix	**Economic and Geographic Asymmetric Matrix**
Moran's I-value	0.1668	0.1606
Moran's I-statistic	16.0149	14.7915
Significant value	0.0000	0.0000
Standard deviation	0.0106	0.0110

3.5. Model Setting Options

Before applying the appropriate spatial econometric model, it is necessary to carry out the following model selection diagnostics. First, the Lagrange multiplier method (LM) test is used to determine whether the spatial error model (SEM) or the spatial autoregressive model (SAR) should be chosen. Second, the likelihood ratio (LR) test is used to assess the joint significance of time and space effects, allowing the identification of spatial fixed effects, time fixed effects, and spatiotemporal fixed effects. Third, the Hausman test is used to determine the suitability of the spatial Durbin model (SDM). If the null hypothesis is rejected, fixed effects estimation methods should be used; otherwise, random effects estimation methods are appropriate. Fourth, the Wald test is used to determine whether the SDM is superior and more generally applicable than the SAR and SEMs and to further confirm whether the SDM can degenerate into the SAR or SEM. Table 3 presents the diagnostic report of the spatial econometric panel model under the geographical distance weighting matrix.

Based on the results presented in Table 3, first, the results of the Lagrange multiplier (LM) test indicate that both the spatial error model (SEM) and the spatial autoregressive model (SAR) are viable choices, passing the 1% significance threshold. Second, the results of the likelihood ratio (LR) test reject the null hypothesis at the 1% significance level, suggesting the presence of dual fixed effects related to both time and space. Third, the Haus results reject the null hypothesis, indicating the need to implement fixed-effects estimation methods. Finally, both the Wald and LR tests reject the null hypothesis at the 1% significance level, confirming the choice of the spatial Durbin (SDM), which degenerates into the SAR or SEMs. Based on these analyses, this study will use the SDM model with two fixed effects related to time and space for the empirical analysis. Additionally, the empirical results of the SEM, SAR, and SLX models are reported to ensure the robustness of the findings.

Table 3. Spatial econometric model applicability tests under the economic–geography matrix.

Test Content	Test Method	Test Result	
		Statistical Value	Significant Value
SAR and SEM tests	LM-lag test	91.3582	0.0000
	R-LM-lag test	13.3182	0.0000
	LM-err test	193.4393	0.0000
	R-LM-err test	115.3993	0.0000
Fixed-effects test	SFE-LR test (null hypothesis: no spatial-fixed effects)	490.7232	0.0000
	TFE-LR test (null hypothesis: no time-fixed effects)	129.3191	0.0000
	STFE-LR test (null hypothesis: no spatiotemporal-fixed effects)	528.4022	0.0000
Hausman test	Hausman test (null hypothesis: random effects model should be used)	45.9519	0.0000
Simplified test	Wald-lag test (null hypothesis: SDM model can be degraded to SAR model)	23.5968	0.0000
	LR-lag test (null hypothesis: SDM model can be degraded to SEM)	23.8793	0.0000
	Wald-err test (null hypothesis: SDM model can be degraded to SEM)	23.8510	0.0000
	LR-err test (null hypothesis: SDM model can be degraded to SAR model)	23.6513	0.0000

3.6. Results of Model Regression

The spatial weight matrix used in this study adopts an economically and geographically asymmetric matrix. To ensure robustness, the SAR, SEM, SLX, and SDM models were used for econometric estimation. The estimation results are presented in Table 4. From the results listed in Table 4, it can be seen that the spatial autoregressive coefficients of the aforementioned models are significantly greater than zero. Therefore, we can infer the existence of significant spatial interaction effects between the green total factor productivity (GTFP) of different cities in the Yangtze River Delta and their respective explanatory variables. Of particular note is the result derived from the spatial Durbin model (SDM), which shows a significant positive spatial autoregressive coefficient, indicating the presence of both exogenous and endogenous spatial interaction effects. The spatial panel estimation results in Table 4 show that the estimated coefficient of land transfer (Ln LAND) in the Yangtze River Delta region on green total factor productivity (Ln GTFP) is significantly positive at 1%, indicating that land transfer in this region contributes to the improvement of GTFP. In addition, within the spatial Durbin model, the spatial lag term of land transfer ($W \times$Ln LAND) is significantly positive and passes the test of statistical significance. This confirms Hypothesis 3, showing that land transfer in neighboring areas generates spatial effects and consequently influences local GTFP.

