

# Research on the Spatial Effect of Digital Economy Development Enabling Green Technology Innovation in Yangtze River Delta region

Xingyu Bai<sup>\*</sup>, Zimeng Zheng

College of Statistics and applied mathematics, Anhui University of Finance and Economics,  
Bengbu, China

## ABSTRACT

At the time of the transformation of old and new driving forces for economic growth, green technology innovation enabled by the digital economy has gradually become a powerful driving force for scientific and technological innovation and the improvement of the development level of green economy in the Yangtze River Delta region. This paper takes 41 cities in the Yangtze River Delta region as the research object, and empirically analyzes the spatial correlation degree and the spillover effect of green technology innovation in the Yangtze River Delta region from 2016 to 2020 by constructing the spatial Dubin model. The results show that: (1) Digital economy has a strong positive impact on green technology innovation and development, and has an empowering effect on regional green technology innovation and development. (2) The development of green technology innovation in the Yangtze River Delta showed a significant positive spatial autocorrelation, and the spatial autocorrelation decreased with the increase of years, and the trend of unbalanced development of green technology innovation increased. (3) The level of digital economy, the level of opening up to the outside world, the rate of urbanization and the level of scientific and technological development have a spatial spillover effect on regional green technology innovation and development. Based on the above conclusions, the paper puts forward some countermeasures and suggestions to promote the innovation and development of green technology enabled by digital economy in Yangtze River Delta region.

## KEYWORDS

Digital economy; Green technology innovation; Spatial Dubin Model

## 1. INTRODUCTION

The digital economy takes modern information networks as its main carrier, the integration of information and communication technologies and the all-factor digital transformation as its important driving force, and promotes a new economic form that is more unified in fairness and efficiency. With the full penetration and application of new technologies such as 5G, artificial intelligence and cloud computing in the social economy to release a new round of digital dividends, the digital economy has become a new engine to promote supply-side structural reform, carrying an important function of reshaping the economic pattern, transforming growth momentum and building new advantages. The scale of China's digital economy is on the rise, and the growth rate is basically maintained at more than 10%.

Green technology innovation is a general term for technological innovation and management innovation aimed at environmental protection, and is a kind of technological innovation. The "Guidance on Building a Market-oriented Green Technology Innovation System" issued by the

National Development and Reform Commission and the Ministry of Science and Technology clearly states that it is necessary to actively carry out the deep integration of digital economy and green development, and take green technology innovation as a priority support area. This puts forward a new proposition for accelerating regional green innovation development with the help of digital economy.

Therefore, in the context of the "dual carbon" strategy, studying how to make use of the major opportunities and forces brought by the development of digital economy to achieve the "digital + green" transformation to cultivate and enhance the independent innovation ability of green technology has important practical significance for China to shape green competitive advantages and drive the high-quality development of green economy.

## 2. LITERATURE REVIEW

At present, the academic community has studied the development of digital economy empowerment, the level of green technology innovation and the spatial effect from multiple dimensions and has made relevant progress.

From the perspective of relevant studies on digital economy empowerment, the concept of digital economy was first proposed by Tapscott(1996) [1]. There is a lot of research focused on the relationship between the digital economy and innovation. At the theoretical level, Zhang Xinwei (2019)[2]discussed how the allocation of innovation resources and the innovation mode change under the condition of digital economy, and summarized the operation mode of government-led and enterprise-led innovation ecosystems with heterogeneous platforms. At the empirical level, Zhang Xuliang et al. (2017) [3] Based on China's provincial panel data from 2005 to 2015, found that Internet development has a positive direct effect and spatial spillover effect on regional innovation. Zhao Binyuan (2021) [4] used city-level panel data to verify that the digital economy has the same effect. Wen Jun et al. (2019)[5] empirically analyzed the nonlinear relationship between digital economy and innovation capability by constructing a city-level digital economy indicator system. Xiong Li et al. (2020) [6] found that the development of digital economy in the Yangtze River Delta urban agglomeration has a significant positive impact on technological innovation from the perspective of product innovation and technological innovation. In addition, relevant studies have found that the impact mechanism of digital economy on the improvement of innovation ability includes human capital, financial development and industrial upgrading, and R&D capital investment.

