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Empirical Study of the Spatial Spillover Effect of Transportation Infrastructure on Green Total Factor Productivity

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Abstract: Transportation infrastructure promotes the regional flow of production. The construction and use of transportation infrastructure have a crucial effect on climate change, the sustainable development of the economy, and Green Total Factor Productivity (GTFP). Based on the panel data of 30 provinces in China from 2005 to 2017, this study empirically analyses the spatial spillover effect of transportation infrastructure on the GTFP using the Malmquist–Luenberger (ML) index and the dynamic spatial Durbin model. We found that transportation infrastructure has direct and spatial spillover effects on the growth of GTFP; highway density and railway density have significant positive spatial spillover effects, and especially-obvious immediate and lagging spatial spillover effects in the short-term. We also note that the passenger density and freight density of transportation infrastructure account for a relatively small contribution to the regional GTFP. Considering environmental pollution, energy consumption, and the enriching of the traffic infrastructure index system, we used the dynamic spatial Durbin model to study the spatial spillover effects of transportation infrastructure on GTFP.

Keywords: transportation infrastructure; green total factor productivity; Malmquist–Luenberger index; spatial Durbin model; spatial spillover effect

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1. Introduction

As a kind of advanced social capital, transportation infrastructure is a necessary condition for the rapid development of a regional economy. It can drive the growth of related industries and has a wide-ranging, multi-level direct and indirect impact on the development of the national economy. The construction of transportation infrastructure is also one of the important means by which the government can carry out economic regulation. In order to pursue a more sustainable future, some governments have begun to investigate ways to promote alternative types of transportation infrastructure.

Spatial networks and spillover are the results of the social production of transport infrastructure [1,2], and due to the heterogeneity of space and time, transportation infrastructure can create entirely different dynamics of spatial spillover effects [3,4]. The effects of transportation infrastructure on regional economic growth can be divided into multiplier effects brought about by investment, direct effects brought about through accessibility, and indirect effects, such as externality [5]. The spatial spillover effect of transportation infrastructure on economic growth stems from the fact that sound transportation infrastructure will accelerate the flow of factors between regions, thereby promoting the economically-sustainable development of related regions.

The research on transportation infrastructure mainly focuses on the study of the spatial spillover effects of transportation infrastructure on economic growth or on total factor productivity; Jiang et al. (2017) and Qi (2017) found that transportation infrastructure has a certain spatial spillover effect while promoting regional economic development [6,7]; Yu et al. (2013) and Ayuso et al. (2016) argued that improving transportation facilities would

have a negative effect on the different regions [1,8]. However, the above studies ignored byproducts/undesirable outputs (e.g., SO_2 emissions and dust emissions), and lacked the measurement of green total factor productivity. In addition to this, the choice of the independent variable is mainly the transportation infrastructure stock index (e.g., road density); few scholars have considered the flu index of transportation infrastructure (e.g., road passenger density). From the perspective of research methods, the traditional model adds transportation infrastructure variables into the production functions. Recently, Peng and Wang (2019) adopted the PSM-DID (Propensity Score Matching- Difference-in-Differences) method to analyze the spatial spillover effect of transportation infrastructure and the transportation industry [9]. However, the dynamic spatial Durbin model with spatial lag is rarely used to analyze the spatial spillover effects of transportation infrastructure, or the effects of transportation infrastructure on total factor productivity. In this article, the total quantity of sulfur dioxide emissions and dust emissions are used as undesired outputs to measure the green total factor productivity, and the dynamic spatial Durbin model is used to reflect the exogenous interaction effect of transportation infrastructure on the growth of provincial green total factor productivity. The addition of combined transport infrastructure stock and flow indicators also enriches the conclusions of the existing research; this is more conducive to the reflection of the direct effects and the short-term spatial spillover effects. It was found that various types of transportation infrastructure have affected the growth of green total factor productivity, and that the degree of this impact is different.

2. Green Total Factor Productivity (GTFP)

Green Total Factor Productivity, also called green technology innovation [10], means the incorporation of resource consumption and environmental pollution as natural inputs and undesired outputs into the traditional Total Factor Productivity measurement system, in order to measure economic development trends under green and sustainable conditions. It is the behavior of creating environmentally friendly new technologies of product and process, pursuing the economic growth benefits brought about by technology innovation, and seeking the green ecological benefits of energy cleaning and emission reducing [11], and it is committed to the pursuit of a 'win–win' development pattern of the environment and economy [12].

