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Original Paper

Research on the Impact of Labor Resource Allocation on Green Technology Innovation

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Abstract

Facing increasingly severe environmental pollution and resource scarcity, China has accelerated its pace of green and low-carbon transformation. Green technological innovation helps economic development by reducing ecological pollution and lowering resource consumption. As an important factor of production for social development, the labor force plays a very significant role in optimizing the economic development structure of our country and achieving high-quality leapfrog development. This article explores the relationship between the allocation of labor resources and green technology innovation based on the aforementioned practical motivations, from both theoretical mechanisms and empirical perspectives. Using provincial panel data from China between 2000 and 2021, a spatial Durbin model was constructed to empirically test the spatial spillover effects of labor resource allocation on green technology innovation and to draw relevant conclusions. Subsequently, to further investigate the heterogeneous impact of labor resource allocation on green technology innovation, China was divided into three major regions—eastern, central, and western—and empirical model tests were conducted on separate samples. The following conclusions have been drawn: Over time, during the 22 years from 2000 to 2021, China's overall labor resource allocation has shown an overall upward trend; China's green technology innovation capability has significantly improved, but regional development is uneven, with a large gap in development between the eastern, central, and western regions; through the study of the spatial Durbin model on the impact of labor resource allocation efficiency on green technology innovation, the results indicate that labor resource allocation has a significant main effect and spillover effect on green technology innovation, meaning that the improvement in labor resource allocation efficiency will promote the increase in the level of local green technology innovation, while the decline in labor resource allocation efficiency will inhibit the increase in the level of local green technology innovation; the impediment effect of the decline in labor resource allocation efficiency on regional green technology innovation varies significantly across *different regions, with the central region being the most prominent, followed by the western region, and then the eastern region. Based on the conclusions, the following suggestions are made: Regions should strengthen cooperation and exchanges to promote the coordinated development of green technology innovation. Eastern provinces and cities with a higher level of green technology innovation should lead the surrounding provinces and cities with weaker development, actively engage in cooperation and exchanges in infrastructure and green technology, and establish a more orderly and open green technology trading market, thereby promoting the coordinated development of green technology innovation between regions; adopt market-oriented approaches to remove barriers to the autonomous and orderly flow of labor factors. Give the market a decisive role in resource allocation, reasonably play the role of the government, promote the rational and orderly flow of capital and labor resources between regions, and improve the efficiency of resource allocation.*

Keywords

Labor force resource allocation, Green technology innovation, Spatial Durbin model

1. Introduction

Since the reform and opening up, China's economy has experienced rapid development mainly relying on an "extensive growth model," which is characterized by high input and low efficiency and is unsustainable. For developing countries, improving the efficiency of factor allocation can significantly increase productivity and output levels. The underlying economic mechanism is that if some production factors are reallocated from sectors or enterprises with lower productivity to those with higher productivity, then even if the total input remains constant, the overall output of society will increase. Therefore, the distribution of labor, land, and other production factors across various sectors is a crucial component of total productivity, and the reallocation of factors from sectors with lower productivity to those with higher productivity is key to the growth of total productivity.

The efficiency of labor resource allocation is one aspect of factor allocation efficiency. Its improvement is characterized by workers moving based on market signals of employment opportunities and relative labor prices, from regions and industries with lower productivity to new regions or industries with higher productivity. The inefficiency of labor resource allocation is the main cause of the coexistence of "employment difficulties" and "recruitment difficulties" in China's labor market, severely damaging the quality of economic development. On the one hand, low efficiency in labor resource allocation causes a loss of 2%-18% in total factor productivity, and this loss is showing a trend of gradual expansion; on the other hand, there are regional differences in the efficiency of labor resource allocation in China, which have significantly exacerbated the imbalance in regional economic development; moreover, China's demographic dividend is gradually disappearing, and the days of large-scale labor input driving economic growth are gone forever. High-quality growth also demands higher efficiency in labor resource allocation. On March 20, 2020, the State Council issued the "Opinions on Building a More Perfect Market-Oriented Allocation System for Factors," which pointed out the need to improve factor allocation efficiency to promote a transformation in the quality, efficiency, and dynamics of economic development.