From the perspective of relevant research on green technology innovation, the research on the influencing factors of green technology innovation mainly focuses on environmental regulation and government subsidies. At the micro level, Qi Shaozhou et al. (2018) [7] found that pilot emission trading policies induced green technology innovation activities of listed companies by using triple difference research. Li Qingyuan et al. (2020) [8] were found that environmental subsidies hindered enterprises' green technology innovation. At the macro level, Liu Chang et al. (2020) [9] took urbanization as an intermediary variable to empirically study the promoting effect of regional environmental protection investment on green technology innovation. Si Lijuan (2020) [10] found that environmental regulation in the Yellow River Basin has positive local effect and spatial spillover effect on green technology innovation by using the spatial Dubin model. Chen Xiao et al. (2019) [11] verified the existence of an inverted U-shaped relationship between environmental regulation and green technology innovation by constructing static and dynamic intermediary effect models.

Through literature review, it is found that the academic literature on the impact of digital economy on green technology innovation mostly focuses on the analysis of the relevant theoretical categories of big data and green development [12], and the analysis of the impact of digital economy on green technology innovation at the provincial scale [13], and there is a lack of relevant research on the empowerment of green technology innovation by digital economy.

### 3. MODEL BUILDING AND VARIABLE SELECTION

#### 3.1. Model Building

##### 3.1.1. Reference regression model

Based on the panel data of 41 prefecture-level cities in the Yangtze River Delta region from 2016 to 2020, this paper explores the impact of digital economy on green technology innovation and development. Referring to the research of relevant scholars, the Hausman test before the formal regression showed that the P-value was less than 0.05, so the null hypothesis was rejected and the fixed-effect panel model was adopted. A time-fixed effect model with explained variable as green technology innovation level ( $GTI$ ), core explanatory variable as Digital economy index ( $del$ ), and a series of control variables is constructed as a regression model. The model is as follows.

$$GTI_{it} = \alpha + \beta del_{it} + \gamma X_{it} + \eta_t + \varepsilon_{it} \quad (1)$$

Where, the green technology innovation level  $GTI_{it}$  it is the explained variable, representing the green technology innovation level of the  $i$  prefecture level city in the  $t$  year. Alpha is a constant term. Digital economy index  $del_{it}$  is the core explanatory variable, representing the digital economy level of the  $i$  prefecture-level city in the  $t$  year. Beta represents the impact of digital economy on the development of green technology innovation.  $X_{it}$  represents the control variable.  $\eta_t$  indicates the time fixed effect of the  $t$  period.  $\varepsilon_{it}$  is a random perturbation term.

##### 3.1.2. Moran index

Moran index is an important index to measure spatial correlation, which can be divided into global Moran index and local Moran index. The global Moran index is used to describe the average degree to which all spatial units are related to the surrounding area over the whole area. The formula is as follows.

$$Moran' I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (2)$$

$$S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n} \quad (3)$$

Where  $x_i$  is the observed value,  $S^2$  is the sample variance,  $n$  is the total number of samples, and  $w_{ij}$  represents the space weight matrix. The value range of the global Moran index is -1 to 1, and the Moran index greater than 0 indicates that the spatial autocorrelation between regions is positive. When the Moran index is less than 0, the spatial autocorrelation between regions is negative. A Moran index equal to 0 indicates that there is no spatial autocorrelation between regions.

In the face of spatial autocorrelation between specific regions, the local Moran index is selected to measure, and the formula is as follows.

$$I_i = \frac{n(x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}, i \neq j. \quad (4)$$

### 3.1.3. Spatial weight matrix

The commonly used spatial weights are divided into adjacency matrix, geographical distance matrix and economic distance matrix. Geographical distance matrix can more accurately describe the distance between various regions, so this paper chooses geographical distance matrix to carry out research. The formula is as follows.

$$w_{ij} = 1 / d_{ij}. \quad (5)$$

### 3.1.4. Spatial econometric model

Common spatial measurement models include spatial lag model, spatial error model and spatial Dubin model. This paper constructs a spatial Dubin model to explore the role of green technology innovation level under the digital economy and the spatial spillover effect.

$$GTI_{it} = \alpha_0 + \theta_1 \sum_{j \neq i}^n w_{jt} GTI_{jt} + \theta_2 \sum_{j \neq i}^n w_{jt} del_{jt} + \beta del_{it} + \gamma X_{it} + \eta_t + \mu_i + \varepsilon_{it}. \quad (6)$$

$\theta_1$  is the spatial autoregressive coefficient,  $\theta_2$  is the coefficient of the digital economy level of the core explanatory variable,  $\gamma$  is the coefficient of the control variable,  $\eta_t$  represents the time fixed effect of the t period.  $\mu_i$  represents a fixed effect in space, and  $\varepsilon_{it}$  is a random disturbance term.