The green transformation of the economy is closely related to the construction of sustainable infrastructure, but the negative impacts on the environment, resource pressure, high investment, and the low return rate during the construction process mean that people have to weigh the pros and cons of infrastructure construction with a cautious attitude. Transportation infrastructure is a key link in infrastructure construction, and it has a significant role in promoting environmental efficiency; sound transportation infrastructure will speed up the flow of production factors by improving the optimal allocation of resources and alleviating the distortion of the allocation of labor factors, thereby promoting the improvement of GTFP [10,11]. Meanwhile, some studies have shown that infrastructure investment and transportation infrastructure stock will have a moderate impact on GTFP, and that its restraining or promoting effect is related to the stock of infrastructure and the limit of economic development [12]; from the perspective of the non-linear relationship, there is a single threshold effect between transportation infrastructure and GTFP [13].

Green technological efficiency and progress are the key to the growth of GTFP. The growth of GTFP includes the following four factors. First is the growth of gross domestic product (GDP) [14]. The steady increase in GDP is the economic foundation for the growth of green total factor productivity. The second is technological progress; the main manifestation of technological progress is that technological innovation in high-efficiency areas promotes the movement of the production frontier. The third is efficiency improvement, which includes technological efficiency [15] and scale efficiency [16]; the improvement of GTFP can be achieved by strengthening green system innovation or by increasing green scale. The fourth is the support of policies and systems. The operation of the market cannot be separated from the support of policies and systems, and the

recognition of consumers. The balanced growth of the economy based on human-oriented thinking is an indispensable condition for the growth of green total factor productivity.

When evaluating GTFP, we should consider not only economic output, but also the by-products of economic activities, such as environmental pollutants [17]. In this paper, we take into account the balanced returns of the capital market and the ecological environment, in addition to the requirements of Cooper on the robustness of performance evaluation in 2011; meanwhile, referring to Fukuyama [18], we chose the SBM (Slack Based Model) directional distance function efficiency measurement model. The output-oriented SBM directional distance function is as follows:

$$\vec{D_v^t} = \left(x^{t,q'}, y^{t,q'}, b^{t,q'}, g^x, g^y, g^b\right) = max\beta \tag{1}$$

$$= \max_{s^x, s^y, s^b} \frac{\frac{1}{I}\sum_{i=1}^{I} \frac{s_i^x}{g_i^x} + \frac{1}{J+N}\left[\sum_{j=1}^{J} \frac{s_j^x}{g_j^x} + \sum_{n=1}^{N} \frac{s_n^b}{g_n^b}\right]}{2} \tag{2}$$

$$\text{s.t.} \begin{cases} \sum\limits_{q=1}^{Q} \lambda_q^t x_{qi}^t + S_i^x = x_{qi}^t, \forall i; \\ \sum\limits_{q=1}^{Q} \lambda_q^t x_{qj}^t - S_j^y = y_{qj}^t, \forall j; \\ \sum\limits_{q=1}^{Q} \lambda_q^t x_{qn}^t + S_n^b = b_{qn}^t, \forall n; \\ s_i^x \geq 0, \forall i; \\ s_j^y \geq 0, \forall j; \\ s_n^b \geq 0, \forall n; \end{cases} \tag{3}$$

In Equations (1)–(3), let us define: $x = I$ kinds of inputs, $x = x_i$; $y = J$ kinds of expected outputs, $y = y_j$; $b = S$ kinds of unexpected outputs, $b = b_n$; λ_q^t = sample weights for each section; $x^{t,q'}$ = input vector; $y^{t,q'}$ = expected output vector; $b^{t,q'}$ = unexpected output vector; g^x, g^y, g^b = direction vector; s^x, s^y, s^b = slack variables; on industry decision-making units based on non-radial, non-angle, and taking into consideration the undesirable output after comprehensive judgment. The Malmquist–Luenberger index is used to analyze the growth of the productivity index and the contribution of technological progress or efficiency to productivity growth. Färe et al. developed the Malmquist input-based productivity index in order to measure productivity growth in Swedish pharmacies, and—in 1994—used the Malmquist output based productivity index to analyze the productivity growth in industrialized countries and Swedish hospitals, and calculated it into technical Efficiency Change (Technical Efficiency Change, EC) and Technical Progress Index (Technical Change, TC) [19,20]. In 1997, Chung et al. applied the directional distance function containing undesired outputs to Malmquist to obtain the Malmquist–Luenberger productivity growth index [21].

