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A Study on the Impact of Data Elements on Green Total Factor Productivity in China's Logistics Industry

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Abstract

This study aims to explore whether and how data elements affect the green total factor productivity (GTFP) of China's logistics industry, and conducts empirical tests using the super-efficiency SBM model, Malmquist exponential model, and spatial Dubin model. Based on the relevant data of 30 provinces in China from 2013 to 2021, we employ the Super-efficiency SBM model and the Malmquist dynamic index model to calculate the green total factor productivity of the logistics sector. We then establish a three-tier evaluation framework for data elements, employ the entropy method to determine the weighting of each indicator, and utilize linear weighting to calculate the comprehensive evaluation value of data elements. By incorporating appropriate control variables and employing the spatial Durbin model, this study examines the impact of data elements on the GTFP of the logistics industry. It is found that data elements have a contributing effect on improving GTFP of the logistics industry in the local region as well as a positive spillover effect on the neighboring regions, and this is achieved by improving the level of technical progress. In addition, the coefficients are decomposed into direct, indirect, and total effects by partial differentiation, again verifying the above conclusions. This study investigates the impact of data elements on GTFP in the logistics industry from theoretical mechanisms and empirical tests, and analyzes the dual impact of data elements and other factors on the local region and neighboring regions. The findings of this study can provide references for better empowering the development of the logistics industry with data elements.

Keywords: data elements; digital economy; green total factor productivity; high-quality development of the logistics industry; spatial Durbin model



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1. Introduction

At present, China's economy is entering a new normal, and the focus of development shifts from high-speed growth to high-quality development. The traditional crude economic model needs to be transformed urgently, and it is imperative to achieve sustainable development. The core of this lies in improving total factor productivity, so that the overall effect of the contribution of each production factor to economic growth is greater than the sum of partial inputs. Especially in the face of serious environmental problems and resource scarcity, increasing green total factor productivity (GTFP) is crucial for economic transformation [1]. As a key link in economic development, the logistics industry carries the entire chain of social production, distribution, and consumption. However, the logistics industry's high energy consumption and environmental pollution problems have become a major challenge to its green development. With the booming development of the digital

economy, the value of data, a new type of production factor, is becoming more and more prominent, injecting new momentum into the low-carbon transformation of the logistics sector. In the context of the 'dual-carbon' goal, relying on data to empower green technologies and driving the digital transformation of the logistics industry has become crucial for enhancing its green, low-carbon efficiency and production levels.

How to use data elements to drive the green upgrading of the logistics industry and promote the unity of economic and ecological benefits has become a key topic currently attracting significant attention within academic circles. To start with, as the 'oil' in the era of digital economy, 'data' has become an important resource and production factor. Previously, more foreign scholars associated data and information [2,3], and later gradually extracted 'data' from the 'information' as an overly broad concept and gave it a special status. Farboodi and Veldkamp [4] pointed out that data is different from information: data is a kind of information that can be used to reduce prediction errors. On this basis, the definition of data elements and data is different. In the era of digital economy, data plays a fundamental and critical role in production activities, the nature of the production factor of it is becoming more and more prominent, so it is gradually and universally recognized as a new type of production factor [5]. Currently, Scholars have highlighted the enabling role of data elements across various industries [6,7]. Some researchers have also focused on its role in promoting green development within industries [8,9]. However, few scholars noted that data elements differ from traditional factors of production such as labor, capital, and land. They possess characteristics including replicability, unlimited scalability, non-exclusivity, and increasing returns to scale [10], capable of generating spillover effects on the industrial and economic development of neighboring regions.

Furthermore, numerous scholars have focused on GTFP of the logistics industry, with related research primarily concentrated in the following areas. First, regarding the measurement and indicator selection for GTFP, the mainstream methods currently include the Stochastic Frontier Analysis (SFA) parametric approach and the Data Envelopment Analysis (DEA) nonparametric approach. Building upon these, the Malmquist index model and the super-efficiency SBM model [11,12] are widely applied to address more practical issues. Second, regarding the analysis of the current status of GTFP in the logistics industry, scholars examined this metric at various levels—including provincial [13,14] and economic zone [15] scales—based on the natural and social characteristics of different regions. Third, studies on the determinants of GTFP in the logistics industry revealed that environmental regulations [16], urbanization [17], industrial agglomeration [14], and foreign direct investment [14] are all significant factors influencing GTFP in the logistics industry.

Finally, regarding the impact of data elements on the green development of the logistics industry, many scholars argued that the transformation and upgrading of modern logistics relies on horizontal collaboration [18] and artificial intelligence innovation [19]. However, data elements serve as the critical "fuel" enabling such collaboration and intelligent innovation. Research indicated that digital transformation exerts a positive influence on logistics sustainability [20]. The implementation of digital technologies significantly enhances the competitiveness of logistics management within commercial environments [21], while also driving the efficient integration of data elements and the rapid iteration of digital logistics technologies. This effectively strengthens logistics resilience [22]. Li and Wang [23] pointed out that the digital economy holds significant practical importance for promoting carbon emission reductions in the logistics industry. Jia F et al. [24] discovered a U-shaped relationship between the digital economy and the GTFP within the transport industry. Duan [25] found that the digital factor resource endowment has a significant positive impact on the expansion and quality improvement of the commerce and circulation industry, and the positive empowering effect on high-quality development is stronger than the scale

of development. Regrettably, existing studies have predominantly focused on the digital economy itself, with scant attention paid to its crucial component—data elements. Studies specifically examining the relationship between data elements and the green development of the logistics industry remain scarce, and most remain confined to theoretical analysis rather than empirical research.

In summary, existing literature provides a crucial foundation for this study, yet certain limitations remain. Based on this, this study integrates data elements, GTFP measurement, and spatial spillover effects into a unified framework. By quantifying data elements and GTFP in the logistics industry and constructing a spatial econometric model, we examine the dual impact of data elements on both local and neighboring regions' GTFP in the logistics industry. This research provides a robust theoretical foundation and empirical support for formulating relevant policies. Compared to existing literature, this paper offers three potential marginal contributions. (1) We develop a comprehensive data element evaluation index system from novel perspectives and empirically analyze the impact of data elements on GTFP of the logistics industry and its underlying mechanisms. (2) Based on the characteristics of fast transmission speed and wide radiation range of data elements, we apply the spatial Durbin model to study the direct impact of data elements on the local area and the spillover effect on the adjacent area. (3) We decompose GTFP of the logistics industry into technical progress and technical efficiency, and investigate the mechanism linking data elements to technical progress and technical efficiency.

The remainder of this paper is structured as follows: Section 2 presents a theoretical analysis of the impact of data elements on the GTFP of the logistics industry, and formulates the research hypotheses. Section 3 outlines the empirical model required for analysis, describing the relevant variables and data. Section 4 conducts empirical testing and analyzes the results to validate the research hypotheses. Section 5 discusses the similarities and differences between the findings of this study and existing studies. Section 6 shows the conclusions of the study, offers policy recommendations, and notes the limitations of the research.

2. Theoretical Analysis and Research Hypothesis

2.1. The Direct Impact of Data Elements on GTFP in the Logistics Industry

Through analyzing the application of data in the logistics industry, it is found that data elements can enhance the GTFP of the logistics industry and have a dual impact on the region and neighboring regions. The specific performance is as follows:

First, the integration of data elements with the entire operation process of the logistics industry optimizes the site selection, transportation, warehousing, and other links, improves the level of intelligent decision-making, reduces environmental pollution, and enhances the GTFP of the logistics industry. Secondly, data elements promote market stability and sustainable development by optimizing supply and demand matching, thereby improving the GTFP of the logistics industry. Finally, the integration of data elements and traditional production factors optimizes the factor structure and accelerates the change in production mode.

Based on this, the first research hypothesis of this study is proposed:

Hypothesis 1. *Data elements have a promoting effect on green total factor productivity growth of the logistics industry in the local region and also have a positive spillover effect in neighboring regions.*

2.2. Intrinsic Reasons for Data Elements to Improve GTFP in the Logistics Industry

Based on the characteristics of data elements, the intrinsic reasons for data elements to increase the GTFP of the logistics industry are attributed to the promotion of technical progress, which is reflected in the following:

On the one hand, the sharing and availability of data elements reduce the cost of information acquisition and technology upgrading, and promote the green development of logistics facilities. On the other hand, data elements need to rely on technology to be transformed into valuable resources.