2. Literature Review

Restuccia & Rogerson (2008) deduced through the deductive results of growth models that economic tax policies such as property taxes and labor income taxes affect the efficient allocation of resources, which significantly reduces the production of goods and total factor productivity. Aoki (2008) conducted a model hypothesis test on Japan's agricultural and non-agricultural sectors under two hypothetical conditions. The first hypothesis is that Japan's labor market has allocative efficiency, and this labor resource allocation efficiency has significantly inhibited the country's economic growth; the second hypothesis is that the labor market does not have allocative efficiency. Through the examination of the two hypotheses, it is evident that Japan's labor market has allocative efficiency. Jones (2011) differs from previous studies in that he established a two-sector model from a micro perspective and explored the impact mechanism of resource allocation efficiency on TFP, pointing out that the degree of labor resource allocation efficiency varies greatly among countries, and the reason for this difference may be the different degrees of distortion in the labor resource markets and labor markets of various countries. Yuan Zhigang and Xie Dongdong (2011) used data from China from 1978 to 2007 for research and also concluded that labor resource allocation efficiency has an inhibitory effect on TFP. Dong Zhiqing and Wang Linhui (2013) summarized the existing literature on allocation efficiency and pointed out that improving the level of resource allocation efficiency in China can enhance production allocation efficiency. Li Ping and Ji Yongbao (2014) studied the impact of labor price distortion on technological innovation from the perspectives of employees and employers, and through econometric models, they found that the degree of distortion of labor prices in China is positive and has an inhibitory effect on corporate innovation activities. Zhu Lin et al. (2017) found through the use of econometric models that there is allocative efficiency between urban and rural areas, within cities, and among the three major regions in China, and the overall labor resource allocation efficiency in China and the changes in the allocation efficiency of agricultural and non-agricultural labor resources basically show the same trend, which is an inverted U-shape. From a regional perspective, the overall and agricultural and non-agricultural labor resource allocation efficiency in China is low in the eastern region and high in the western region. There is a significant difference between traditional technological innovation and current green technological innovation, which is reflected in the emphasis on the concept of "green". Zhao Cheng, Wang Banban (2019) proposed that compared with traditional innovation, green technological innovation not only brings positive spillover effects but also internalizes negative environmental effects. Jing Weimin et al. (2014) believe that the measurement of green technological innovation can be referenced but not solely relied on the previous measures of technological innovation, such as patents, R&D, and total factor productivity, because these data are limited and often start from a holistic concept without delving into the green field in detail. From a macro perspective, the Institute of Industrial Economics of the Chinese Academy of Social Sciences in 2011 believed that green technological innovation could become the core means of global development of low-carbon economy and green transformation; from a micro perspective, an effective way for enterprises to enhance competitive advantage is green technological innovation.

As a signal carrier reflecting the structure of economic endowment, the relative prices of factors are an important factor in determining corporate production and R&D decisions. In light of this, Huang Peng and Zhang Yu (2014) were the first to analyze the impact of relative price distortions of factors on corporate innovation activities from the perspective of the relative distortion of labor and labor resources prices, using micro data and a semi-parametric estimation method based on the LP approach to calculate the degree of relative distortion of factor prices. Subsequently, Zhang Yu and Ba Hailong (2015) also examined the impact of factor market distortions on regional R&D intensity from the perspective of the relative distortion of labor and labor resources, by decomposing regional-level industrial R&D intensity indicators, and considered two aspects: green technology and industrial value chains. They found that the underestimation of labor relative to labor resources prices not only directly hinders regional green technology and the optimization and upgrading of the industrial chain but also weakens the positive effect of labor resource deepening on R&D. Gai Qien et al. (2015) studied the impact of factor market distortions on total factor productivity from a broad perspective, arguing that factor market distortions have two effects on total factor productivity: a direct effect (factor market distortions lead to different marginal outputs among incumbent firms, reducing total factor productivity) and an indirect effect (factor market distortions create barriers to the entry and exit behavior of firms through monopolistic power, reducing total factor productivity). Dai Kuizao and Liu Youjin (2016) characterized factor market distortions by the degree of distortion of the factor market relative to the product market in the representative firm's region. This approach implies that the allocation efficiency of labor resources and labor is the same, and the impact of the two types of factor allocation efficiency on innovation efficiency is equal. This assumption does not align with reality and cannot reflect the impact of different degrees of distortion of labor and labor resources on innovation efficiency. Based on this, Bai Junhong and Bian Yuanchao (2016) took the distortion of the labor factor market and the distortion of the labor resource factor market as entry points and separately elaborated on the internal mechanisms by which the two types of factor market distortions affect innovation production efficiency. The results indicate that both labor factor market distortions and labor resource factor market distortions have a significant negative impact on the development of China's innovation activities and the improvement of efficiency.