However, the marginal impact of land transfer in the Yangtze River Delta region on GTFP cannot be fully and accurately interpreted by this estimation result [56]. It is necessary to further explain the impact of land transfer on the GTFP of a city in the region separately through direct and indirect effects. Therefore, this study analyzes the direct and indirect effects of the spatial Durbin model under an asymmetric economic–geographical distance weight matrix, as detailed in the estimation results in Table 5.

Table 4. Spatial panel estimation results of land transfer and green total factor productivity.

Variable	SAR	SEM	SLX	SDM
LnLAND	0.0046 *	0.0046 *	0.0066 ***	0.0066 ***
	(0.0026)	(0.0026)	(0.0025)	(0.0025)
W×LnLAND			0.0404 **	0.0410 *
			(0.0231)	(0.0228)
log-lik	1338.0017	1338.1157		1349.9414
Obs	574	574	574	574
R^2	0.7116	0.7124	0.7253	0.7251

Note: robustness standard errors are in brackets; * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 5. Direct and indirect effects of land transfer on green total factor productivity.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
LnLAND	0.0067 ***	0.0025	0.0431 *	0.0236	0.0498 **	0.0238
LnOPEN	−0.0040 *	0.0021	−0.0593 **	0.0246	−0.0633 **	0.0249
LnEDU	−0.0144 ***	0.0051	0.1663 ***	0.0619	0.1519 **	0.0638
LnSCI	−0.0098 **	0.0043	−0.0668 *	0.0361	−0.0766 **	0.0362
LnFIN	−0.0400 ***	0.0086	0.0929	0.1007	0.0529	0.1023
LnINFR	−0.0132 **	0.0052	0.0536	0.0558	0.0404	0.0577

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Based on the estimation results in Table 5, it is clear that land transfer in the Yangtze River Delta region not only increases the GTFP of the cities but also contributes to the increase in GTFP in neighboring cities. First, the direct effects are statistically significant at the 1% level and positive in nature. This suggests that land transfer can significantly promote the improvement of GTFP through channels such as technological progress and industrial layout adjustments. Second, the spatial spillovers of land transfer show significant positive effects. This means that land transfer activities in local cities in the Yangtze River Delta region are beneficial for improving the GTFP of neighboring cities. One possible reason for this is that land transfer activities in local cities stimulate further optimization of resource allocation between neighboring cities. In addition, it strengthens economic linkages and promotes healthy competition and effective cooperation between governments and enterprises, leading to positive spatial effects on GTFP.

The analysis of the remaining control variables shows that both the direct and indirect effects of economic openness are significantly negative. This implies that the actual use of foreign investment has a restraining effect on the improvement of GTFP in the Yangtze River Delta region. A possible reason for this is that the relatively high environmental regulatory intensity in the region increases the cost of foreign investment, which to some extent hinders the inflow of foreign capital and the formation of industrial competition. The direct effect of education and technology is negative, while the indirect effect of education on neighboring cities is positive. This reflects the fact that higher education human capital tends to be concentrated in technology- and capital-intensive areas, leading to competition for higher education capital and the outflow of regional human capital and other factors of production. This is detrimental to the growth of the local GTFP. In addition, there are barriers to technological innovation and barriers to technological imitation. In relative terms, actual production capabilities may be more important in influencing regional GTFP than the signaling or screening mechanisms reflected in educational attainment. The Yangtze River Delta region, being relatively developed, relies more on fossil energy for economic development. The economic benefits of technological progress, especially in renewable energy technology, have not yet been fully realized. They may be offset or even aggravated by negative environmental impacts, leading to a decline in GTFP.