Based on this, the second hypothesis of this study is proposed:

Hypothesis 2. *The catalyst for data elements to enhance the green total factor productivity of the logistics industry is to improve the level of technical progress.*

3. Research Design

3.1. Methodology

3.1.1. GTFP Calculation Model for Logistics Industry

- Super-efficiency SBM model

Tone [26] proposed the SBM model in 2001, which is a non-radial and non-angular efficiency evaluation method. The model overcomes the bias of traditional methods by introducing slack variables and optimizing efficiency values. However, the SBM model cannot further evaluate and compare effective decision-making units with an efficiency value of 1. To solve this problem, the advantages of the super-efficiency model and the SBM model can be combined, so the super-efficiency SBM model was proposed [27].

The number of decision-making units (DMUs) is n ($n \in [1, 30]$). Each DMU has three characteristic variables: input, desirable output, and undesirable output, which are set as $x \in R^m$, $y^g \in R^{s_1}$, $y^b \in R^{s_2}$, respectively. The input variable matrix X , the desirable output matrix Y^g and the undesirable output matrix Y^b are:

$$X = [x_1, \dots, x_n] \in R^{m \times n} > 0 \quad (1)$$

$$Y^g = [y_1^g, \dots, y_n^g] \in R^{s_1 \times n} > 0 \quad (2)$$

$$Y^b = [y_1^b, \dots, y_n^b] \in R^{s_2 \times n} > 0 \quad (3)$$

For the k -th DMU, the calculation method of the super-efficiency SBM model, including undesirable outputs, is as in Equation (4):

$$p^* = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{ik}}}{1 - \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{rk}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{rk}^b} \right)} \quad (4)$$

$$\text{s.t.} \begin{cases} \sum_{j=1, j \neq k}^n \lambda_j x_{ij} - s_i^- \leq x_{ik}, i = 1, 2, \dots, m \\ \sum_{j=1, j \neq k}^n \lambda_j y_{uj}^g + s_u^g \geq y_{uk}^g, u = 1, 2, \dots, s_1 \\ \sum_{j=1, j \neq k}^n \lambda_j y_{vj}^b - s_v^b \leq y_{vk}^b, v = 1, 2, \dots, s_2 \end{cases} \quad (5)$$

In Equation (4), m is the number of input variables, s_1 and s_2 are the number of desirable output and undesirable output variables, respectively, x_{ik} represents the i -th input variable of the k -th DMU, y_{uk}^g represents the u -th desirable output variable of the k -th DMU, S^- , S^g and S^b are the input variables, desirable and undesirable output slack

variables, λ is the weight vector, and the objective function value p represents the GTFP of the logistics industry.

The three inequality constraints are transformed into matrix form as follows:

$$\text{s.t.} \begin{cases} XE(K(0))\lambda - S^- \leq x_{\cdot k} \\ -Y^g E(K(0))\lambda - S^g \leq -y_{\cdot k}^g \\ Y^b E(K(0))\lambda - S^b \leq y_{\cdot k}^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0 \\ \lambda \geq 0 \end{cases} \quad (6)$$

where $E(K(0))$ is to set the k -th column of matrix X to 0. The introduction of $E(K(0))$ is just to facilitate the expression of the model in the form of matrices; in practice, one does not need to deliberately multiply such a matrix. Directly, the k th column can be set to 0.

- Malmquist dynamic index model

In order to verify the intrinsic reasons for data elements to improve GTFP in the logistics industry, we need to further decompose GTFP. Using the Malmquist dynamic index model, total factor productivity can be further decomposed into efficiency change (ECH) and technical progress change (TCH) [28], so we apply the Malmquist index model to explain the factors affecting the change in total factor productivity, see Equation (7):

$$\text{TFPCH} = \text{ECH} \times \text{TCH} = \frac{D_k^{t+1}(x^{t+1}, y^{t+1})}{D_k^t(x^t, y^t)} \times \left[\frac{D_k^t(x^{t+1}, y^{t+1})}{D_k^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_k^t(x^t, y^t)}{D_k^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (7)$$

In Equation (7), ECH is the rate of change in technical efficiency between two periods under the established technical conditions, indicating the degree of catching up of the actual production point to the production possibility boundary in the current period. It is generally used to explain the efficiency of resource allocation and the amount of savings on input factors. $\text{ECH} > 1$ indicates that the technical efficiency has improved compared with that of the previous year. TCH is the rate of change in technical progress between two periods under the condition of unchanged inputs. $\text{TCH} > 1$ indicates that the level of technical progress has improved compared with the previous year, and the current production possibility frontier (or optimal output level) has expanded outward, which is mainly achieved through technological research and development or technology introduction. If either ECH or TCH is greater than 1, this indicates that it has made a positive contribution to the increase in total factor productivity and is the main reason for the increase in total factor productivity, if it is less than 1, it indicates that it is the main reason for the decrease in total factor productivity.

3.1.2. The Test Model of the Impact of Data Elements on GTFP in Logistics Industry

When studying the impact of data elements on the GTFP of the logistics industry, if the traditional regression model is used, ignoring the spatial interaction of the explanatory variables and the explained variables in the neighboring regions is not in line with reality. Therefore, the spatial Durbin model (SDM) is introduced to consider the endogenous interaction effect of the dependent variable and the exogenous interaction effect of the independent variable at the same time. It is more in line with the reality that the GTFP of the logistics industry is affected by both the explanatory variables and control variables of the local province and city, and is also affected by the variables of other neighboring regions. The spatial Durbin model is constructed based on the selected core explanatory variable data elements and control variables, as shown in Equation (8), where $GTFP_{it}$ is the explained variable, representing the GTFP of the logistics industry of each decision-making

unit, DA_{it} is the core explanatory variable, $\beta_1 \sim \beta_{10}$ are the regression coefficients of the core explanatory variables and control variables, ρ is the spatial autoregression coefficient of the explained variable, W_{ij} is the spatial weight matrix, $\theta_1 \sim \theta_{10}$ are the spatial lagged regression coefficients of the explanatory variables and control variables, μ_i , λ_t and ε_{it} are the spatial effect, time effect and random disturbance terms, respectively.

$$\begin{aligned}
 GTFP_{it} = & \rho \sum_{j=1}^n W_{ij} GTFP_{jt} + \beta_1 DA_{it} + \beta_2 GOVN_{it} + \beta_3 OPEN_{it} + \beta_4 FDI_{it} \\
 & + \beta_5 GATH_{it} + \beta_6 CITY_{it} + \beta_7 INS_{it} + \beta_8 IND_{it} + \beta_9 LOGS_{it} \\
 & + \beta_{10} STRU_{it} + \theta_1 \sum_{j=1}^n W_{ij} DA_{jt} + \theta_2 \sum_{j=1}^n W_{ij} GOVN_{jt} \\
 & + \theta_3 \sum_{j=1}^n W_{ij} OPEN_{jt} + \theta_4 \sum_{j=1}^n W_{ij} FDI_{jt} + \theta_5 \sum_{j=1}^n W_{ij} GATH_{jt} \\
 & + \theta_6 \sum_{j=1}^n W_{ij} CITY_{jt} + \theta_7 \sum_{j=1}^n W_{ij} INS_{jt} + \theta_8 \sum_{j=1}^n W_{ij} IND_{jt} \\
 & + \theta_9 \sum_{j=1}^n W_{ij} LOGS_{jt} + \theta_{10} \sum_{j=1}^n W_{ij} STRU_{jt} + \mu_i + \lambda_t + \varepsilon_{it}
 \end{aligned} \quad (8)$$

3.2. Variable Measurement

3.2.1. Explained Variable

With reference to relevant literature on GTFP, we construct an ‘input-output’ indicator system for calculating GTFP of the logistics industry, in which the input indicators include labor, capital, logistics network mileage, and energy consumption; the desirable output indicators include logistics industry added value, cargo turnover, and freight transport volume; and the undesirable outputs are carbon emissions. Regarding the selection of the number of indicators, since the data envelopment analysis method used to measure GTFP has a degree of freedom requirement, it is generally required that the number of decision-making units K and the number of input indicators M and output indicators N should satisfy the relationship: $2(M + N) \leq K$, otherwise the credibility of the evaluation results will be reduced [29]. At present, the number of decision-making units is 30 for provinces, cities, autonomous regions, and the number of input indicators of the evaluation indicators is 3, and the number of output indicators is 4, which meets the requirements. Specific indicator descriptions and variable selection are as follows:

- Input indicators and data description

(1) Labor input: Labor input is an input factor that combines labor efficiency and labor quantity [30], but in practice, there is a lack of quantitative data on labor time and labor efficiency indicators. Therefore, referring to the practice of most literature, without considering the specific type and quality of labor, this study selected the number of employees in the transportation, warehousing, and postal industries of urban non-private units in each province at the end of the year as the labor input indicator of the logistics industry.