Through the induction and arrangement of the aforementioned literature, scholars both domestically and internationally have conducted a wealth of research on the measurement, influencing factors, and economic effects of resource allocation, with the majority of the literature focusing on China as the subject of study. This has provided significant reference for the conceptual definition, measurement, and theoretical analysis of labor resource allocation in this paper. However, there are still some shortcomings in the research focus on the causes and impacts of labor resource allocation efficiency: First, most existing literature focuses on the issue of resource misallocation between enterprises or departments. However, the imbalance in resource flow and low allocation efficiency between regions are prominent issues in the current development of China's regional economy, yet few studies have addressed this, and the discussions are relatively rough. Second, research directly exploring the relationship between resource efficiency and innovation is still in the exploratory stage and has not yet formed a complete theoretical system and analytical framework. Third, there is insufficient discussion on the mechanism by which labor resource allocation efficiency affects innovation, and empirical verification of the transmission mechanism is also rare.

3. Research Design

3.1 Data Sources

This study selected 30 provincial-level regions, excluding Tibet and the Hong Kong, Macao, and Taiwan regions, as research samples. Due to data unavailability, Tibet and the Hong Kong, Macao, and Taiwan regions are not included in the scope of the study. The data mainly comes from the "China Statistical Yearbook," "China Environmental Statistics Yearbook," China National Research Data Service Platform (CNRDS), provincial statistical yearbooks, "Statistical Bulletin on National Science and Technology Funding Input," annual development statistical bulletins of each province, annual environmental bulletins of each province, and other provincial statistical yearbooks. Missing data were filled using interpolation methods. The research period spans from 2000 to 2021. To reflect the actual changes in prices, this article uses the regional gross domestic product index to deflate all nominal variables, except for relative indicators, to comparable prices with 2000 as the base year. To reduce the impact of heteroscedasticity, logarithmic processing is applied to the absolute quantity indicators.

3.1.2 Variable Selection

(1) Explanatory Variable Description

Green technology innovation (lntech). Data comes from the China National Research Data Service Platform (CNRDS), where the number of green patent applications for each province (excluding Tibet) from 2000 to 2021 is aggregated into a provincial dataset, and then the number of patent applications for each province is logarithmically processed.

(2) Core Explanatory Variable Description

Labor resource allocation efficiency. Its measurement method is detailed in previous chapters, measured by the absolute value of the difference between the degree of labor mismatch and 1. The closer the value is to 0, the higher the labor resource allocation efficiency in region i; the greater the value is greater than 0, the lower the labor resource allocation efficiency in region i.

(3) Control Variable Description

Control variables:

① Government emphasis (lngov). In China's economic development, the government plays a very important role (Lin Yifu, 2002; Lin Yifu and Liu Peilin, 2003). This article uses scientific research expenditure in fiscal spending (in ten thousand yuan) to measure the government's role in technological innovation and economic development.

② Research personnel (lnresea): Research personnel are the main body engaged in innovative activities. To eliminate the impact of the economic size on R&D funding and personnel input, this article uses the logarithm of the number of employees in scientific research and the technical service industry to measure the input of research personnel in each region.

③ Per capita GDP (ln pgdp): The original economic foundation of the region is a powerful promoter in the process of building a new science and technology city. This study selects per capita GDP to represent the economic foundation.

④ Industrial structure upgrading index (str): Industrial structure upgrading indicates the evolution of industries from lower-level forms to higher-level forms. This article adopts the proportion of the added value of the tertiary industry as the indicator for the industrial structure upgrading index, following the practices of most literature.

⑤ Financial development level (Fin): Literature research finds that financial development constraints will affect green technology innovation. Following the method of Li Aizhen et al. (2022), the ratio of the total loan balance of financial institutions to GDP is used as an indicator to measure the level of financial development.

⑥ Urbanization level (ur): The trend of urbanization can significantly concentrate local factors of production. The agglomeration effect and economies of scale promote the efficiency of resource utilization and enhance the level of green technology innovation. This article selects the proportion of urban population to total population to represent this control variable.

⑦ Transaction volume of the technology market (ln vol): The transaction volume of technology contracts is a barometer of the effectiveness of technological innovation in a region. A sound and mature technology market is conducive to the circulation of green technology elements, releasing the vitality of researchers, and enhancing the innovative development of green technology.

3.2 Descriptive Statistical Analysis

To gain an overall understanding of the data for empirical analysis of the model, this paper conducted a descriptive statistical analysis on various variables, as shown in Table 4-1. The results indicate that the average value of green technology innovation in China from 2000 to 2021 is 6.9088, with a minimum value of 1.0986 and a maximum value of 11.1163. The significant difference between the maximum and minimum values suggests that there is a considerable variation in the development of green technology innovation across different provinces in China. The average value of the labor resource allocation efficiency index is 0.4382, with a minimum value of 0.009 and a maximum value of 2.2495. The considerable difference between the maximum and minimum values indicates that there are variations in the labor resource allocation efficiency across different provinces in China, and there are also significant differences in the intensity of labor resource allocation policies implemented.