The research uses 30 first-level administrative regions in China's provinces (considering the availability and continuity of basic data, the Tibet Autonomous Region, Hong Kong, Macao, and Taiwan are not included); the measurement period consists of 13 years starting in 2005 (that is, the years between 2005 and 2017); the selection of the variables of the factor input and output is consistent with the Cobb–Douglas model. The input variables include labor, capital, and natural resources. The labor input is measured by the number of employees at the end of a year. The capital input is measured by the stock of physical capital. The natural resource input is measured by the total energy consumption. Due to the choice of an earlier base year, which brings smaller errors in subsequent years, the article applies the perpetual inventory method in order to obtain the actual value of the investment at a constant price in 2000 (the base year) after deflating the fixed asset price index. Referring to the research method of Zhang Jun, the depreciation rate (for fixed assets) is 9.6% [22], and the capital stock in the base year is 10 times the total

fixed capital in that year; the GDP is selected as the variable for the desirable output, and the actual regional GDP is obtained by deflation in 2005 [22]. Because sulfur dioxide and dust compounds are the main sources of pollution in the transportation industry, and because carbon dioxide is not a harmful gas, the total emissions of sulfur dioxide, smoke, and dust [9,23] are selected as the variables for the undesirable output, according to the Chinese Environmental Economic Accounting Report and the China Statistical Yearbook on the Environment. Other relevant data came from Statistical Yearbook of China in 2006–2018, the China Statistical Yearbook on the Environment in 2006–2018, and the statistical yearbooks of each sample region.

According to the foregoing measurement method, the MaxDEA Pro software is used to calculate the growth rate of GTFP. The green productivity index (GML) is decomposed into green technological progress (GTC) and green technological efficiency changes (GEC), while green technological efficiency changes (GEC) can be decomposed into green pure technological efficiency changes (GPEC) and green scale efficiency changes (GSEC). The results of this decomposition are shown in Table 1: it shows that, after considering the resource input, undesirable output and slack variables, the resource consumption and environmental pollution have significantly reduced China's economic growth performance; the growth of green total factor productivity in China is slower than the GDP growth (during the same period, the growth rate of China's GDP is 13.16%). Although this paper does not measure the intensity of environmental regulations, the green technology progress and the green productivity index are the main driving forces of GTFP growth, and their changing trends are the most consistent. According to related research, reasonable environmental policy regulations can promote enterprise technological progress and technology to innovate to improve GTFP [10]; the income from innovation can offset or even exceed the cost of pollution control, realize innovation compensation, and ultimately strengthen the possibility of 'win-win' pollution control and economic growth [24]; this conclusion verifies the 'Porter Hypothesis' to a certain extent.

Table 1. Average green total factor productivity growth and its decomposition in the sample regions from 2005 to 2017.

Period	GML	GEC	GTC	GSEC	GPEC	GTFP
2016~2017	1.06	0.99	1.07	1.00	0.99	2.28
2015~2016	1.06	1.00	1.06	1.00	1.00	2.15
2014~2015	1.06	0.99	1.07	1.00	0.99	2.03
2013~2014	1.04	0.99	1.05	1.00	0.99	1.91
2012~2013	1.07	0.99	1.08	1.00	0.99	1.84
2011~2012	1.07	1.01	1.06	1.01	1.00	1.72
2010~2011	1.06	0.99	1.06	1.00	0.99	1.61
2009~2010	1.08	1.01	1.07	1.00	1.01	1.52
2008~2009	1.08	1.00	1.08	1.00	1.00	1.40
2007~2008	1.08	1.01	1.07	1.00	1.01	1.29
2006~2007	1.10	0.99	1.11	1.00	0.99	1.20
2005~2006	1.09	0.99	1.10	1.00	0.99	1.09
Annual average	1.07	1.00	1.07	1.00	1.00	1.67

3. Spatial Spillover Effects of Transport Infrastructure on GTFP

3.1. Variable Selection

The interpreted variable is the green total factor productivity (GTFP) of each provincial administrative region; the explanatory variable is the combination of the stock and flow indicators. The stock indexes include the density of each grade of highway, and the railway density, and use passenger and freight density as the flow index; when selecting the control variables, the article takes into account the fact that China, as a developing country, is still in the process of becoming a strong country, in which traditional and modern economies coexist; rural labor surplus cannot be properly resettled for a long time, and the degree

of the socialization of production needs to be improved. The 'non-agricultural' variable, that is, "the ratio of the output value of the secondary and tertiary industries to GDP" is selected; in addition, because 'non-physical capital' directly determines the speed of economic growth in provincial regions, the 'average years of education of the population' is selected as the proxy indicator.

With the index system of the above explained, the explained and controlled variables are shown in Table 2.

Table 2. Index system of each variable.