(2) Capital input: Using the perpetual inventory method, based on fixed asset investment data, the capital stock at constant prices over the years with 2013 as the base period is calculated, as shown in Equation (9):

$$K_{i,t} = K_{i,t-1}(1 - \delta) + I_{i,t} \quad (9)$$

In the equation, $K_{i,t}$ is the capital stock of logistics industry in year t of region i , $K_{i,t-1}$ is the fixed capital stock in year $t - 1$ of region i , $I_{i,t}$ is the current investment in period t of region i , δ is the capital depreciation rate, and the specific descriptions of each variable are as follows:

① Capital depreciation rate δ : 5.42% is selected as the capital depreciation rate of the logistics industry [31].

② The current year investment flow $I_{i,t}$: Common indicators of investment in the current year include accumulation, fixed asset investment, gross fixed capital formation, etc. [32], but based on the availability and uniformity of data, the fixed asset investment in the logistics industry at constant price after deflating the fixed asset investment price index is selected as the indicator of investment flow of the current year [30].

③ Base period capital stock K_0 : Since the perpetual inventory method calculates the current period capital stock based on the previous period capital stock and the current period investment flow, this recursive method needs to determine the base period capital stock first. Methods for estimating the base period capital stock include the growth rate estimation method, the investment backtracking method, etc. [33]. Among them, the growth rate estimation method is a dynamic calculation method based on the assumption that the average growth rate of capital stock and investment is equal under the steady state of the economy. It is less affected by subjective influences and is simple and intuitive. Many scholars [34–36] have adopted this method. The calculation formula is as follows:

$$K_0 = \frac{I_0}{g + \delta} \quad (10)$$

where K_0 is the capital stock in the base year 2013, I_0 is the fixed asset investment in the logistics industry in the base year 2013, g is the average annual growth rate of fixed asset investment, δ is the depreciation rate.

(3) Logistics network mileage: Infrastructure construction is an important component of production factors. The most important infrastructure in the logistics industry includes logistics network mileage. The railway, highway, and water transport mileage are uniformly converted into highway mileage and then summed to represent the logistics network mileage [37].

(4) Energy input: The seven most common and one-time energy consumption in the logistics industry are raw coal, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and natural gas. The above energy consumption is uniformly converted into standard coal and summed up to obtain the energy input of the logistics industry in the region [38]. The conversion coefficients of various energy sources into standard coal are shown in Table 1. The data comes from the energy balance table of each region in the “China Energy Statistical Yearbook”.

- Output indicators and data description

Table 1. Reference table of carbon emission estimation coefficient.

Energy Type	Average Low Calorific Value	Carbon Emission Coefficient	Carbon Oxidation Factor	Converted Standard Coal Coefficient
Raw coal	20,908 kJ/kg	25.8 kgC/GJ	0.94	0.7143 kgC/kg
Gasoline	43,070 kJ/kg	18.9 kgC/GJ	0.98	1.4714 kgC/kg
Kerosene	43,070 kJ/kg	19.6 kgC/GJ	0.98	1.4714 kgC/kg
Diesel	42,652 kJ/kg	20.2 kgC/GJ	0.98	1.4571 kgC/kg
Fuel oil	41,816 kJ/kg	21.1 kgC/GJ	0.98	1.4286 kgC/kg
Liquefied petroleum gas	50,179 kJ/kg	17.2 kgC/GJ	0.98	1.7143 kgC/kg
Natural gas	38,931 kJ/m ³	15.3 kgC/GJ	0.99	1.3301 kgC/m ³

(1) Output of the logistics industry: Following the academic convention, the added value of the transportation, warehousing, and postal industries is used as the output indicator of the logistics industry. At the same time, in order to eliminate the impact of

price changes, we took 2013 as the base year and used the GDP index of transportation, warehousing, and postal services in the GDP index to price-deflate the data for 2014 and later years.

(2) Cargo turnover and freight volume: In addition to the added value of the logistics industry, which is an economic output, cargo turnover and freight volume reflect the scale of social demand for the logistics industry and are not affected by price factors. They are a kind of scale output in physical form [38].

(3) Undesirable output: environmental pollution in the logistics industry. The logistics industry is a service industry, and the type of pollutant emissions is not as complex as those in the industrial or manufacturing industries. The pollutants mainly come from carbon oxides generated during transportation, especially carbon dioxide. In the study of GTFP in the logistics industry, scholars generally regard carbon dioxide emissions generated by various fuel consumption as undesirable outputs of the logistics industry [39].

At present, the official data on carbon dioxide emissions have not been published, and the data published in the International Greenhouse Gas Emissions Database do not conform to China's specific situation. Therefore, it is necessary to estimate the carbon dioxide emissions from the one-time energy consumption of the logistics industry. The commonly used method is to combine the coefficients given in the IPCC (2006) Carbon Emission Calculation Guidelines and adopt the reference method for carbon dioxide emissions estimation recommended by the Intergovernmental Panel on Climate Change of the United Nations. The formula is as follows:

$$\text{CO}_2 = \sum_{i=1}^7 E_i \times \text{NCV}_i \times \text{CEF}_i \times \text{COF}_i \times \frac{44}{12} \quad (11)$$

where E_i represents the consumption of the i -th energy, including the 7 energy types mentioned in the energy input index, NCV_i represents the average low calorific value of the i -th energy (unit: kJ/kg), from the "China Energy Statistical Yearbook", CEF_i represents the carbon emission coefficient (unit: kgC/GJ), COF_i represents the carbon oxidation factor, 44 and 12 are the molecular weights of carbon dioxide and carbon. The specific values are shown in Table 1.

3.2.2. Explanatory Variables

The existing theoretical literature has a relatively rich explanation of the conditions and process of data element generation, formation mechanism and value evolution, and its form transformation at different stages of production activities [40–42]. By combing through the above literature, we constructed four secondary indicators across four dimensions: data element flow, data subject capabilities, data industry ecology, and resource support. These include data element transportation [43], data element resource processing and asset trading, data element value transformation, and scenario application [42], and data element development potential [25]. Then, combined with existing empirical research and taking data availability into consideration, we refined the third-level indicators and selected appropriate representation variables. In terms of indicator weighting, we first performed dimensionless processing on indicators from different units, then employed the entropy method to objectively assign weights to the evaluation indicators. Finally, using the linear weighting method, we calculated the comprehensive evaluation values of data elements for China's 30 provinces, municipalities, and autonomous prefectures from 2014 to 2021.

- Data element transportation level

First, data is a new type of production factor, and liquidity is an important attribute for production factors to participate in production activities and distribution in the market, and it is also an important way to realize the transformation and value evolution of data from

“resources” to “assets”, then to “commodities” and even “capital”. Therefore, based on the perspective of data flow, three indicators, including Internet broadband access ports [44,45], the number of domain names [45], and mobile Internet access traffic [44], are selected from the perspective of data carrying traffic to measure the level of data element carrying [43].

- Data element resource processing and asset trading level

Secondly, data starts from the initial scattered state and goes through the stages of collection, storage, coordination, and resource utilization. In this process, market subjects such as individuals and enterprises use a variety of technical means to collect, organize, and analyze data on demand, so that it can be transformed into production factors with actual value. Therefore, based on the data subject’s ability and technology utilization perspective, two dimensions are differentiated by subject from client-side data generation and enterprise-side data processing [43]. The number of web pages [25,44,45], Internet broadband access users [44,45], and mobile phone penetration rate [44,45] are used to measure the scale of client data resources. The number of computers used by enterprises per 100 people [43,45], the proportion of enterprises with e-commerce transactions [43,45], and the number of employees in information transmission, software, and information technology service industries [43] are used to measure the demand conversion and productivity conversion capabilities of the enterprise side, so as to indicate the level of resource processing and asset transaction of data elements [42].