Table 1. Descriptive Statistics of Variables

Variable	Observation values	Average	Standard Deviation	Minimum value	Maximum value
Green technology innovation	660	6.9088	1.8619	1.0986	11.1163
Labor resource allocation	660	0.4382	0.4801	0.0009	2.2495
Government's level of attention	660	0.0161	0.0142	0.0022	0.0892
Research personnel investment	660	6.1501	1.2697	2.1377	9.0885
Per capita GDP	660	10.1833	0.8651	7.9226	12.1417
Industrial structure upgrading	660	0.4582	0.0908	0.2964	0.8373
Level of financial development	660	2.8957	1.1031	1.2882	8.1310
Urbanization level	660	0.5167	0.1585	0.1389	0.8960
Level of development in the technology market	660	0.0119	0.0232	0.0000	0.1750

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China National Research Data Service Platform (https://www.cnrds.com).

3.3 Model Construction

3.3.1 Spatial Autocorrelation Test

To study the relationship between the efficiency of labor resource allocation and green technology innovation based on spatial models, it is necessary to test whether the use of spatial models is reasonable. The first step is to conduct a spatial autocorrelation test. The principle of spatial autocorrelation is the first law of geography (Tobler, 1970), which states that everything is related to everything else, but things closer together are more related than things farther apart. If the empirical analysis ignores the spatial perspective, the results obtained may be biased. Therefore, it is necessary to conduct a spatial autocorrelation test to verify whether carbon emission efficiency has spatial dependence and whether the spatial econometric model is applicable. Spatial autocorrelation analysis is used to verify whether the relationship between a region and its surrounding areas in the study area is spatially positive, negative, or independent. This study uses Moran's I to conduct a spatial autocorrelation test, and its calculation method is:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{SS\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

The results of the global autocorrelation test for green technology innovation from 2000 to 2021 are shown in Table 2. The Moran's I is the measured Moran index, and Z is the Z-score. The values for each year are positive and have passed the significance test, with Z values rejecting the null hypothesis at the 1% level.

Additionally, Figures 1(a)-(d) report the Moran scatter plots for green technology innovation in the years 2000, 2007, 2014, and 2021, respectively. The scatter plot shows the distribution of green technology innovation clusters across the provinces in four quadrants: The first quadrant indicates high levels of green technology innovation both locally and in neighboring areas, representing a "high-high" cluster; the second quadrant indicates low levels of local green technology innovation but high levels in neighboring areas, representing a "low-high" cluster; the third quadrant indicates "low-low" clusters, showing low levels of green technology innovation both locally and in neighboring areas; the fourth quadrant indicates high levels of local green technology innovation but low levels in neighboring areas, representing a "high-low" cluster. From Figure 1, it can be seen that most provinces are located in the first and third quadrants, indicating a significant positive spatial autocorrelation in green technology innovation across the provinces over the years. Therefore, this study can employ a spatial econometric model.

Table 2. Global Autocorrelation Moran's I Index

Year	Moran'I	Z value	Year	Moran'I	Z value
2000	0.071***	2.925	2011	0.100***	3.752
2001	0.080***	3.191	2012	0.098***	3.671
2002	0.077***	3.135	2013	0.090***	3.457
2003	0.078***	3.139	2014	0.096***	3.614
2004	0.081***	3.295	2015	0.103***	3.802
2005	0.084***	3.322	2016	0.107***	3.897
2006	0.091***	3.492	2017	0.103***	3.781
2007	0.099***	3.729	2018	0.111***	4.011
2008	0.092***	3.498	2019	0.118***	4.210
2009	0.097***	3.644	2020	0.118***	4.195
2010	0.095***	3.591	2021	0.110***	3.983

Note. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China Research Data Service Platform (https://www.cnrds.com).