The direct impact of finance and infrastructure is negative. This can be attributed to the current problem of resource waste and pollution in infrastructure development, which hinders the improvement of GTFP. The high degree of financial marketization in the Yangtze River Delta region, driven by profit motives, often leads investors to prioritize other options over green innovation projects. Financial institutions do not provide sufficient credit support for such projects, resulting in a misallocation of resources and hindering the development of GTFP. The indirect and total effects were not significant, reflecting the low investment efficiency of financial markets and their weak role in lowering barriers to advanced green technologies and enhancing the spillover of technological progress.

3.7. Robustness Check

In addition to reporting the empirical results of the SEM, SAR, and SLX in the sixth part of this chapter to demonstrate the robustness of the results, we considered replacing the spatial weight matrix and using per capita land premium (PLAND) as a new proxy variable for land transfer to test the robustness of its impact on GTFP.

Moreover, we all know that the year 2020 was affected by the COVID-19 pandemic. Whether the data is still representative? Whether the data still follows the same logic as the earlier years? To prove that, we selected the period ending in 2019 as a robustness check to see whether the findings still hold. The estimated results of the direct and indirect effects of these measures in the spatial Durbin model are presented in Tables 6–8.

Table 6. Robustness test results (I): replaced with geographic distance–spatial weighting matrix.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
LnLAND	0.0070 **	0.0027	0.0546 *	0.0331	0.0617 *	0.0337
LnOPEN	−0.0048 **	0.0022	−0.0695 **	0.0280	−0.0743 **	0.0287
LnEDU	−0.0147 ***	0.0052	0.1139 *	0.0667	0.0991	0.0688
LnSCI	−0.0107 **	0.0042	−0.0750 *	0.0384	−0.0857 **	0.0390
LnFIN	−0.0388 ***	0.0087	0.0531	0.1146	0.0143	0.1169
LnINFR	−0.0146 **	0.0059	−0.0312	0.0934	−0.0458	0.0962

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 7. Robustness test result (II): replaced with per capita land premium (PLAND).

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
LnPLAND	0.0037 *	0.0025	0.0524 **	0.0220	0.0562 **	0.0221
LnOPEN	−0.0049 **	0.0021	−0.0660 ***	0.0249	−0.0709 ***	0.0253
LnEDU	−0.0146 ***	0.0053	0.1562 ***	0.0588	0.1416 **	0.0602
LnSCI	−0.0104 **	0.0043	−0.0766 **	0.0368	−0.0870 **	0.0366
LnFIN	−0.0409 ***	0.0086	0.1069	0.0961	0.0660	0.0977
LnINFR	−0.0129 **	0.0052	0.0592	0.0525	0.0464	0.0543

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

Table 8. Robustness test result (III): replaced with data ending with 2019.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
LnLAND	0.0047 **	0.0023	0.0267	0.0209	0.0314 *	0.0211
LnOPEN	−0.0049 **	0.0020	−0.0242	0.0198	−0.0291	0.0199
LnEDU	−0.0157 ***	0.0044	0.0912 *	0.0510	0.0754	0.0525
LnSCI	−0.0088 **	0.0040	−0.0700 **	0.0312	−0.0787 **	0.0311
LnFIN	−0.0419 ***	0.0084	−0.0329	0.0881	0.0748	0.0895
LnINFR	0.0057	0.0051	0.0688	0.0514	0.0744	0.0529

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

The direct, indirect, and total effects of per capita land transfer premiums (PLAND), as a proxy for land transfer, on GTFP can be observed in Table 7. By replacing the spatial weight matrix and selecting the period ending with 2019, the effects of land transfer on GTFP can be observed in Tables 6 and 8 separately.

Overall, these results show the positive impact of land transfer on the improvement of GTFP in the Yangtze River Delta region. In addition, it shows a positive effect on the GTFP of neighboring cities. These results are in line with the estimates presented in Table 5. Moreover, the consistent interpretation of the control variables further strengthens the robustness of this study's investigation in terms of the mechanism of the model's impact on GTFP in the YRD region.