- The ability of data element value transformation and scenario application

In addition, data resource processing and asset trading are aimed at promoting the comprehensive application of data elements in various economic and social scenarios, thereby promoting the upgrading of industrial value and economic growth. Therefore, based on the perspective of industrial ecology, the value transformation and scenario-based application capabilities of data elements [42] are measured from the two dimensions of digital industrialization and industrial digitization [46]. Four industries with clear data element application scenarios and high dependence on data elements are selected, namely the software industry, telecommunications industry, express delivery industry, and e-commerce industry. The total amount of telecommunication business [47] and the software business revenue [45] of the first two industries’ economic output represents the data value of the information industry, and the output of e-commerce sales [43] and express business revenue [43] of the latter two industries represent the economic value created and transformed by data elements in the application scenarios of the real industry.

- Data element development potential

Finally, as a production factor, the development potential of data elements is also an important aspect for it to give full play to its factor value and further transform into productivity. Therefore, based on the resource support of data elements, from the perspectives of technical support and economic support, we select the number of domestic invention patent authorizations [25,47], research and development (R&D) expenditures [25], and local fiscal science and technology expenditures [25] to measure the development potential of data elements [25].

3.2.3. Control Variables

In the relevant literature [1,48,49] studying the influencing factors of green and low-carbon efficiency in the logistics industry, most of them consider the government, economy, industry, transportation, and other perspectives. The following nine control variables were selected after comprehensive consideration (Table 2).

Table 2. Selection of Control Variables.

Variable name	Notation	Representation Indicator
Government norms	GOVN	The proportion of local general public budget expenditure to the local GDP
Open to the outside world	OPEN	The proportion of total import and export trade to GDP
Foreign direct investment	FDI	The proportion of total foreign investment to GDP
Logistics industry gathering	GATH	Location entropy
Urbanization rate	CITY	The proportion of urban population in the total population of the region
Industry structure	INS	The proportion of the tertiary industry in GDP
Industrialization level	IND	The proportion of the secondary industry in GDP
Logistics strength	LOGS	The ratio of total logistics turnover to regional GDP
Transport structure	STRU	The proportion of road transport in total turnover

(1) Government norms (GOVN): The appropriateness of government norms directly influences industrial infrastructure development, resource allocation, and sectoral regulations. Local protectionism tends to create regional barriers, diminishing the efficiency of the logistics industry. The proportion of local general public budget expenditure to the local GDP is selected as an indicator of GOVN.

(2) Open to the outside world (OPEN): Expanding foreign trade can stimulate logistics demand, broaden market coverage, and promote cross-industry synergy, thereby enhancing the development level of the logistics industry. However, it may also intensify domestic market segmentation, hinder the flow of production factors, and reduce logistics efficiency. The proportion of total import and export trade to GDP is selected as an indicator of OPEN.

(3) Foreign direct investment (FDI): Within the dual circulation framework, FDI introduces advanced technologies and management concepts locally, thereby elevating the green development level of the logistics industry. Conversely, foreign entry creates competitive pressure on domestic enterprises, squeezing their market space and potentially introducing monopoly risks, which may hinder factor mobility and efficiency gains. The proportion of total foreign investment to GDP is selected to indicate the level of FDI.

(4) Logistics industry gathering (GATH): Industrial gathering may generate positive economies of scale, spillover effects, and negative crowding effects. The logistics industry gathering significantly impacts the GTFP of the logistics industry. Positive economies of scale can promote factor synergy and industrial innovation, while negative crowding effects lead to resource misallocation and reduced industry efficiency. Location entropy LQ_{ij} represents GATH, calculated as follows:

$$LQ_{ij} = \frac{q_{ij}/q_j}{q_i/q} = \frac{q_{ij}/\sum_{j=1}^m q_{ij}}{\sum_{i=1}^n q_{ij}/\sum_{i=1}^n \sum_{j=1}^m q_{ij}} \quad (12)$$

where LQ_{ij} is the location entropy of industry i in region j in the country. The larger the value, the higher the level of industrial gathering in the region. q_{ij} is the output value of industry i in region j , q_j is the output value of all industries in region j , q_i is the output value of industry i nationwide, and q is the output value of all industries in the country. Generally, when $LQ_{ij} > 1$, it means that the economy of industry i in region j has certain advantages in the country, and when $LQ_{ij} < 1$, it means that the economy of industry i in region j has disadvantages in the country.

(5) Urbanization rate (CITY): Cities typically surpass rural areas in transportation infrastructure development and density, enabling more efficient movement of resources and providing space for the logistics industry to upgrade and transform. This facilitates a shift from an extensive to an intensive model, thereby promoting green development. CITY is measured as the proportion of the urban population in the total population of the region.

(6) Industrial structure (INS): China is currently undergoing a critical phase of industrial restructuring. As a vital component of the tertiary sector, the logistics industry will see shifts in demand driven by these structural changes, which in turn will impact its efficiency. The proportion of the tertiary industry in GDP is selected to indicate INS.

(7) Industrialization level (IND): Industrial goods logistics constitute a major component of total social logistics volume. As industrialization accelerates, the secondary sector continuously contributes to and creates demand for the logistics industry. A favorable market environment attracts more high-quality logistics enterprises, stimulating the overall vitality of the logistics industry. The proportion of the secondary industry in GDP is selected to represent IND.

(8) Logistics strength (LOGS): Transport intensity reflects the volume of logistics services required per unit of economic output. Changes in this indicator directly relate to the efficiency of logistics resource allocation and technological innovation capabilities, thereby influencing GTFP of the logistics industry. The ratio of total logistics turnover to regional GDP is selected to represent LOGS.

(9) Transport structure (STRU): Currently, the primary transport modes in China are road, rail, and water transport. Different modes generate varying levels of environmental pollution in the logistics transport segment, exerting differing impacts on GTFP of the logistics industry. The proportion of road transport in total turnover is selected to represent STRU.

3.3. Data Sources

At present, the logistics industry is not listed in China's "National Economic Industry Classification and Code", but according to existing relevant literature and statistics, the added value of transportation, warehousing and postal industries accounts for more than 80% of the added value of the logistics industry, so the data of transportation, warehousing and postal industries are selected to represent the logistics industry data. All data used in this study are from the "China Statistical Yearbook" and "China Energy Statistical Yearbook" from 2013 to 2021. Due to the serious lack of relevant data in Tibet, Macao, Hong Kong, and Taiwan, the empirical part of this study mainly involves 30 provinces, cities, and autonomous regions. China comprises 34 provincial-level administrative regions. Due to the "one country, two systems" policy implemented in Hong Kong, Macau, and Taiwan, their stages of economic development, industrial structures, governmental functions, and levels of marketization exhibit fundamental differences from mainland provinces. Consequently, these regions are excluded from this study. Additionally, the Tibet Autonomous Region, constrained by natural conditions, historical factors, and its level of economic development, suffers from short time series or significant gaps in many key economic and social data. It is therefore also excluded from the empirical analysis. Consequently, this study ultimately covers 30 provinces, autonomous regions, and municipalities directly under the central government in mainland China. These regions account for over 99% of the mainland's population and economic output, demonstrating strong representativeness and providing a comprehensive reflection of China's overall national conditions.

4. Results and Discussions

4.1. Test Results

4.1.1. Spatial Autocorrelation Test

In order to analyze the heterogeneity and correlation between the allocation levels of data elements in various regions, as well as the changes in time series, we used Geoda (1.14) software to generate spatial weight matrices for 30 provinces and municipalities. Based on the idea of exploratory spatial data analysis (ESDA), we utilized Stata 15.1 software to

conduct global and local spatial autocorrelation tests on the measurement results of data elements in 30 provinces, municipalities, and autonomous prefectures in China.