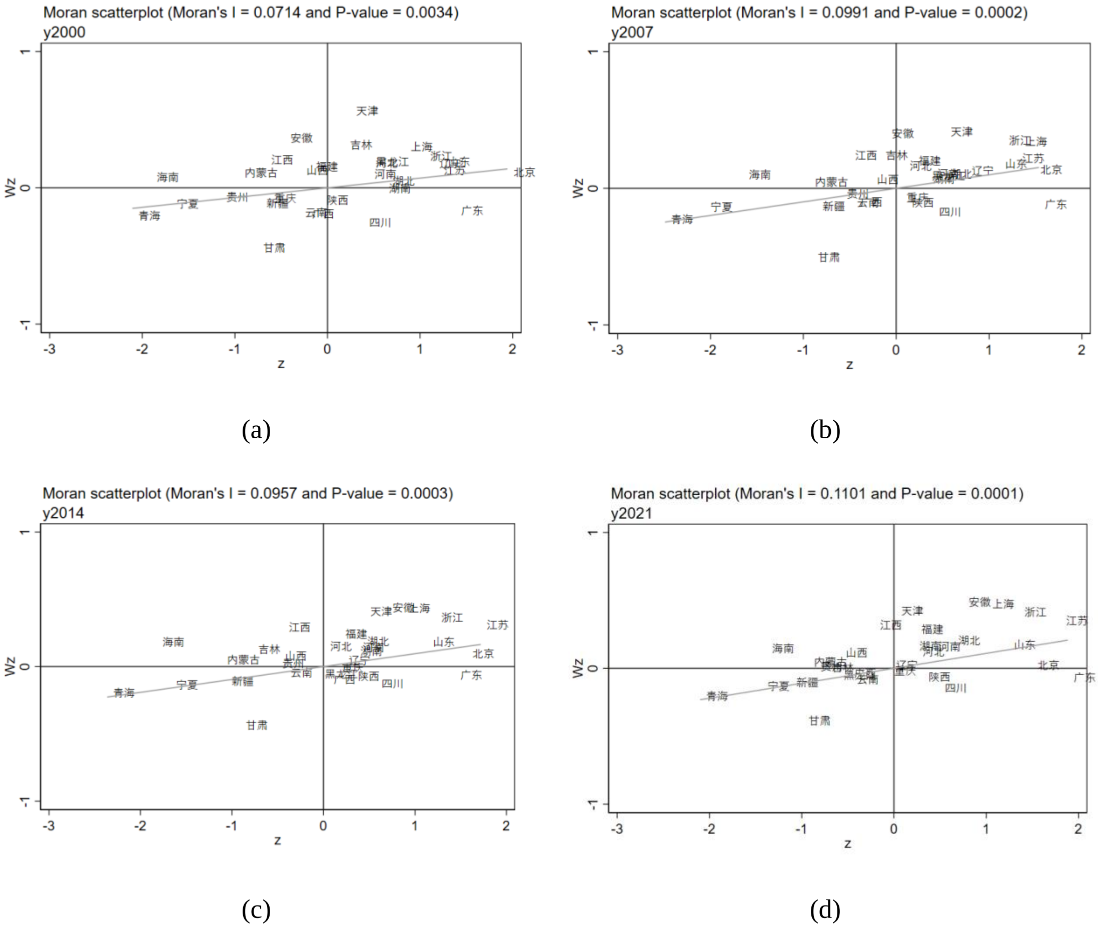

Figure 1. Scatter Plot of Moran's I index for Green Technology Innovation

3.3.2 Spatial Econometric Models and Selection Methods

After determining through the Moran index that spatial econometric models can be used in this study, the next step is to test which econometric model is more suitable. This paper sequentially carries out Lagrange Multiplier (LM) test, Likelihood Ratio (LR) test, Hausman test, and Wald test. First, by estimating the model without spatial effects using OLS, the Lagrange Multiplier (LM) and its robust statistics (R-LM) are obtained to test whether to choose a spatial autoregressive (SAR) model or a spatial error model (SEM). Second, if the LM test indicates that the panel econometric model contains spatial effects, according to Elhorst (2014), the more general SDM model can be directly used for spatial econometric estimation. Third, the Likelihood Ratio (LR) test method is used to test the fixed effects of the spatial Durbin model, to determine whether the spatial Durbin model contains spatial fixed effects (SFE). Fourth, a Hausman test is conducted on the spatial Durbin model to determine its fixed effects and random effects. Fifth, a Wald test is conducted on the spatial Durbin model to determine whether it will weaken into a SAR or SEM model. The test results are shown in Table 3, indicating that the spatial Durbin model with double fixed effects in three types of spatial weight matrices is more suitable for the spatial econometric estimation in this paper.