## 3.2. Select the Explained Variable

In view of the existing studies, many scholars choose the number of green patent applications and grants to measure the development level of green technology innovation. The number of green invention licenses in a region can fully reflect the enthusiasm of green technology innovation in this region. Therefore, this paper chooses the number of authorized green inventions to measure the regional green technology innovation level (*GTI*).

## 3.3. Core Explanatory Variable Digital Economy Level Measure

For the digital economy, this paper draws on the research achievements of relevant scholars to build a digital economy evaluation index system from seven indicators in three dimensions: digital infrastructure, digital industrialization and digital technology level. Specific indicators are listed in Table 1.

**Table 1.** Digital economy evaluation index system

Primary index	Secondary index	Unit	Nature
Digital infrastructure	Mobile phone penetration	%	+
	Internet users per 100 people	Person	+
Digital industrialization	Share of employees in information transmission, computer services and software industries	%	+
	Telecommunications traffic per capita	Hundred million yuan	+
Digital technology level	Number of patent applications granted	One	+
	Number of R&D personnel	Person	+
	Internal expenditure of R&D funds	Hundred million yuan	+

The index data were mainly collected from China City Statistical Yearbook, provincial Statistical Yearbook of Yangtze River Delta Region and statistical yearbook of prefecture-level cities. The original data of indicator variables were collected, and the missing values were supplemented by interpolation method. In order to compare the data of different years, this paper refers to the research of Yang Li et al. (2015) [14] and uses the improved entropy method to calculate the index weight and comprehensive development index. In order to eliminate the dimensional difference between the data, the index is standardized first. Then determine the index entropy, and confirm the index information utility value and weight. Finally, the comprehensive development index (*del*) of digital economy is calculated as the core explanatory variable.

In addition to the core explanatory variables, this paper introduces other control variables that may affect the level of green technology innovation: (1) Innovation greening (*gi*) is expressed by the percentage of green inventions in the total number of patents obtained in a region; (2) The level of economic opening to the outside world (*open*) is expressed by the total value of imports and exports; (3) The level of urbanization (*urban*) is represented by the regional urbanization rate; (4) The development level of tertiary industry (*tl*) is represented by the added value of tertiary industry; (5) The level of scientific and technological development (*tech*) is expressed by the proportion of science and technology expenditure to general public budget expenditure. Descriptive statistics were made for explained variables, explanatory variables and control variables, as shown as follows.

**Table 2.** Descriptive statistics

Variable type	Variable name	Obs	Mean	SD	Min	Median	Max
Explained variable	GTI	205	213.63	349.769	2	81	1668
Core explanatory variable	del	205	0.11	0.122	0.0196	0.0678	0.8443
Control variable	gi	205	7.09	2.455	1.49	6.84	14.4
	open	205	0.23	0.562	0.0019	0.0472	3.5479
	urban	205	63.71	10.864	38.28	64.3	89.3
	tl	205	0.27	0.412	0.2	0.1473	2.8310
	tech	205	3.82	2.471	0.4376	3.1644	14.0275

As can be seen from the statistical results, the difference between the maximum and minimum values of the explained variable green technology innovation level (*GTI*) and the core explanatory variable Digital economy index (*del*) is obvious, the standard deviation is high, and the levels of the two indicators are greatly different among prefecture-level cities. There are also great differences in the greening of innovation, economic opening up, urbanization level, tertiary industry development, and scientific and technological development among different regions.

## 4. ANALYSIS OF THE IMPACT OF DIGITAL ECONOMY ON THE DEVELOPMENT OF GREEN TECHNOLOGY INNOVATION

### 4.1. The Impact of Digital Economy on Green Technology Innovation

The basic model of this paper is a time-fixed effect model, the explained variable is green technology innovation, digital economy as the core explanatory variable, and the control variable is introduced to carry out regression of innovation greening, economic opening to the outside world, urbanization level, tertiary industry development, and scientific and technological development. In order to enhance the robustness of the data, the data are processed logarithmically and a variety of effect models are used for auxiliary validation. The correlation regression results are as follows.