Table 3 presents the global Moran index of data elements across China's 30 provinces, municipalities, and autonomous regions from 2014 to 2021. As shown in Table 3, the global Moran indices of data elements in all provinces and municipalities in the past 8 years are all greater than 0, indicating a positive spatial correlation nationwide. This suggests that regions with similar levels of data element allocation generally exhibit clustering characteristics. We further calculated the local Moran index of data elements across regions in both the initial year (2014) and the final year (2021). The analysis revealed that provinces consistently classified in the “high-high agglomeration” zone for data element allocation included Jiangsu, Zhejiang, Shanghai, and Shandong. Conversely, provinces persistently categorized in the “low-low agglomeration” zone were Heilongjiang, Liaoning, Jilin, Shanxi, Inner Mongolia, Shaanxi, Qinghai, Ningxia, Gansu, Xinjiang, Guizhou, Yunnan, Chongqing, and Hubei. Provinces consistently in the “high-low agglomeration” zone include Guangdong and Beijing, while those consistently in the “low-high agglomeration” zone include Jiangxi, Guangxi, Hunan, Hainan, Hebei, and Tianjin.

Table 3. Global spatial autocorrelation results of data elements.

Year	Global Moran Index	z-Value	p-Value
2014	0.132	1.558	0.060 *
2015	0.125	1.495	0.067 *
2016	0.133	1.573	0.058 *
2017	0.131	1.561	0.059 *
2018	0.109	1.374	0.085 *
2019	0.104	1.332	0.091 *
2020	0.095	1.245	0.107
2021	0.100	1.282	0.100 *

Note: * indicates significance at the 10% level.

4.1.2. Endogeneity Test

The core endogeneity issue in this study lies in the potential bidirectional causal relationship between data element configuration and GTFP in the logistics industry. On one hand, the input of data elements can enhance GTFP in the logistics industry by optimizing resource allocation and improving operational efficiency. On the other hand, logistics enterprises or regions with higher GTFP often exhibit greater demand for data elements and stronger capabilities in applying them, which in turn influences their level of data element configuration. Furthermore, unobservable factors (e.g., corporate management quality and technological innovation capabilities) may affect both variables simultaneously. These omitted variables could introduce bias into ordinary least squares (OLS) estimation results, preventing accurate identification of the causal effect of data elements on GTFP of the logistics industry.

To mitigate the aforementioned endogeneity issues, we employed the instrumental variables approach, using the lagged ($t - 1$ period) level of data elements (L.DA) as the instrumental variable for the endogenous explanatory variable in the current period. Selecting L.DA as an instrumental variable is highly justified. First, regarding the correlation condition, the results of the first-stage regression (Table 4) show that the coefficient for L.DA is 0.9470 and is significant at the 1% level. This indicates a strong correlation between the instrumental variable and the endogenous explanatory variable. Second, regarding exogeneity, the lagged-period data elements primarily reflect the state of factor inputs during the historical period and are uncorrelated with the random disturbance term of the

current-period GTFP in the logistics industry, thus satisfying the exogeneity requirement for instrumental variables.

Table 4. Endogeneity test results (instrumental variables regression).

	Stage 1	Stage 2
	DA	GTFP
DA		2.4743 *** (3.57)
L.DA	0.9470 *** (45.16)	
GOVN	0.0627 (1.23)	−2.6627 ** (−1.99)
OPEN	−0.0358 (−0.91)	−0.6444 (−1.01)
FDI	−0.0001 (−0.30)	0.0298 (1.51)
GATH	0.0153 (1.21)	0.3085 (1.01)
CITY	−0.0077 (−0.13)	0.4752 (0.23)
INS	0.2413 *** (3.52)	7.0232 *** (2.73)
IND	0.1554 (1.67)	8.3442 ** (2.18)
LOGS	−0.0104 (−1.00)	0.5601 (0.73)
STRU	−0.0168 * (−1.70)	1.5859 *** (4.47)
N	210	210
R2	0.9609	0.4862
Kleibergen-Paap rk LM		18.1211 ***
Kleibergen-Paap rk Wald F		785.9942 > 16.38

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in brackets are z-test values; data processing was performed by StataSE15.

The estimation results from the two-stage least squares method (Table 4) indicate that data elements exert a significant positive effect on GTFP of the logistics industry. In the second-stage regression, the coefficient on DA is 2.4743 and is statistically significant at the 1% level. This implies that a one-unit increase in the level of data element configuration leads to a 2.4743-unit increase in GTFP of the logistics industry. Weak instrumental variable tests further validate the validity of the estimation: the Kleibergen-Paap rk LM statistic is 18.1211, significant at the 1% level, rejecting the null hypothesis of “insufficient identification of instrumental variables”; the Kleibergen-Paap rk Wald F statistic is 785.9942, far exceeding the critical value of 16.38, indicating no weak instrumental variable issues exist.

4.1.3. Multicollinearity Test

To test for multicollinearity among the independent variables in panel data, the variance inflation factor (VIF) is calculated by treating the panel data as cross-sectional data. Generally speaking, $VIF < 10$ indicates that there is no serious multicollinearity problem. As shown in Table 5, the variance inflation factor VIF values of data elements (2.59), government norms (1.91), open to the outside world (5.16), foreign direct investment (1.57), logistics industry gathering (2.10), urbanization rate (4.43), industry structure (8.3), industrialization level (4.65), logistics strength (2.46), transport structure (2.41) are all less

than 10, and the mean value of VIF is less than 5, indicating that there is no serious problem of multicollinearity among independent variables, which is suitable for regression analysis.

Table 5. Multicollinearity test results.

Variable Name	Notation	VIF	1/VIF
Data elements	DA	2.59	0.387
Government norms	GOVN	1.91	0.523
Open to the outside world	OPEN	5.16	0.194
Foreign direct investment	FDI	1.57	0.636
Logistics industry gathering	GATH	2.10	0.477
Urbanization rate	CITY	4.43	0.226
Industry structure	INS	8.30	0.121
Industrialization level	IND	4.65	0.215
Logistics strength	LOGS	2.46	0.407
Transport structure	STRU	2.41	0.415
Mean VIF		3.56	

4.1.4. Lagrange Multiplier Test (LM Test)

As shown in Tables 6–8, the results show the simultaneous existence of spatial lag and spatial error terms. The Lagrange multiplier values of the spatial error model and the spatial lag model of GTFP, ECH, and TCH all passed the 1% significance level test, rejecting the null hypothesis of no spatial lag terms and no spatial error terms. It is necessary to consider using the spatial Durbin model, and in the subsequent model regression, the R^2 statistic and log-likelihood function value of the SDM are better than the SAR and SEM models (the larger the Log-likelihood and R^2 , the higher the model fit), indicating that the spatial Durbin model should be used to perform regression analysis on the panel data of influencing factors.

Table 6. LM test results with GTFP as the explained variable.

GTFP	Statistic	<i>p</i> -Value
Spatial error model		
Moran's I	5.272	0.000 ***
Lagrange multiplier	20.049	0.000 ***
Robust Lagrange multiplier	6.591	0.010 ***
Spatial lag model		
Lagrange multiplier	13.798	0.000 ***
Robust Lagrange multiplier	0.340	0.560

Note: *** indicates significance at the 1% level.

Table 7. LM test results with ECH as the explained variable.

ECH	Statistic	<i>p</i> -Value
Spatial error model		
Moran's I	5.719	0.000 ***
Lagrange multiplier	24.097	0.000 ***
Robust Lagrange multiplier	0.152	0.696
Spatial lag model		
Lagrange multiplier	29.808	0.000 ***
Robust Lagrange multiplier	5.864	0.015 **

Note: **, *** indicate significance at the 5%, and 1% levels.

Table 8. LM test results with TCH as the explained variable.

TCH	Statistic	p-Value
Spatial error model		
Moran's I	6.801	0.000 ***
Lagrange multiplier	35.415	0.000 ***
Robust Lagrange multiplier	2.767	0.096 *
Spatial lag model		
Lagrange multiplier	34.448	0.000 ***
Robust Lagrange multiplier	1.800	0.180

Note: *, ** indicate significance at the 10%, and 1% levels.

4.1.5. Hausman Test

The Hausman test is often used to select the best model between two or more models. Here, it is used to determine whether to use a fixed effect model or a random effect model. Fe is a fixed effect, and re is a random effect. The null hypothesis is “there is no significant difference between the two models”. The chi-square statistic is calculated to compare the difference between the estimated results and the actual observed values, and the chi-square distribution is used for hypothesis testing. As shown in Table 9, according to the results of Hausman's test, when GTFP, ECH, and TCH are the explanatory variables, the results of the test all reject the null hypothesis, and all pass the 1% significance level test, so the fixed effect model should be used.

Table 9. Hausman test results.