Category	Index		Specific Indicators	Variable Name	Unit
Interpreted variable	Green economy		Green total factor productivity	green TFP	-
Explanatory variables	Transportation infrastructure index system	stock index	Road density	Road	Km/100 square kilometers
			Off-highway density	Apart road	Km/100 square kilometers
			Highway density	Highways	Km/100 square kilometers
			First-class highway density	FstLvl RD	Km/100 square kilometers
			Second-class highway density	ScdLvl RD	Km/100 square kilometers
			Third-class highway density	ThdLvl RD	Km/100 square kilometers
			fourth-class highway density	FthLvl RD	Km/100 square kilometers
			Railway density	Railways	Km/100 square kilometers
		Flu index	Road passenger density	Rd passenger	Billion people
			Railway passenger density	Rw passenger	Billion people
			Road freight density	Rd freight	100 million tonnes
			Railway freight density	Rw freight	100 million tonnes
Control variable	'Non-agricultural' variables		The proportion of secondary and tertiary industries in GDP	Gdp	-
	Intangible capital		Average years of education of the population	Pop	Year

3.2. Construction of the Spatial Weight Matrix and Statistical Test

The degree of the correlation of the spatial section units between economic or geographic locations can be reflected by the spatial weight matrix. In order to objectively analyze the spatial correlation between the variables, to obtain more robust results, and to measure the spatial overflow of transportation infrastructure, this article draws on previous research results and constructs five types of space weight matrix (Wij), as shown in Table 3.

Table 3. Spatial weight matrix.

Index	Equation
Adjacency matrix	$W1$: $W_{ij} = \begin{cases} 0, & \text{Areas } i \text{ and } j \text{ are not adjacent} \\ 1, & \text{Areas } i \text{ and } j \text{ are adjacent} \end{cases}$
Great circle distance matrix	$W2$: $W_{ij} = \begin{cases} 0, (i = j) \\ \frac{1}{d_{ij}}(i \neq \mathrm{j}), d_{ij} = 2R \times \arcsin\left(\min\left(1, \sqrt{sin^2\left(\frac{\Delta X}{2}\right) + \cos X_i \cos X_J sin^2\left(\frac{\Delta Y}{2}\right)}\right)\right) \end{cases}$ (R: The radius of the earth; X_i and X_J represent the longitude of point i and point j on the earth respectively; ΔX and ΔY represents the longitude and latitude difference of two points respectively)
Euclidean distance matrix	$W3$: $W_{ij} = \begin{cases} 0, (i = j) \\ \frac{1}{d^2_{ij}}(i \neq \mathrm{j}), d_{ij} = \sqrt{\sum(x_i - y_i)^2} \end{cases}$ (X_i and X_J represents the theorem coordinates of space elements)
Economic spatial weight matrix	$W4$: $W_{ij} = \begin{cases} 0, (i = j) \\ \frac{1}{\lvert x_i - x_j \rvert} \end{cases}$ (x represent the proxy variable of economic development level, this article selects GDP)
Spatial Weight Matrix of Economic Distance	$W5$: $Wij = W2 \times W4$

Since the Moran I value of the yearly residuals is not significant at the residual level of 10%, the LM test of the spatial autoregressive effect, which has no spatial residual correlation, is first selected to test whether the model has a spatial substantial correlation, and then the rest of the space statistics are used to test the 'economic significance' of the transportation infrastructure variables to the explanatory variables. According to the Hausman test and the combined significance test, the type of effect is determined, and the LR significance judgment is selected for the final test. The specific test results are shown in Table 4.

Table 4. Test results.

Inspection Item	W1	W2	W3	W4	W5
LM Spatial Error	48.63 ***	171.57 ***	150.12 ***	127.641 **	48.80 ***
LM Spatial Lag	117.23 ***	297.29 ***	274.94 ***	217.36 ***	120.68 ***
Robust LM Spatial Error	7.49 ***	11.63 ***	12.88 ***	6.98 ***	7.79 **
Robust LM Spatial Lag	76.09 ***	137.34 ***	137.70 ***	76.63 ***	79.68 ***
Hausman Test	101.74 ***	23.47 *	13.97 (0.3762)	57.30 ***	41.53 ***
LR Test(SAR)	101.06 ***	50.21 ***	62.65 ***	99.51(0.649)	74.48 ***
LR Test(SEM)	176.48 ***	77.80 ***	88.33 ***		134.31 ***
Joint significance			LR statistics		
Time period fixed	361.90 ***	380.29 ***	386.21 ***	367.37 ***	415.70 ***
Spatial fixed	61.31 ***	19.96 **	20.57 ***	24.62 ***	18.05 *

Note: *, **, *** means passing the significance test at the 10%, 5%, and 1% levels.

3.3. Model Selection

As shown in the Table 4, in the joint significance test and the Hausman test of the LR statistics, W1 (0–1 adjacency weight matrix), W2 (great circle distance matrix) and W5 (Spatial Weight Matrix of Economic Distance) are significant at the 10% significance level.