**Table 3.** Model result summary

Variable	(1)	(2)	(3)	(4)	(5)
	lnGTI	lnGTI	lnGTI	lnGTI	lnGTI
$\alpha$	7.915** (4.868)	1.069 (0.317)	4.132 (1.705)	8.002** (4.929)	5.706 (1.444)
Indel	0.968** (6.470)	0.495* (2.577)	0.663** (4.030)	0.975** (6.367)	0.281 (1.295)
Ingi	0.825** (7.673)	0.678** (7.876)	0.694** (8.147)	0.899** (8.056)	0.824** (9.047)
Inopen	-0.013 (-0.237)	0.180* (2.582)	0.175** (3.014)	-0.006 (-0.104)	0.160* (2.216)
lnurban	-0.521 (-1.428)	0.906 (1.209)	0.370 (0.690)	-0.575 (-1.572)	-0.440 (-0.456)
Intl	0.412** (4.786)	-0.035 (-0.244)	0.246* (2.446)	0.396** (4.516)	-0.083 (-0.533)
Intech	0.270** (3.705)	0.009 (0.076)	0.087 (0.902)	0.273** (3.768)	-0.024 (-0.208)
$R^2$	0.886	0.761	0.870	0.885	0.477
Sample size	205	205	205	205	205

Note: \*\*\*, \*\* and \* represent significant levels of 1%, 5% and 10% respectively; The values in parentheses are t statistics.

Model (4) in Table is a time-fixed effect model, which is the benchmark model of this paper. The results show that the digital economy index (del) estimate presents a significance level of 0.05, indicating that the digital economy has a significant positive impact on the development of green technology innovation. At the same time, model (1) is an OLS mixed regression model, model (2) is an individual fixed effect model, model (3) is a random effect model, and model (5) is a double fixed effect model. The coefficient estimates of the first three models are all positive and meet the requirement of significance level, indicating that the improvement of the level of digital economy can enable the innovation and development of green technology. On the whole, it is conducive to the high-quality development of green technology innovation level.

In addition, taking the fixed effect model as the benchmark model, we can see that. For the control variable innovation greening (*gi*), the coefficient estimates are significantly positive. It shows that the higher the regional innovation green level, the higher the proportion of green inventions in the total number of patents obtained in the region, and has a significant positive impact on the development of regional green technology innovation level.

For the tertiary industry development level (*tl*), the coefficient is significantly positive. The higher the development level of regional tertiary industry, the booming development of new producer services, closely related to people's lives, its development needs to consume a lot of resources and energy. The vigorous development of the tertiary industry will cause the government and enterprises to attach importance to the development of green technology innovation, increase the cost input of green technology innovation, and have a positive impact on the development of green technology innovation level.

For the level of technological development (*tech*), the coefficient is estimated to be significantly positive. It shows that the higher the level of scientific and technological development, the more it can promote the power and ability of technology developers to carry out technological innovation, improve innovation efficiency, and have a significant positive impact on the development of regional green technology innovation.

## 4.2. Robustness Analysis

In this paper, the robustness test is carried out by replacing the explained variable, and the explained variable is replaced by the number of green utility model applications, which is used as an index to evaluate the level of green technology innovation. After replacing the explained variables, the digital economy has a significant positive impact on the number of green utility model applications in the same direction, indicating that the regression results are robust and the construction of core indicators is reasonable and reliable.

## 5. THE SPATIAL SPILLOVER EFFECT OF DIGITAL ECONOMY ON GREEN TECHNOLOGY INNOVATION AND DEVELOPMENT

### 5.1. Spatial Correlation Test

#### 5.1.1. Global Spatial Correlation

In this paper, green technology innovation related samples of prefecture-level cities in the Yangtze River Delta region from 2016 to 2020 are selected, combined with the geographical distance weight matrix, and the global Moran index is used for spatial autocorrelation analysis. The results are as follows.