Explained Variable	Chi2 Statistic	p-Value
GTFP	190.36	0.0000 ***
ECH	495.09	0.0000 ***
TCH	64.35	0.0000 ***

Note: *** indicates significance at the 1% level.

4.1.6. Likelihood Ratio Test (LR Test)

The LR test is used to determine whether the spatial Durbin model (SDM) is superior to the spatial lag model (SAR) and the spatial error model (SEM), whether the SDM can be degraded to the latter two models, and whether to use the time fixed effect model, individual fixed effect model, or mixed fixed effect model. As shown in Table 10, when the GTFP, ECH, and TCH of the logistics industry are the explained variables, they all reject the null hypothesis that SDM can be degraded to SAR and SEM, and all of them pass the significance level test of 1% or 5%, which indicates that the spatial Durbin model needs to be used for the regression analysis. Table 11 shows the R^2 of the three explained variables using the time fixed effect, individual fixed effect, and mixed fixed effect models, respectively. The comparison shows that each explained variable needs to use the time fixed effect model, because the larger the R^2 statistic indicates the higher the goodness of fit.

Table 10. LR test-whether SDM can be degraded to SAR and SEM.

Explained Variable	Null Hypothesis H_0	LR chi2 Statistic	p-Value
GTFP	H_0 : SDM can be degraded to SAR	82.97	0.0000 ***
	H_0 : SDM can be degraded to SEM	82.58	0.0000 ***
ECH	H_0 : SDM can be degraded to SAR	48.26	0.0000 ***
	H_0 : SDM can be degraded to SEM	48.33	0.0000 ***
TCH	H_0 : SDM can be degraded to SAR	20.33	0.0263 **
	H_0 : SDM can be degraded to SEM	21.31	0.0190 **

Note: **, *** indicate significance at the 5%, and 1% levels.

Table 11. R^2 of each explained variable under different fixed effect types.

Explained Variable	Fixed Effect Type	R^2
GTFP	Time fixed	0.3656
	Individual fixed	0.0130
	Mixed fixed	0.0671
ECH	Time fixed	0.2852
	Individual fixed	0.0083
	Mixed fixed	0.0062
TCH	Time fixed	0.5082
	Individual fixed	0.0221
	Mixed fixed	0.0068

4.1.7. Robustness Test

To ensure the reliability of the benchmark regression results, we further employed an economic distance matrix to construct a spatial Durbin model for robustness testing. As shown in Table 12, after replacing the spatial weight matrix, the estimated coefficient for data elements (DA) is 1.6075 and remains statistically significant at the 1% level. This indicates that data elements still significantly promote GTFP in the logistics industry. Although the coefficient value decreased compared to the benchmark regression results, its significance and positive impact remained robust. This indicates that the core driving role of data elements in GTFP of the logistics industry did not undergo any fundamental change due to the alteration of the spatial weight matrix. This result further validates the reliability of the benchmark model estimation, demonstrating that the promotional effect of data elements on the green development of the logistics industry exhibits strong robustness.

Table 12. Regression results of the spatial Durbin model replaced with the economic distance matrix.

	GTFP
DA	1.6075 *** (4.83)
GOVN	−0.5887 ** (−2.01)
OPEN	−0.1506 (−0.50)
FDI	0.0338 *** (4.33)
GATH	0.5462 *** (4.31)
CITY	1.0860 ** (2.10)
INS	−0.8228 (−0.80)
IND	−0.7003 (−1.02)
LOGS	0.3071 (1.29)
STRU	0.0075 (0.04)
W*DA	5.9952 *** (2.79)
W*GOVN	−23.3927 * (−1.91)
W*OPEN	−1.6753 (−1.28)
W*FDI	−0.0672 (−0.25)
W*GATH	6.3486 *** (3.49)
W*CITY	8.8039 (0.71)
W*INS	−29.5115 (−1.01)
W*IND	−26.1765 (−0.91)
W*LOGS	−4.2523 (−1.56)
W*STRU	−1.5661 (−0.72)
$\rho(W * y)$	0.0042 (0.02)
R^2	0.2501

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in brackets are z-test values; data processing was performed by StataSE15.

Regarding spatial spillover effects, the coefficient for the spatial lag term ($W*DA$) of data elements is 5.9952, which is significantly positive at the 1% level and markedly larger than the direct effect. This indicates that improvements in data element allocation levels in the local region exert a stronger driving force on GTFP of the logistics industry in neighboring regions. This spatial spillover effect likely stems from the network externalities inherent in data elements. Developments in neighboring regions—such as advancements in data infrastructure and digital technology applications—can benefit surrounding areas through channels like knowledge dissemination and technology diffusion.

4.2. Discussions of Empirical Results

4.2.1. Impact Mechanism Analysis

Since the green total factor productivity change (GTFPCH) of the logistics industry, calculated using the Malmquist dynamic index model, is actually the rate of change in the GTFP of the logistics industry in each province in the neighboring two years, while the explained variable is the green total factor productivity (GTFP) of the logistics industry. Therefore, before carrying out the model regression analysis, the base year 2013 GTFP of the logistics industry is taken as 1, and the annual GTFP value of each province's panel data since 2014 is processed by multiplying the rate of change year by year to obtain the time-continuous GTFP value. The GTFPCH decomposition indices of the logistics industry in each province—technical efficiency change (ECH) and technical progress change (TCH)—are also processed in the same way. The results of the spatial Durbin model regression are shown in Table 13.

Table 13. Spatial Durbin model regression results under different explained variables.

	GTFP	ECH	TCH
DA	1.0968 *** (2.95)	−0.9992 * (−1.72)	2.2814 *** (8.30)
GOVN	−1.0062 *** (−3.16)	−1.4385 *** (−2.88)	0.1657 (0.70)
OPEN	0.1442 (0.52)	−0.5587 (−1.29)	0.3169 (1.54)
FDI	0.0295 *** (3.65)	0.0608 *** (4.81)	−0.0099 * (−1.67)
GATH	0.4947 *** (3.82)	0.2523 (1.25)	0.3556 *** (3.72)
CITY	1.6328 *** (2.81)	2.4350 *** (2.68)	−0.5232 (−1.22)
INS	0.0779 (0.10)	3.3723 *** (2.81)	−1.9970 *** (−3.51)
IND	1.2305 * (1.79)	1.3266 (1.24)	−0.6166 (−1.20)
LOGS	0.5958 ** (2.48)	−0.1889 (−0.51)	0.3189 * (1.78)
STRU	0.1993 (1.16)	0.2197 (0.81)	−0.1221 (−0.94)
$W*DA$	1.7273 *** (3.04)	1.3378 (1.59)	1.1307 ** (2.42)
$W*GOVN$	2.35 *** (3.96)	2.6909 *** (2.91)	−0.2016 (2.42)
$W*OPEN$	2.3043 *** (5.06)	2.6905 *** (3.78)	−0.3140 (−0.93)
$W*FDI$	0.0622 * (1.86)	0.0572 (1.09)	0.0083 (0.34)
$W*GATH$	0.7072 *** (3.09)	0.9138 *** (2.60)	0.2685 (1.53)
$W*CITY$	−2.8939 *** (−2.88)	−2.6631 * (−1.65)	−0.5602 (−0.76)
$W*INS$	−8.4058 *** (−4.67)	−6.9626 ** (−2.54)	−2.0256 (−1.54)
$W*IND$	−5.9939 *** (−3.83)	−1.2171 (−0.5)	−3.2119 *** (−2.79)
$W*LOGS$	−0.1686 (−0.26)	0.6396 (0.63)	−0.7630 * (−1.60)
$W*STRU$	1.8829 *** (3.62)	2.3109 *** (2.80)	−0.7452 * (−1.90)
$\rho(W*y)$	0.0564 (0.66)	−0.0419 (−0.44)	−0.3006 *** (−3.22)
R^2	0.3656	0.2852	0.5082

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in brackets are z-test values; data processing was performed by StataSE15.

Data elements (DAs) have a significant positive effect on the GTFP and TCH in China's logistics industry, and pass the 1% significance level test, while it has a negative effect on ECH. At the same time, data elements of the local province also have a significant positive spillover effect on GTFP and TCH in the logistics industry in neighboring regions, passing

the 1% and 5% significance level tests, respectively, preliminarily verifying Hypothesis 1, and the specific impact effect values will be further analyzed later. In addition, data elements do not have a positive impact on ECH. The positive promotion of data elements to GTFP in the logistics industry is mainly due to the promotion of TCH. Hypothesis 2, “The catalyst for data elements to enhance the GTFP of the logistics industry is to improve the level of technical progress”, is preliminarily verified.