Therefore, the spatial-temporal double fixed effects are selected, while the insignificant W3 (Euclidean distance matrix) at the 10% significance level is selected to use random effects; at the same time, both SAR and SEM in the LM test are significant at the 10% significance level, so the spatial Durbin model is used for the subsequent effect size analysis. According to the test results, in the LR Test (SAR), W4 fails to pass the significance at the 10% level. The spatial Durbin model can be reduced to the spatial autoregressive model; therefore, it is not included in the further analysis.

The static spatial models used to study spillover effects are mainly the spatial error model and spatial lag model. When endogenous interaction effects and autocorrelation disturbance terms cannot reasonably explain spatial effects, the spatial Durbin model—which includes both the spatial model and the spatial lag model is introduced.

Elhorst believes that each spatial unit in each observation time series and the different spatial distributions of each time point are interdependent. The direct and indirect (spillover) effects of the explanatory variables can be determined by the dynamic spatial Durbin Model. As a dynamic space model based on time series samples to assess the goodness of fit of such unpredictable spatiotemporal effects, the Dynamic Spatial Durbin Model (DSDM) can be expressed as:

$$Y_{it} = \tau Y_{\mathrm{i,t}-1} + \beta X_{it} + \delta \sum_{j=1}^{N} W_{ij} Y_{jt} + \eta \sum_{j=1}^{N} W_{ij} Y_{j,t-1} + \theta \sum_{\mathrm{i}=1}^{N} W_{ij} X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

In the Equation (4), the observed values of the dependent variable and the independent variable are Y_{it} and X_{it}; Yj, $t-1$ is the time lag term of Y; $\sum^{N} W_{ij} X_{it}$ represents the spatial lag term of X; $\sum^{N} W_{ij} X_{Jt}$ represents the spatial lag term of Y; Wij represents the Space Weight Matrix; u_i is a spatial effect; λ_t is a time effect; and ε_{it} is a spatial error term, subject to independent distribution. τ denotes the temporal lag coefficient of the X; if $\tau = 0$, the DSDM model can be simplified to the SPDM model; if $\theta = \delta = 0$, the DSDM model can be simplified to the DPDM model; if $\tau = \eta = \theta = \delta = 0$, the DSDM model can be simplified to the common panel data model.

Considering the long periodicity of the transportation infrastructure construction, this article only studies the short-term effects under the fixed effect weight matrix, and the long-term effects under the random effect weight matrix. At the same time, the article further analyzes the direct and spillover effects of transportation infrastructure by partial differentiation:

$$\left[\frac{\partial Y}{\partial X_{1\mathrm{k}}} \cdots \frac{\partial Y}{\partial X_{\mathrm{Nk}}}\right]_t = \begin{bmatrix} \frac{\partial Y_1}{\partial X_{1\mathrm{k}}} & \cdots & \frac{\partial Y_1}{\partial X_{\mathrm{Nk}}} \\ \cdots & \cdots & \cdots \\ \frac{\partial Y_N}{\partial X_{1\mathrm{k}}} & \cdots & \frac{\partial Y_N}{\partial X_{Nk}} \end{bmatrix} = (I - \delta W)^{-1} \begin{bmatrix} \beta_K & W_{12}\theta_K & \cdots & W_{1N}\theta_K \\ W_{21}\theta_K & \beta_K & \cdots & W_{2N}\theta_K \\ \vdots & \vdots & \vdots & \vdots \\ W_{N1}\theta_K & W_{N2}\theta_K & \cdots & \beta_K \end{bmatrix}$$

According to the formula: (1) the diagonal elements in the partial derivative matrix reflect the direct effects, while the non-diagonal elements reflect the indirect effects; (2) different individuals have different direct and indirect effects; (3) direct and indirect effects have nothing to do with the period.

3.4. Model Results

In view of the existence of the spatial-temporal lag terms in the dynamic spatial Durbin model, the estimation using the ordinary least squares techniques (OLS) is not accurate. Therefore, the maximum likelihood estimation (ML) is used. The results are shown in Table 5. The estimated results of the explanatory variables under each effect are similar, indicating that the subsequent research is robust.

Table 5. Coefficient estimation of dynamic spatial Durbin model.