Table 3. Spatial Econometric Model Test Results

Testing method	Statistical value	p-value
LM-Lag	182.203	0.000
LM-Lag(robust)	128.325	0.000
LM-Error	54.021	0.000
LM-Error(robust)	0.492	0.000
Hausman	83.52	0.000
LR	108.95	0.000
Wald Test for SAR	71.44	0.000
Wald Test for SEM	75.39	0.000

Note. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China Research Data Service Platform (https://www.cnrds.com).

3.3.3 Model Specification

After the analysis above, the spatial econometric model generally chooses the fixed effects model. By comparing the coefficients, spatial auto-regression coefficients, and other indicators of individual fixed, time fixed, and double fixed models, it can be determined that the spatial Durbin model with double fixed effects is superior to the other two. The efficiency of labor resource allocation has a spatial spillover effect on green technology innovation. Therefore, the following spatial Durbin model is constructed for empirical analysis:

$$\mathrm{Ln}GT_{it} = \rho\sum_{j}^{n} W_{ij}LnGT_{it} + \alpha_0 + \beta_1 L\mathrm{n}(Xit) + \sum_{j=1}^{n} W_{ij}LnGT_{it}(X_{it})\gamma_1 + \mu_i + \lambda_t + \varepsilon_{it}$$

GTit represents the spatial effects generated by green technology innovation, Xit is the influencing factor, ρ is the spatial lag regression coefficient, which is used to measure the degree of mutual influence of innovation capability or economic development between adjacent areas, γ represents the spatial lag regression coefficient of the independent variable, when γ=0, the model can be degenerated into a spatial lag model, when γ+ρβ=0, the model can be degenerated into a spatial error model. λi represents the individual effect, μt represents the time effect, εit represents the error term, and Wij is the spatial weight matrix. According to the above description, this paper chooses the geographical distance reciprocal matrix W.

4. Analysis of Empirical Results

4.1 Analysis of Regression Results

Based on the above analysis, a spatial Durbin model is constructed to analyze the spatial spillover effects of labor resource allocation efficiency on green technology innovation. Table 4 presents the regression results of the spatial Durbin model for labor resource allocation efficiency on green technology innovation. Based on the geographical distance inverse matrix W, where Main represents the main effect, and Wx represents the spillover effect. The efficiency of labor resource allocation has an inhibitory effect on green technology innovation in the local area and a promoting effect on neighboring regions. When the degree of labor resource allocation efficiency index increases, meaning the efficiency of labor resource allocation decreases, it leads to additional increases in innovation costs and decreases in innovation benefits, thereby inhibiting the improvement of green technology innovation levels. However, an increase in the degree of the labor resource allocation efficiency index has a promoting effect on green technology innovation in neighboring regions. When the labor resource allocation efficiency index in the local area increases, neighboring regions observe the distortion of labor resource allocation caused by the decrease in efficiency, and in order to prevent the adverse effects of factor distortion on total factor productivity, they tend to engage in research and development innovation activities, thereby increasing the level of green technology innovation. Therefore, the labor resource allocation efficiency index has a positive spatial spillover effect on green technology innovation. The results of the control variables indicate that the spillover effect of per capita GDP is significantly positive. When the level of local economic development increases, it is expected to provide more support for research and development innovation to neighboring regions, promoting the improvement of green technology innovation efficiency.

Table 4. Regression Results of the Spatial Durbin Model

VARIABLES	Main	Wx	Spatial	Variance
Labor resource allocation	-0.133**	1.097**		
	(0.0636)	(0.452)		
Government's emphasis	10.47***	10.79		
	(1.366)	(6.667)		
Research personnel investment	0.00938**	-0.0509		
	(0.0071)	(0.0512)		
Per capita GDP	0.855***	0.895		
	(0.116)	(0.604)		
Industrial structure upgrading	2.020***	-1.326		
	(0.385)	(2.815)		
Level of financial development	0.150***	0.607***		
	(0.0324)	(0.173)		
Urbanization level	0.899***	6.342***		
	(0.174)	(1.146)		
Level of development in the technology market	1.126	0.969		

	(1.08)	(6.643)		
rho			-0.124**	
			(0.15)	
sigma2_e				0.0412***
				(0.00227)
Observations	660	660	660	660
R-squared	0.695	0.695	0.695	0.695
Number of code	30	30	30	30

Note. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China Research Data Service Platform (https://www.cnrds.com).