Government norms (GOVN) negatively impact GTFP and ECH in China’s logistics industry, likely due to local protection policies that hinder resource flow and create redundant logistics infrastructure. On the contrary, government norms have a positive spillover effect on the GTFP and ECH in surrounding areas.

Opening up to the outside world (OPEN) has no significant impact on the GTFP and its decomposition indicators of the logistics industry, suggesting issues in supply chain integration, multimodal transport, market competition with foreign logistics companies, etc. However, OPEN positively affects GTFP and ECH in the logistics industry in neighboring areas.

Foreign direct investment (FDI) has a significant positive impact on the GTFP and ECH in the logistics industry, but a negative impact on TCH, indicating that the high-end level of the logistics industry needs to be further improved. In addition, FDI has a significant positive spillover effect on the GTFP of the logistics industry in the neighboring regions, but its technical spillover effect in the neighboring provinces has not been apparent.

Logistics industry gathering (GATH) has a significant positive impact on the GTFP and TCH in China’s logistics industry, but the impact on ECH is not significant, indicating that the positive scale effect generated by China’s logistics industry gathering is conducive to the collaborative sharing of resources and factors, and promotes technological innovation. In addition, local GATH has a significant positive spillover effect on GTFP in neighboring regions, which is mainly reflected in ECH.

The urbanization rate (CITY) has a significant positive impact on the GTFP and ECH in the logistics industry, and has a significant negative spillover effect on neighboring regions. This means urbanization concentrates production factors and optimizes the industrial chain, thus improving the greening level of the logistics industry. However, provinces with high urbanization rates will cause the loss of resources in surrounding areas, which is not conducive to the improvement of GTFP in neighboring regions.

Although the industrial structure (INS) has a non-significant effect on GTFP in the logistics industry, it has a significant positive effect on the growth of its decomposition index of ECH, and a significant negative effect on TCH. Since the INS indicator is selected as the proportion of the tertiary industry, it means that while the scale of the tertiary industry is expanding, it is necessary to focus on green technology innovation, combined with the improvement of technical efficiency.

The level of industrialization (IND) has a significant positive effect on GTFP in the logistics industry, which shows that the improvement of the industrialization level is conducive to promoting the market concentration of the logistics industry, encouraging logistics enterprises to optimize resource allocation. In addition, regions with a high level of industrialization will show obvious negative technology spillover effects on surrounding provinces, which is not conducive to the improvement of GTFP in neighboring regions.

Logistics strength (LOGS) has a significant positive effect on GTFP in the logistics industry, mainly by improving the level of TCH. This indicates that higher transport strength tends to reduce the waste of transport space and improve transport efficiency. At the same time, the increasing transport strength forces technical progress, thereby achieving the effect of improving the level of green logistics.

The effect of transport structure (STRU) on GTFP in the logistics industry in the local region is not significant, but it has a positive spillover effect on GTFP in the surrounding areas, and it is mainly manifested in driving the improvement of ECH, and it has a negative spillover effect on TCH.

In addition, in the regression results of the spatial Durbin model, when the explained variable is the decomposition index TCH of the GTFP of the logistics industry, the regression coefficient ρ of the spatial lag term is significantly negative, indicating that there is a significant negative spatial spillover effect of green technology in China's logistics industry from 2013 to 2021, and the improvement of technical progress in various places has not effectively driven the green technical progress of the logistics industry in neighboring provinces and cities.

4.2.2. Decomposition Effect Analysis

Due to the existence of the spatial lag term of the independent variables in the SDM, the regression coefficients in Table 13 cannot accurately reflect the marginal effects of the independent variables on the dependent variable, but can only reflect the direction and significance of the effect of each variable on the explained variable. Therefore, it is necessary to decompose the coefficients into direct effect, indirect effect, and total effect through the partial differential method recognized by the academic community, so as to further measure the influence of the explanatory variables and control variables on the local explained variables and the spatial spillover effect on the neighboring regions. The direct effect includes the direct effect of the explanatory variable on the local explained variable, as well as the feedback effect through the spillover effect on the explained variables in the neighboring regions and reacting on the explained variables in the local region. The indirect effect is the influence of the independent variable of the neighboring region on the explained variables of the local region. The total effect is equal to the sum of the direct effect and the indirect effect. The specific mechanism of action is shown in Figure 1. The three effect estimation results of the time fixed effect spatial Durbin model, with GTFP of the logistics industry and its decomposition index, ECH, and TCH as explained variables, are shown in Tables 14 and 15.

As shown in Table 14, the direct and indirect effects of data elements on the GTFP of the logistics industry in local region are significantly positive, with coefficients of 1.3331 and 1.86, respectively, and they have passed the 1% significance level test, indicating that improving the allocation of data elements resources has a promoting effect on improving the GTFP of the logistics industry in local region, and will also promote the improvement of the GTFP of the logistics industry in neighboring regions. This once again verifies Hypothesis 1.

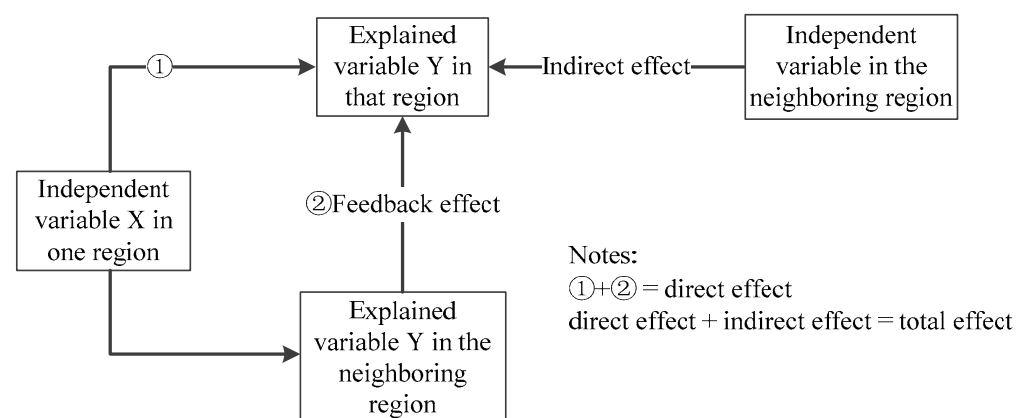


Figure 1. Mechanisms of direct effect, indirect effect, and total effect.

Table 14. Direct, indirect, and total effects of GTFP as explained variable.

	Direct Effect	Indirect Effect	Total Effect
DA	1.1331 *** (2.94)	1.8600 *** (3.04)	2.9931 *** (3.52)
GOVN	−0.9857 *** (−3.23)	2.4477 *** (3.69)	1.4620 ** (1.99)
OPEN	0.1885 (0.69)	2.4407 *** (4.70)	2.6392 *** (4.48)
FDI	0.0304 *** (3.81)	0.0679 * (1.89)	0.0983 *** (2.60)
GATH	0.5114 *** (3.97)	0.7538 *** (3.22)	1.2652 *** (5.15)
CITY	1.6041 *** (2.84)	−2.9344 *** (−2.87)	−1.3303 (−1.29)
INS	−0.0739 (−0.09)	−8.6489 *** (−4.93)	−8.7229 *** (−4.74)
IND	1.1103 (1.53)	−6.0793 *** (−3.81)	−4.9690 *** (−3.05)
LOGS	0.6033 ** (2.48)	−0.1302 (−0.19)	0.4731 (0.60)
STRU	0.2387 (1.36)	2.0449 *** (3.70)	2.2837 *** (3.51)

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in brackets are z-test values; data processing was performed by StataSE15.

Table 15. Three effects when GTFP decomposition indicators ECH and TCH are explained variables.