Index	W1	W2	W3	W5
Gtfp(−1)	1.3050 ***	1.1738 ***	–	0.6678 ***
W*Gtfp(−1)	0.9986 ***	3.5793 ***	–	−1.3250 ***
Road	0.0082 **	0.1767 ***	−0.0759 ***	−0.0211 ***
Apart road	−0.0304	−1.5995 ***	2.4497 ***	1.1047 ***
Highways	6.2926 ***	42.0458 ***	41.5821 ***	−4.3626 ***
FstLvlRD	−1.4193 ***	−0.3285	−1.5530 ***	−10.2041 ***
ScdLvlRD	−2.7667 ***	−27.6498 ***	−20.6077 ***	−7.0196 ***
ThdLvlRD	−0.3515	14.8719 ***	48.1798 ***	5.1308 ***
FthLvlRD	−0.2312 ***	−1.9839 ***	2.7140 ***	0.2790 ***
Railways	13.8533 ***	116.2010 ***	143.9018 ***	43.5676 ***
Rd passenger	0.0022	0.7686 ***	0.6025 ***	0.0018
Rw passenger	0.0239 ***	0.1680 ***	0.1562 ***	0.0793 ***
Rd freight	−0.0286 ***	0.2313 ***	−0.2624 ***	0.0692 ***
Rw freight	0.0007	0.0415 ***	0.0483 ***	−0.0052 ***
Gdp	0.0124 *	0.0358 ***	0.6069 ***	−0.2288 ***
Pop	−0.0059 **	−0.0079 ***	−0.0713 ***	0.0058 **
W*Road	0.0369 ***	1.2172 ***	0.4738 ***	−0.0871 ***
W*Apart road	−0.9679 ***	−7.9955 ***	110.0544 ***	−4.0549 ***
W*Highways	16.9387 ***	495.0082 ***	3069.1330 ***	62.7593 ***
W*FstLvlRD	−1.2252	−115.5768 ***	−151.1221 ***	−43.0092 ***
W*ScdLvlRD	−9.5558 ***	−296.1458 ***	−1404.8290 ***	−24.1090 ***
W*ThdLvlRD	4.2174 ***	263.5375 ***	2313.6060 ***	27.2862 ***
W*FthLvlRD	−1.2775 ***	−16.7008 ***	213.4736 ***	−2.1571 ***
W*Railways	50.5076 ***	1346.9830 ***	7905.1810 ***	291.7889 ***
W*Rd passenger	0.1005 **	6.8967 ***	56.8705 ***	0.3067 ***
W*Rw passenger	0.0585 ***	1.2268 ***	13.1259 ***	0.2295 ***
W*Rd freight	−0.0823 ***	1.8555 ***	−1.3825 ***	−0.3008 ***
W*Rw freight	0.0058 ***	0.4909 ***	0.6526 ***	0.0229 ***
W*Gdp	0.0548 ***	0.3085 ***	30.8710 ***	−0.3527 ***
W*Pop	−0.0132 ***	−0.3806 ***	−3.6652 ***	0.0305 ***
R-squared	0.9567	0.6910	0.8183	0.8353
sigmaˆ2	0.0009	0.0008	0.0008	0.0009

Note: *, **, *** means passing the significance test at the 10%, 5% and 1% levels.

It can be seen that, except for the great circle distance matrix, the first-order lag coefficients of the explained variables under the fixed effect have all passed a significance test with a confidence level of 99%, which once again proves that there is a significant spatial-temporal dependence on the growth of GTFP in China's provincial regions. The estimated value of the coefficient of the highway and railway density and its spatial lag term is greater than 0, which shows that road and railway transportation infrastructure have immediate and lagging effects on the growth of green total factor productivity, the indirect effect of the densities of the highway, and the densities of the highway on the growth of green total factor productivity are 6.293 and 13.853 with a significant level of 1%, the reason may be that compared with expressways, high-speed railways, driven by the national 'four vertical and four horizontal' plans, have a greater positive effect on the growth of GTFP. The estimated values of the coefficients of highway and railway density and their spatial lag are the largest, which are prominent and occupy the vast majority of the shares.

The density of each level of road has a small contribution to the growth of green total factor productivity; the first-class highway and second-class highway have certain negative effects under each weight matrix; in the spatial lag term, the negative effects of the density of the first and second-class highway increased sharply under each weight, and the positive effects of the density of the third-level highway also increased significantly; the road and railway passenger and freight volume density have minor contributions to the growth of green total factor productivity; the highway freight density has a weaker negative effect

(estimated value −0.0823), and highway passenger density and its spatial lag term have obvious positive externalities.

Considering that the flow index is greatly affected by the time span, this article further explores the short-term effect value of the transportation infrastructure and its subdivisions during the study period by effect decomposition. The results are shown in Table 6.

Table 6. Decomposition of short-term effects in dynamic space Durbin model.