To further address the endogeneity issue arising from the causal relationship between the explanatory and dependent variables, this study adopts the spatially lagged variable model (SLX). Inspired by the approach of Zeng et al. (2019), the lagged one-period Ln LAND(-1) of land transfer, as well as its spatially lagged counterpart W×Ln LAND(-1), are used as instrumental variables in a two-stage least squares (2SLS) estimation [57]. This is an ideal form of testing for endogeneity problems in the spatial panel Durbin model [58]. The estimation results of the SLX model are presented in Table 9.

Table 9. SLX estimation results for land transfer and GTFP.

Variable	LnLAND	W×LnLAND	The Other Control Variables	R^2	F-Test: IV: Ln LAND(-1)	F-Test: IV: W×Ln LAND(-1)	Hausman Test
Estimation result	0.0125 ** (0.0062)	0.0384 * (0.0227)	YES	0.7459	109.66 [0.0000]	44.61 [0.0000]	11.3306 [0.000]

Note: robustness standard errors are in brackets; * indicates $p < 0.10$, ** indicates $p < 0.05$.

The results of the Hausman test in Table 9 indicate the existence of endogenous explanatory variables in the model. The results of the F-test indicate the appropriateness of the selection of instrumental variables, and the selected instrumental variables are highly correlated with the endogenous explanatory variables. The results show that land transfers are conducive to local GTFP enhancement and positive spatial spillovers to GTFP in surrounding areas. The core explanatory variables are consistent with the conclusions of the baseline regression, and the parameter estimates of the other control variables are also basically consistent. Thus, the robustness of the model's estimation results is established.

4. Further Discussion

4.1. Analysis of the Impact Mechanism of Land Transfer on GTFP

According to the hypotheses derived from previous theoretical mechanism research, this paper attempts to further explore the transmission mechanism of land transfer in the Yangtze River Delta on green total factor productivity through the analysis of industrial structural transformation and upgrading effects. Following the methods of Jiang [59], we construct the following model [60] to examine the role of land transfer in promoting industrial structural transformation and upgrading by replacing the dependent variable in the main regression with industrial upgrading (STRU):

$$\mathrm{STRU}_{it} = \alpha'' + \beta''\mathrm{LAND}_{it} + \varphi'' z_{it} + \rho'' \sum_{j=1, j\neq i}^{N} w_{ij}\mathrm{STRU}_{jt} + \theta'' \sum_{j=1}^{N} w_{ij}\mathrm{LAND}_{ijt} + \lambda'' \sum_{j=1}^{N} w_{ij} z_{ijt} + \mu_i'' + \nu_t'' + \varepsilon_{it}'', \quad (7)$$

where z denotes the set of control variables, including the degree of openness to the outside world (OPEN), the level of education (EDU), the level of technological development (SCI), the level of financial development (FIN), and infrastructure (INFR).

From Table 10, it can be seen that the regression in Equation (7) empirically examines the direct and indirect effects of land transfer on the mechanism variable, the transformation and upgrading of industrial structure, and shows a significantly positive impact. This indicates that the improvement of resource allocation through land transfer significantly promotes the process of industrial structural upgrading. The influence of industrial structural transformation and upgrading on green total factor productivity is both direct and obvious. The theoretical analysis section of this paper elucidates this role based on the literature and logical reasoning.

Table 10. Direct and indirect effects of land transfer on industrial structure transformation and upgrading.