	ECH			TCH		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
DA	−0.9936 * (−1.67)	1.3236 (1.54)	0.3299 (0.27)	2.2626 *** (8.13)	0.3613 * (1.79)	2.6239 *** (5.79)
GOVN	−1.4874 *** (−3.11)	2.7299 *** (2.84)	1.2425 (1.20)	0.1739 (0.74)	−0.1821 (−0.46)	−0.0083 (−0.02)
OPEN	−0.5702 (−1.34)	2.6416 *** (3.60)	2.0714 *** (2.61)	0.3540 ** (1.70)	−0.3421 (−1.11)	0.0119 (0.04)
FDI	0.0601 *** (4.82)	0.0536 (1.05)	0.1137 ** (2.17)	−0.0107 * (−1.76)	0.0100 (0.48)	−0.0007 (−0.04)
GATH	0.2542 (1.24)	0.8489 ** (2.50)	1.1031 *** (3.18)	0.3508 *** (3.47)	0.1205 (0.86)	0.4713 *** (3.68)
CITY	2.4754 *** (2.77)	−2.6747 * (−1.75)	−0.1993 (−0.14)	−0.4882 (−1.10)	−0.3137 (−0.49)	−0.8019 (−1.51)
INS	3.3852 *** (2.73)	−6.6604 *** (−2.64)	−3.2752 (−1.30)	−1.9460 *** (−3.19)	−1.0899 (−1.01)	−3.0360 *** (−3.10)
IND	1.2730 (1.11)	−1.0450 (−0.45)	0.2279 (0.10)	−0.4599 (−0.81)	−2.4530 ** (−2.46)	−2.9129 *** (−3.31)
LOGS	−0.1837 (−0.49)	0.6401 (0.67)	0.4564 (0.42)	0.3817 ** (2.17)	−0.7158 * (−1.85)	−0.3341 (−0.79)
STRU	0.2117 (0.81)	2.3017 *** (2.96)	2.5134 *** (2.79)	−0.0669 (−0.55)	−0.5584 * (−1.76)	−0.6252 * (−1.76)

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively; the values in brackets are z-test values; data processing was performed by StataSE15.

In order to further explore how data elements promote the improvement of GTFP in the logistics industry, we further analyzed the impact of data elements on the ECH and TCH of the decomposition index. As shown in Table 15, the direct and indirect effects of data elements on TCH are significantly positive, with coefficients of 2.2626 and 0.3613, respectively, passing the 1% and 10% significance level tests, respectively, indicating that the positive effect of data elements on improving the GTFP of the logistics industry in local region and the positive spillover effect on neighboring regions are achieved by improving technical progress and innovation, further verifying Hypothesis 2. Since the direct effect of data elements on ECH is negative, it offsets part of the positive promotion of data elements on TCH, resulting in the coefficient value of data elements promoting the GTFP of the logistics industry being slightly lower than the effect value on TCH. This may be because although data elements promote technical progress and innovation in the logistics industry, they are also easy to produce, leading to industry homogenization, squeeze competition,

and a congestion effect. If data elements can further improve technical efficiency while maintaining technical progress and innovation, then the effect of improving the GTFP of the logistics industry will be more significant.

The impact of other control variables on the GTFP of the logistics industry is not the focus of the study, and the three decomposition effects in Tables 14 and 15 are highly consistent with those in Table 13 in terms of direction and significance, which has also been explained in the previous section, so they will not be analyzed separately.

5. Discussion

This study calculated GTFP of the logistics industry across provinces, constructed an evaluation index system for data elements, and built an appropriate spatial econometric model. With data elements as the core explanatory variable and incorporating nine control variables, including government norms and so on, the research examined the impact of data elements on GTFP of the logistics industry in both local and neighboring regions.

Compared to previous studies [23–25], this study delved deeper into the impact of data—a core element of the digital economy—on GTFP of the logistics industry. It constructed a relatively comprehensive evaluation framework for data elements, encompassing dimensions such as data element flow, data subject capabilities, data industry ecology, and resource support. The findings reveal: First, data elements exert a significant positive influence on GTFP of China's logistics industry. Given the scarcity of existing research on the influence of data elements on logistics industry development, this finding represents a novel discovery. However, certain studies examining the integration of the digital economy and logistics share similarities with our findings. For instance, Liu et al. [50] utilized panel data from 11 cities in Hebei Province, China, spanning 2013–2022, alongside benchmark regression models and threshold effect models. Their research revealed that the convergence of data elements and the real economy significantly promotes the transformation of the logistics industry. Guo et al. [51] studied data from Anhui Province, China, from 2013 to 2020 using a collaborative degree model and found that the level of synergistic development between the digital economy and the logistics industry showed a fluctuating growth trend. Ptashchenko et al. [52], based on logistics efficiency and quality data from 139 countries in 2023, discovered that the digital transformation of logistics processes can optimize supply chain management and reduce costs. Second, data elements enhance GTFP of the logistics industry primarily through technical progress, where data exerts a significant positive influence on technological progress growth but a negative effect on technical efficiency growth. This conclusion is partially corroborated by the study [53], which applied a fixed-effects model to data from cities along China's Yellow River basin. Its findings indicate that digitalization significantly drives green, high-quality development in the logistics industry, and digitalization indirectly promotes such development through channels including technological innovation inputs and outputs, as well as optimized human capital allocation. Third, data elements within this province also exhibit significant positive spillover effects on GTFP and technical progress growth in the logistics industry of neighboring regions. Previous empirical studies on the total factor productivity of the logistics industry and the impact of data elements on other industries have rarely employed spatial econometric methods to explore spillover effects. As a new type of production factor, data elements possess characteristics such as replicability, non-exclusivity, and mobility. Their primary carrier relies on networks, enabling faster flow speeds and broader reach compared to traditional production factors. Therefore, the findings of this study reveal the direct impact of data elements on the local region and their spillover effects on neighboring areas, transcending analyses confined solely to local impacts.

6. Conclusions

The findings of this study also offer practical contributions to enhancing GTFP of the logistics industry and advancing its digital transformation. First, this research reveals that the intrinsic catalyst behind data elements boosting GTFP of the logistics industry is the enhancement of technical progress. Therefore, to leverage the role of data elements in improving GTFP, it is essential to continuously improve the digital logistics infrastructure to strengthen technological environment support. To this end, logistics companies and decision-makers can vigorously promote the intelligent transformation and digital transition of the logistics industry. By applying new technologies such as AI-based decision support systems to analyze market demand and optimize logistics center locations, rational route planning can reduce detours and empty runs, while digital warehouse scheduling management can minimize inventory backlogs. This approach enhances logistics efficiency, lowers operational costs, reduces environmental pollution, and unlocks new economic growth opportunities for the logistics sector. Second, the enhancement of GTFP in the logistics industry through data elements is primarily achieved through technical progress. The key to unleashing the technological empowerment and value creation potential of data elements lies in their circulation and sharing. This plays a vital role in connecting upstream and downstream enterprises in the logistics chain, integrating logistics, commerce, and information flows, improving the quality of logistics decision-making, and reducing information asymmetry costs. To this end, the government should start from the aspects of data property rights and security systems, data circulation and transaction systems, etc., and improve the institutional guarantee of data elements. Logistics enterprises can obtain more valuable decision support by improving their data screening and verification capabilities. They can also strengthen the resource processing, scenario-based application, and value transformation capabilities of data elements by improving data analysis capabilities. Third, this study demonstrates that data elements not only enhance GTFP of the local logistics industry but also exert a positive spillover effect on GTFP of neighboring regions' logistics industry. However, due to the homogenization effects of competitive pressure and crowding, data elements exert a negative influence on technical efficiency. Therefore, regions should strengthen regional collaboration to reduce homogeneous competition and leverage the positive spillover effects of data elements. For instance, support should be provided for cross-regional digital infrastructure development. Regions lagging in GTFP within the logistics industry and in data element allocation should learn from the development experiences of advanced regions. Simultaneously, based on regional differences, they should tailor approaches to explore locally suitable innovation-driven development models and new forms of productive forces.

The limitations of this paper are primarily manifested in the following aspects: First, constrained by the availability of empirical data, the analysis is confined to 30 provinces in mainland China. Consequently, the conclusions exhibit regional limitations in terms of extrapolation and cross-system applicability. Second, in measuring data elements, certain macro-level indicators (such as blockchain technology application maturity and government data openness levels) proved difficult to obtain or quantify. Consequently, the current indicator system excludes these potentially significant dimensions, limiting the comprehensive identification of data elements' enabling effects. Future research can refine these aspects to more fully and systematically reveal the driving mechanisms of data elements in promoting green development within the logistics industry.

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