Short-Term Effects	W1			W2		
	Total Effect	Indirect Effect	Direct Effect	Total Effect	Indirect Effect	Direct Effect
Road	0.0313 ***	0.0264 ***	0.0049	0.3367 ***	0.2431 ***	0.0937 ***
Apart road	−0.6826 ***	−0.7560 ***	0.0734	−2.3178 ***	−1.0869 ***	−1.2309 ***
Highways	15.6524 ***	10.8560 ***	4.7964 ***	129.2778 ***	133.1483 ***	−3.8704
FstLvlRD	−1.7197 **	−0.3714	−1.3484 ***	−27.8588 ***	−42.1336 ***	14.2748 ***
ScdLvlRD	−8.3453 ***	−6.4628 ***	−1.8825 ***	−77.9827 ***	−76.7970 ***	−1.1857
ThdLvlRD	2.5783 ***	3.4198 ***	−0.8415 *	66.9641 ***	79.6143 ***	−12.6501 ***
FthLvlRD	−1.0225 ***	−0.9200 ***	−0.1025	−4.4996 ***	−3.8395 ***	−0.6601 ***
Railways	43.4860 ***	34.3401 ***	9.1459 ***	352.3039 ***	360.3361 ***	−8.0322
Rdpassenger	0.0695 *	0.0781 **	−0.0086	1.8453 ***	1.6418 ***	0.2035 ***
Rwpassenger	0.0557 ***	0.0367 ***	0.0190 ***	0.3357 ***	0.2554 ***	0.0803 ***
Rdfreight	−0.0750 ***	−0.0535 ***	−0.0215 ***	0.5016 ***	0.4127 ***	0.0889 ***
Rwfreight	0.0044 ***	0.0043 ***	0.0001	0.1282 ***	0.1323 ***	−0.0041
Gdp	0.0456 ***	0.0389 ***	0.0068	0.0831 ***	0.0726 ***	0.0105
Pop	−0.0125 ***	−0.0076 **	−0.0049 *	−0.0931 **	−0.1302 ***	0.0371 ***
Short-Term Effects	**W3**			**W5**		
	Total Effect	Indirect Effect	Direct Effect	Total Effect	Indirect Effect	Direct Effect
Road	0.0287 ***	0.1143 ***	−0.0857 ***	−0.2101 ***	−0.1738 ***	−0.0363 ***
Apart road	7.9214 ***	6.0018 ***	1.9196 ***	−5.8329 ***	−6.3719 ***	0.5390 ***
Highways	219.3397 ***	194.9359 ***	24.4038 ***	115.0899 ***	109.7105 ***	5.3794 *
FstLvlRD	−10.7128 ***	−10.0687 ***	−0.6441	−105.0123 ***	−87.0680 ***	−17.9444 ***
ScdLvlRD	−100.5516 ***	−87.6629 ***	−12.8887 ***	−61.4700 ***	−49.9928 ***	−11.4772 ***
ThdLvlRD	166.5394 ***	129.7949 ***	36.7446 ***	63.9690 ***	54.0400 ***	9.9290 ***
FthLvlRD	15.2342 ***	13.7274 ***	1.5068 ***	−3.71237 ***	−3.6677 ***	−0.0447
Railways	567.6396 ***	464.6288 ***	103.0107 ***	662.3346 ***	568.1652 ***	94.1694 ***
Rdpassenger	4.0519 ***	3.7829 ***	0.2691 ***	0.6129 ***	0.5611 ***	0.0518
Rwpassenger	0.9368 ***	0.8560 ***	0.0808 ***	0.6097 ***	0.4869 ***	0.1228 ***
Rdfreight	−0.1156 ***	0.1613 ***	−0.2770 ***	−0.4576 ***	−0.4837 ***	0.0261 *
Rwfreight	0.0495 ***	0.0012	0.0482 ***	0.0350 ***	0.0369 ***	−0.0019
Gdp	2.2197 ***	1.7688 ***	0.4509 ***	−1.1484 ***	−0.8439 ***	−0.3045 ***
Pop	−0.2632 ***	−0.2104 ***	−0.0527 ***	0.0724 ***	0.0611 ***	0.0112 ***

Note: *, **, *** means passing the significance test at the 10%, 5% and 1% levels.

Table 6 shows the results of the direct, indirect, and total effects. The effect decomposition of the combined index verifies the robustness of the coefficient estimation results, and the effect of the matrix decomposition of each weight under the fixed effects and random effects is significant. The spatial spillover effect coefficient values of all of the transportation infrastructure indicators on green total factor productivity are greater than

the direct effect; for a single province, the indirect effect is much smaller than the direct effect. In particular, the spatial spillover effect of railways on green total factor productivity is more significant than the other factors; the regression coefficients are 34.3401, 360.3361, 464.6288, and 568.1652, with a significance level of 1%. This indicates that railways, as an emerging mode of transportation, are more conducive to the promotion of the flow of production factors across the country. Moreover, the spatial spillover effects based on economic factors are higher than those based on geographic factors, meaning that economic development factors in the sample areas are more conducive to increasing the spatial spillover of the total factor productivity than geographic factors.