Variable	Direct Effect		Indirect Effect		Total Effect	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
LnLAND	0.0048 *	0.0027	0.3529 ***	0.0750	0.3577 ***	0.0770
LnOPEN	−0.0006	0.0013	0.0132	0.0433	0.0126	0.0438
LnEDU	0.0231 ***	0.0025	0.3622 ***	0.0914	0.3853 ***	0.0934
LnSCI	0.0057 ***	0.0019	0.2639 ***	0.0594	0.2696 ***	0.0610
LnFIN	0.0497 ***	0.0036	0.4318 ***	0.0906	0.4815 ***	0.0931
LnINFR	0.0462 ***	0.0044	1.2517 ***	0.1395	1.2979 ***	0.1431

Note: * indicates $p < 0.10$, *** indicates $p < 0.01$.

From the above analysis, it can be inferred that the transfer of land in the Yangtze River Delta region has been validated to improve green total factor productivity through the effects of industrial structural transformation and upgrading. By strategically allocating land resources to industries with high-value-added development needs, enterprises or projects can be attracted, including high-tech enterprises and institutions, facilitating industry–academia cooperation and creating an innovative ecosystem. Optimizing land allocation enhances the service-oriented nature of industries in the Yangtze River Delta while increasing the sophistication of manufacturing, thus driving the evolution of the industrial structure towards higher levels of competitiveness. This development enables industries to move up the value chain, while the application of green production methods and technologies improves efficiency and reduces costs. In addition, the process of industrial transformation and upgrading promotes the development of synergies among industries. Through effective industrial governance, such as the clustering of related industries in industrial parks or technological innovation zones, the provision of appropriate facilities and supporting measures promotes the exchange and sharing of technology, experience, and resources, further promoting sustainable development and the realization of a green economy. Ultimately, this contributes to the growth of GTFP.

4.2. Regional Comparison of Land Transfer and GTFP in the Yangtze River Delta Region

“The National New Urbanization Plan” emphasizes the need to enhance the radiating and driving functions of central cities, the need to promote coordinated integration between different types of cities, and the need to achieve integrated urban development. It has been recognized that there is a significant development gap between cities in the Yangtze River Delta, both in government-led planning and academic research. Therefore, based on current research [61], this paper divides the Yangtze River Delta region into a core area and a peripheral area. The core area comprises 16 cities, including Shanghai, Nanjing, Suzhou, Wuxi, Changzhou, Yangzhou, Zhenjiang, Taizhou, Nantong, Hangzhou, Ningbo, Shaoxing, Jiaxing, Taizhou, Huzhou, and Zhoushan. Historically, the level of development of these core cities, the early initiation of integration processes, and the depth of inter-city linkages have been considered important criteria for classification in macroplanning and related research.

First, we describe the land transfers and GTFP of the core and peripheral cities. From Table 11, it can be seen that the GTFP of the core area cities is higher than that of the peripheral area cities in terms of mean values and maximum–minimum values. This is in line with reality, as the core area cities are more developed and have stronger economic capabilities. They have made significant achievements in economic development, industrial innovation, and urbanization, with considerable efforts in environmental protection and energy conservation, and have also promoted the development of green industries. It is natural that their GTFP is higher than that of peripheral cities. However, when considering the development level and prospects of core area cities, it is necessary to further explore whether the close economic ties and cooperation among cities have facilitated the optimization of resource allocation and the exploitation of complementary advantages, actively promoting low-carbon transformation. Whether there is good interaction with surrounding cities needs to be further discussed before making judgments.

Table 11. Descriptive statistics on urban land transfer and GTFP in core and peripheral areas.

Variable	Meaning	Number of Observations	Average Value	Standard Deviation	Minimum Value	Maximum Value
GTFP in core cities	CG	224	1.0156	0.0566	0.9332	1.4314
GTFP in peripheral cities	PG	350	0.9773	0.0300	0.8824	1.0865
Land transfer in core cities	CL	224	1.6602	1.1190	0.1046	6.6504
Land transfer in peripheral cities	PL	350	2.1155	1.5586	0.0801	10.5079

The level of land transfer in core area cities is lower than that in peripheral area cities, both in terms of mean and maximum values. The minimum value for core area cities is higher than that of peripheral area cities, which may reflect the dependence of peripheral area cities on land fiscal policies compared to the robust land fiscal policies of core area cities. Of course, further judgment and in-depth analysis are needed to determine the specific impact of land transfer on GTFP in both core and peripheral area cities.