4.2 Analysis of Spatial Spillover Effects

After determining the model, based on the aforementioned analysis, the effects of explanatory variables are decomposed into direct and indirect effects to more fully observe the role of each variable. The total effect is decomposed, and the results are shown in Table 5. Both the direct and indirect effects of labor resource allocation efficiency are significantly negative at the 1% level, indicating that the increase in the labor resource allocation efficiency index has a significant inhibitory effect on the local green technology improvement. The inhibitory effect of the labor resource allocation efficiency index of neighboring areas on the green technology innovation in the local area is significant at the 10% level, indicating that the spillover effect of the labor resource allocation efficiency index is significant. From the perspective of the total effect, for every one-unit increase in the labor resource allocation efficiency index, i.e., a decrease in labor resource allocation efficiency, green technology innovation will decrease by 11.2%. The degree of government attention, per capita GDP, investment in scientific researchers, the level of financial development, the level of urbanization, and the development level of the technology market all have a significant positive effect on the local green technology improvement. The greater the support for innovation activities from government policy tilt, the more conducive it is to the smooth promotion of green technology innovation. The higher the level of economic development in a region, the more advanced the industrial structure, the greater the market vitality, the more mature the development of the technology market, the stronger the driving force for local green technology innovation. In summary, the optimization of labor resource allocation must be synchronized with increased research and development investment, economic development, the improvement of information technology and the development level of the technology market, and the perfection of the industrial structure to fully stimulate the potential for regional technological innovation.

Table 5. Decomposition Results of Spatial Durbin Model Effects

	LR_Direct	LR_Indirect	LR_Total
Labor resource allocation	-0.141**	-0.979**	-1.12*
	(0.0644)	(0.423)	(0.446)
Government's emphasis	10.37***	9.214	19.59***
	(1.326)	(6.054)	(5.837)
Research personnel investment	0.0104**	-0.0484	-0.038
	(0.0068)	(0.0459)	(0.0477)
Per capita GDP	0.847***	0.766	1.613***
	(0.117)	0.588	0.548
Industrial structure upgrading	2.006***	-0.92	-2.926
	(0.372)	(2.68)	(2.83)
Level of financial development	0.148***	0.550***	0.698***
	(0.0316)	(0.185)	(0.182)
Urbanization level	0.866***	5.687***	6.553***
	(0.176)	(1.245)	(1.318)
Level of development in the technology market	1.124**	0.441**	1.565**
	(1.051)	(5.897)	(6.09)
Observations	660	660	660
R-squared	0.695	0.695	0.695
Number of code	30	30	30

Note. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China Research Data Service Platform (https://www.cnrds.com).

4.3 Robustness Test

To test the reliability of the aforementioned results, robustness checks were conducted by replacing the spatial weight matrix and excluding outlier sample points. The matrix replaced was the spatial adjacency matrix. Considering that municipalities directly under the central government are strategic priorities for regional economic development, possessing not only superior innovative resources and economic foundations but also being more likely to receive various policy preferences and resource support, it is essential to exclude Beijing, Tianjin, Shanghai, and Chongqing to truly reflect the impact of various factors on green technology innovation. The specific results are shown in Table 4-6. It can be seen that whether it is the regression results after replacing the matrix or the regression results after excluding provincial capitals and municipalities directly under the central government, the coefficient signs and significance levels are entirely consistent with those in Table 4-3. That is, the explained variable, labor resource allocation efficiency, is significant at the 1% significance level, and the explanatory variable, green technology innovation, is significant at the 5% significance level. The correlation coefficients are -0.191 and -0.221, respectively. The inhibitory effect of the labor resource allocation efficiency index of neighboring areas on green technology innovation in the local region is significant at the 5% and 10% levels, with correlation coefficients of -0.309 and -0.252, respectively. This indicates that the impact of labor resource misallocation on green technology innovation and progress is robust. At the same time, it further demonstrates that the decline in labor resource allocation efficiency significantly hinders green technology innovation and progress in China.

Table 6. Robustness Test Results

Variable	Replace the matrix			Exclude municipalities directly under the central government		
	Main	W_1x	Spatial	Main	Wx	Spatial
Labor resource allocation	-0.191***	-0.309**		-0.221**	-0.252*	
	(0.0594)	(0.152)		(0.114)	(0.235)	
Government's emphasis	10.69***	5.400**		10.33***	10.90***	
	(1.312)	(2.138)		(1.457)	(2.288)	
Research personnel investment	0.00518	-0.0410***		0.00872	-0.0565***	
	(0.00712)	(0.0138)		(0.0075)	(0.0152)	
Per capita GDP	0.938***	0.18		0.967***	0.368*	
	(0.113)	(0.189)		(0.12)	(0.215)	
Industrial structure upgrading	-2.112***	2.291***		-2.092***	2.963***	
	(0.355)	(0.745)		(0.369)	(0.786)	
Level of financial development	0.137***	0.195***		0.194***	0.254***	
	(0.0325)	(0.0563)		(0.0388)	(0.0681)	
Urbanization level	0.435***	0.0684		1.169***	-0.422	
	(0.162)	(0.305)		(0.254)	(0.372)	
Level of development in the technology market	-2.114**	0.483		-5.593***	-4.067	
	(1.034)	(2.143)		(1.522)	(3.286)	
rho			0.147***			0.133**
			(0.055)			(0.059)
Observations	660	660	660	572	572	572