Comparing the weight matrix of the various types, the contribution of flow indicators to the growth of green total factor productivity is weak, but it has a significantly positive externality, indicating that the current travelers' choices produce fewer fluctuations in the development of the regional economy under the green background. Compared to investment and development in the construction of civil transportation infrastructure, transportation indicators such as passenger density or cargo density make a relatively small contribution to the regional economy under the background of resources and environment, and the short-term transportation costs are far lower than the costs of construction and maintenance, as well as environmental protection costs.

4. Conclusions and Implications

Regarding the studies of transportation infrastructure and the spatial spillover effect, the existing literature mainly focused on the related issues at the development of economics, or from the total factor productivity perspective. Studies from the green and environmental protection aspects are rare. Based on the panel data of 30 provinces from 2005 to 2017 in China, this paper analyzed the spatial spillover effects of transportation infrastructure on the growth of green total factor productivity by using the data envelopment analysis (DEA) method [25] and a dynamic spatial Durbin model. Generally speaking, the economic benefits brought by China's vigorous development of the construction of transportation infrastructure are generally sound; all of the types of transportation infrastructures have a certain effect on the promotion of the improvement of green total factor productivity in the region; however, the spillover effects of the different levels of roads on green total factor productivity are significantly different; the construction of highways and railways, especially, has significantly promoted the growth of green total factor productivity compared with the passenger density and freight density; the former has obvious immediate and lagging spatial spillover effects, and the latter has significantly positive externality. The spatial spillover effects of transportation infrastructure on GTFP are mainly achieved by the road and railway facilities, and they are less affected by the density of the passengers and freight.

4.1. Theoretical Implications

The first theoretical contribution is that we extended the selection of the output indicators; we considered the amount of sulfur dioxide, smoke and dust emissions (carbon dioxide has a greater impact on the climate and environment, but it is not a harmful gas, and is the major source of transportation industry pollution) during the construction and use of transportation infrastructure, and measured the green total factor productivity. Moreover, we chose the dynamic spatial Durbin model to analyze the short-term effects of transportation infrastructure; it not only satisfies the external characteristics of transportation infrastructure, but also reflects the lag effect of transportation infrastructure on green total factor productivity, and is therefore more applicable. Furthermore, this article expanded the research index system [26]; the flow indexes (passenger density and freight density) were added to the existing traffic infrastructure stock index, which made the variable index system more perfect, and can reflect the direct effects and spatial spillover effects of the traffic infrastructure in the short term.

4.2. Practical Implications

First, in the process of advancing the construction of transportation infrastructure, each region should pay attention to the construction intensity of the transportation infrastructure of neighboring provinces and the development level of the road network, and should rely on the spatial spillover effects of the transportation infrastructure of the surrounding provinces and trade factor flows to promote the agglomeration and diffusion of economic activities in the region. Provinces can measure and calculate the spatial spillover effects of transportation infrastructure between districts and counties, and combine the significance of the spillover effects to rationally plan the structure of the transportation network in order to achieve regionally-coordinated development.

Second, different cities have differences in their economic development levels and geographic locations; the government should formulate differentiated policies in order to accelerate the formation of urban agglomerations linked by highways, improve the level of urban specialization, and realize the development of regional economic integration. High-speed rail construction should also play a further role in promoting economic growth in the region, while reducing the loss of high-quality resources, continuously acquiring innovative ideas and advanced technologies in developed regions, actively undertaking industrial transfers in developed regions, and coordinating and improving regional economic models.

Finally, the country and government should adjust the industrial structure in a timely manner, control the scale of the industry, and increase the scale efficiency of transportation infrastructure investment. Meanwhile, whilst accelerating the construction of transportation infrastructure, a green transportation system with "zero-distance transfer and seamless connection" should be established, which will then give full play to the economic diffusion effect and achieve high-quality economic development, but attention should be paid to the construction density of all grades of roads.

4.3. Limitation and Future Research

The spatial weight matrix is mostly based on existing research results, and lacks the verification of the matching degree of each weight matrix; subsequent studies could compare and verify them in order to determine the optimal spatial weight matrix; secondly, due to the unavailability of some data, the high-speed railway density refinement indicators are not deep enough. In addition, the impact of spatial spillover effects is affected by the level of opening up and R&D expenditures, etc.; as such, the indicator system needs to be further improved in future research.

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