Next, looking at the regression results, this paper further measures the relationship between land transfer and GTFP in different regions through spatial analysis, and Table 12 reports the estimation results.

There are significant differences in the relationship between land transfer and GTFP in different regions, and land transfer has a greater impact on the GTFP of core cities. Land transfer in area cities mainly contributes to the improvement of the GTFP in neighboring cities. This suggests that in core cities, regional planning that matches supply and demand benefits coordinated development between core cities and the overall improvement of regional green economic sustainability. The impact of land transfer in peripheral areas on GTFP is mainly manifested in direct effects, while indirect effects are not significant. This suggests that the fiscal efficiency of land transfers in peripheral cities is insufficient. Although land transfer activities may generate some fiscal revenues, the impact of land transfers in cities in the peripheral zone on GTFP in neighboring cities is not yet evident relative to the influence and indirect effects of the core cities and their land markets. Peripheral cities typically have relatively weak economic development and industrial structure and limited competitiveness and spillover potential in land transfer activities. In addition, they often lack advantages in terms of infrastructure, talent, and market scale, resulting in inadequate spatial connectivity with the resources of neighboring cities, which limits the indirect effects of land transfer and hinders the highlighted impact on the sustainable economic development of surrounding cities.

Table 12. Decomposition of effects of spatial Durbin models for different regions.

Type of Effect		LnLAND	LnOPEN	LnEDU	LnSCI	LnFIN	LnINFR
Core area	Direct effect	0.0044 (0.0054)	−0.0024 (0.0052)	−0.0505 *** (0.0101)	−0.0049 (0.0120)	−0.0796 *** (0.0181)	−0.0055 (0.0093)
	Indirect effect	0.0674 * (0.0397)	−0.0529 (0.0750)	−0.0806 (0.1196)	0.1132 (0.1774)	0.2373 (0.1938)	0.0567 (0.1480)
	Total effect	0.0719 * (0.0389)	−0.0553 (0.0754)	−0.1310 (0.1212)	0.1083 (0.1784)	0.1576 (0.1918)	0.0512 (0.1515)
Peripheral area	Direct effect	0.0033 * (0.0020)	−0.0033 * (0.0017)	0.0030 (0.0040)	−0.0069 ** (0.0030)	−0.0191 *** (0.0065)	−0.0248 *** (0.0047)
	Indirect effect	0.0296 (0.0594)	−0.0684 (0.0609)	0.3529 (0.3117)	−0.1359 (0.1138)	0.2030 (0.1720)	−0.1004 (0.1489)
	Total effect	0.0329 (0.0598)	−0.0717 (0.0614)	0.3559 (0.3126)	−0.1428 (0.1141)	0.1840 (0.1726)	−0.1252 (0.1496)

Note: * indicates $p < 0.10$, ** indicates $p < 0.05$, and *** indicates $p < 0.01$.

5. Conclusions and Policy Implications

5.1. Conclusions of the Study

This article examines the Yangtze River Delta as a research sample. Using panel data from 2007 to 2020, encompassing 41 cities at or above the prefectural level in the Yangtze River Delta region, this study explores the perspectives of industrial upgrading and spatial imbalances. It proposes and verifies that the rational allocation of land transfers promotes the upgrading and transformation of the regional industrial structure, further driving the optimal allocation of other production factors. This facilitates the expansion of high-value-added industries, thus enhancing the local GTFP. Simultaneously, due to the strong mobility of factors and economic interconnections within the Yangtze River Delta region, the radiation effect strengthens knowledge and technological diffusion between regions, optimizes industrial spatial patterns, and subsequently raises the GTFP of neighboring cities.