R-squared	0.702	0.702	0.702	0.649	0.649	0.649
Number of code	30	30	30	26	26	26

Note. "***", "**", and "*" denote significance at the 1%, 5%, and 10% levels, respectively.

Data source: Compiled based on materials provided by the National Bureau of Statistics (http://www.stats.gov.cn) and the China Research Data Service Platform (https://www.cnrds.com).

5. Conclusions and Recommendations

5.1 Research Conclusions

5.1.1 Over time, the overall labor resource allocation efficiency index in China has gradually decreased between the years 2000-2021, which spans 22 years. This indicates that the overall labor resource allocation efficiency has shown an upward trend, suggesting that the issue of labor misallocation has been effectively alleviated.

5.1.2 The study of the impact of labor resource allocation efficiency on green technology innovation through the spatial Durbin model shows that labor resource allocation has a significant main effect and spillover effect on green technology innovation. The results indicate that a decrease in the labor resource allocation efficiency index, which means an improvement in labor resource allocation efficiency, will promote the increase of local green technology innovation levels, while an increase in the labor resource allocation efficiency index will inhibit the increase of local green technology innovation levels.

5.1.3 The degree of government attention, per capita GDP, investment of scientific research personnel, the level of financial development, the level of urbanization, and the development level of the technology market all have a significant enhancing effect on the local green technology. The greater the support of government policy inclination for innovative activities, the more conducive it is to the smooth promotion of green technology innovation.

5.2 Countermeasure Suggestions

5.2.1 Regions should strengthen cooperation and exchanges to promote the collaborative development of green technology innovation. Based on the analysis above, it is clear that the levels of green technology innovation decrease from east to central and western regions, with the eastern region being significantly higher than the other two. Therefore, the eastern provinces and cities with higher levels of green technology innovation should lead the less developed provinces and cities around them, actively engaging in cooperation and exchanges in infrastructure and green technologies. They should establish a more orderly and open green technology trading market, thereby promoting the collaborative development of green technology innovation among regions.

5.2.2 Adopt market-oriented approaches to eliminate barriers to the autonomous and orderly flow of labor factors. First, rely on market supply and demand relationships to improve the diversified channels of innovative capital financing, increase the supply of effective financial services, leverage the inclusiveness of finance, and promote the improvement of capital allocation efficiency.

5.2.3 There are many factors that affect green technology innovation, and it is necessary to enhance the conditions that can benefit it through multiple approaches. This study finds that the level of government attention, per capita GDP, investment of scientific researchers, the level of financial development, the level of urbanization, and the development level of the technology market all play different roles in green technology innovation. Therefore, it is necessary to improve the factor market system through multiple approaches to achieve spatial growth and flow of resources, improve the efficiency of resource allocation, provide a sufficient resource base and a good institutional environment for technological innovation, and facilitate the sharing and spillover of advanced technology, which is crucial for regional technological innovation, and also beneficial for the sharing and spillover of advanced technology, which is crucial for green technology innovation.

6. Conclusion

To summarize, in the implementation of the strategy of innovation-driven development in our country, there are issues such as extensive investment and utilization methods in innovation, low quality of innovation output, and relatively low innovation efficiency. As the main platform for the agglomeration, flow, and allocation of innovative elements, the degree of perfection of the factor market will have a direct and significant impact on the efficiency of the flow and allocation of innovative elements in various regions. The measurement of the efficiency of labor resource allocation in this article helps various regions to clearly understand the current state and development level of their own labor allocation, to identify differences with surrounding regions, and to provide a reference basis for government decision-making on labor allocation. It guides resources to flow reasonably and orderly between regions, accelerating the economic innovation, coordination, and high-quality development; secondly, it explores the impact path of labor resource allocation efficiency on green technology innovation, as well as the gap in green technology innovation losses caused by the efficiency of resource allocation. It provides appropriate theoretical support and path choices for promoting the improvement of resource allocation conditions and the enhancement of green technology innovation levels, guiding the rational flow of labor resources between regions and promoting green technology innovation to drive sustainable economic development, providing policy inspiration.

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