To examine the heterogeneous effects of regional development, the Yangtze River Delta region is divided into core and peripheral areas for analysis. It is found that land transfer in the core urban areas plays an important role in improving GTFP, while the efficiency of land transfer in the peripheral urban areas needs to be improved and has not significantly improved the green total factor productivity of the surrounding cities. The coordinated development of peripheral urban areas is still inadequate, lacking advantages in market scale and industrial clusters. Therefore, it is necessary to strengthen the free flow of factors and the construction of a unified large market to enhance the competitiveness and premium potential of land transfer activities.

5.2. Policy Implications

The significant spatial spillovers indicate the need to fully consider the formulation of multiple policies and multi-regional coordination, the acceleration of regional spatial factors and technology sharing. In addition, it is essential to enhance the capacity of innovation industry agglomeration to promote green production, promote the optimization and improvement of efficient industrial agglomeration and resource allocation, and ultimately establish a virtuous cycle and development path that enhance green total factor productivity.

The significant mediation mechanism shows the importance of rational allocation of land transfer revenue and the optimization and upgrading of industries. When regulating land transfer, it is necessary not only to stimulate the enthusiasm of local governments, restrict irrational competition for land, and guide the landing of high-quality funds, but also to guide the normal operation of the land market. This will make it possible to allocate land elements to industries with higher efficiency, integrate high-tech industries into the local industrial chain, enhance independent innovation capabilities, and improve the interrelation between industries. This will be more conducive to the improvement of green total factor productivity and ultimately achieve economic modernization and development.

The significant regional heterogeneity indicates that highly adaptable policies should be formulated according to the region's own resource endowments, economic development, and industrial transformation and upgrading needs. The spatial linkage development between cities should be planned based on different degrees of integration to determine the proportion of land transfer. It is necessary to pay more attention to regional coordination, break down administrative barriers that hinder the integration process, deepen regional cooperation, and promote effective interaction between land transfer activities and corresponding urban development. Mobilizing land resources to optimize land allocation, standardizing land transfer activities, attracting high-value-added industries, and stimulating the related effects of advantageous industries are crucial. Strengthening the construction of industrial communities between regions, enhancing the spatial transfer and suitability of industries, strengthening the coordination of industrial chains, and improving the environmental policy system will ultimately drive the improvement of green total factor productivity.

5.3. Shortcomings and Outlook

At present, China's economic development is in a period of major adjustments in green and low-carbon transformation. The report of the Twentieth Congress of the Communist Party of China set out clear requirements for green development, stating that it is necessary to implement a comprehensive environmental protection strategy, develop green and low-carbon industries, coordinate industrial restructuring, pollution control, environmental protection, and response to climate change, and accelerate the green transformation of the development mode. The limitations of this study restrict the completeness of the input–output indicators of GTFP, which are not limited to energy consumption. They can be further improved by adopting comprehensive resource consumption measurements, which will allow for a more scientific and comprehensive calculation of GTFP in the Yangtze River Delta region.

Moreover, this study is based on macro-statistical data and focuses on 41 prefecture-level cities in the Yangtze River Delta region as research units. We attempt to understand the mechanism by which land transfer promotes industrial transformation and upgrading and generates spatial spillovers, thus affecting the regional GTFP at the macro level. However, it remains for future research to investigate whether the same behavioral logic and mechanisms apply at the microlevel of enterprises and to conduct more in-depth and detailed studies in this regard.

Finally, the mechanism analyses in this paper still have certain deficiencies and limitations, and subsequently, we will continue to improve and explore better methods to carry out the study.

Author Contributions: Conceptualization, W.Y. and D.Y.; materials and methods, W.Y.; formal analysis, D.Y.; writing—original draft preparation, W.Y. and D.Y.; writing—review and editing, W.Y. and D.Y.; supervision, D.Y.; project administration, D.Y.; funding acquisition, D.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was funded by the National Natural Science Foundation of China (42101183) and the Major Project of the Research Center for Yangtze River Delta Economic and Social Development, Nanjing University (No. CYD-2020018).

Data Availability Statement: The data used in this study can be found in the relevant publications and have already been cited in the text for illustration. The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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