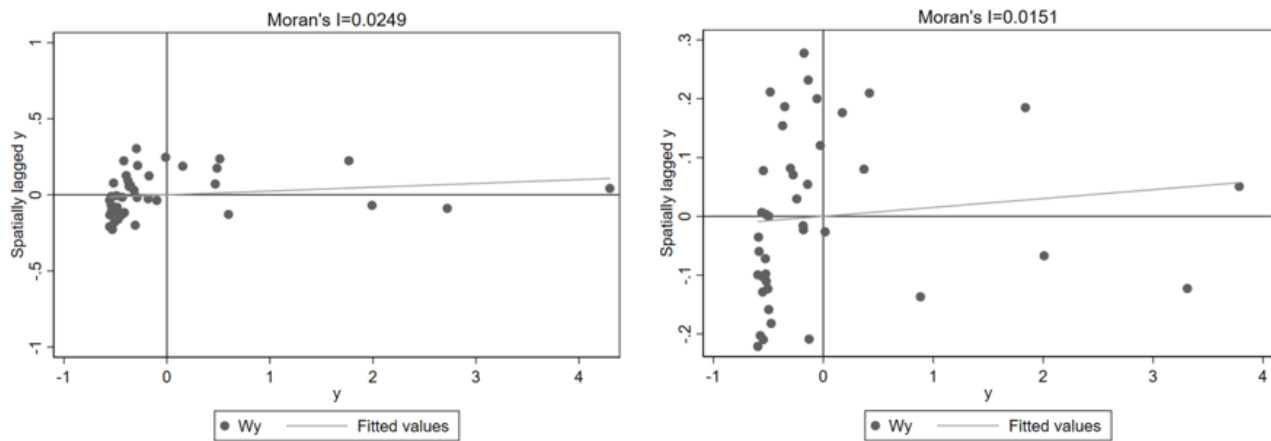
**Table 4.** Global Moran index test results

Year	Moran	P-value	Z-value
2016	0.025	0.010	2.562
2017	0.015	0.043	2.024
2018	0.015	0.046	1.999
2019	0.005	0.132	1.507
2020	0.002	0.183	1.330

The test results show that the global Moran index is positive, and the Moran index shows different degrees of significance at the 5% level in 2016-2018, while it is not significant in 2019 and 2020, but basically indicates that there is a spatial correlation between the development of green technology innovation among prefecture-level cities in the Yangtze River Delta region, and it is necessary to conduct further spatial effect test. On the whole, the Moran index showed a downward trend, indicating that the regional gap in green technology innovation level of cities in Chang-San region was obvious, and the trend of unbalanced development of green technology innovation was increasing.

#### 5.1.2. Local spatial correlation

After testing the global Moran index, the local Moran index is used to further analyze the spatial clustering status of green technology innovation in prefecture-level cities in the Yangtze River Delta region. A scatter plot of the local Moran index for 2016 and 2018 is shown here.



**Figure 1.** Moran scatter plot for 2016(left) and 2018(right)

As can be seen from the figure, most cities in the Yangtze River Delta region are distributed in the first and third quadrants, while a small number of cities are distributed in the second and fourth quadrants. It is further confirmed that the regional green technology innovation level of cities in the Yangtze River Delta region shows a significant positive correlation in space.

Take 2016 as an example, in the first quadrant, Shanghai, Suzhou, Ningbo, Changzhou, Wuxi and Zhenjiang have a higher level of green technology innovation concentration, concentrated in Jiangsu Province and Shanghai. In the second quadrant, the concentration of green technology innovation in Jiaxing, Shaoxing, Xuancheng and other cities is relatively low, concentrated in Zhejiang and Anhui provinces, and there is a gap in the development of green technology innovation compared with the surrounding cities, possibly because Jiaxing is adjacent to the international city of Shanghai, and Shaoxing is adjacent to Ningbo, which is developing rapidly. In the third quadrant, Huaibei, Suzhou, Xuzhou and other cities have a low level of green technology innovation spillover, and most of these cities are from Anhui province. In the fourth quadrant, Hefei, Hangzhou and Nanjing are all provincial capitals with a higher level of scientific and technological development and a higher level of agglomeration compared with surrounding cities, but the spatial spillover effect is not obvious.

With the development of time, the global Moran index in 2018 was 0.0015, which was lower than that in 2016, indicating that the difference in the level of green technology innovation among various regions in the Yangtze River Delta region increased. In 2018, Zhenjiang moved from the first quadrant to the second quadrant, some cities moved from the third quadrant to the second quadrant, and most of the urban attributes remained unchanged. The variation of the quadrants of each region is small, indicating that the spatial agglomeration characteristics of each region are stable. On the whole, the development of green technology innovation in the Yangtze River Delta shows the characteristics of high and high values or low and low values. Ordinary regression model is no longer suitable for the study of influencing factors of green technology innovation and development, and a spatial econometric model should be established for further analysis.

## 5.2. Spatial Spillover Effect in Yangtze River Delta

### 5.2.1. Spatial metrology model selection

After analyzing the spatial correlation of the Yangtze River Delta region, it is concluded that the innovation and development of urban green technology in the Yangtze River Delta region has potential interdependence, and the spatial econometric model is adopted for further analysis. First, LM test is carried out on panel data to determine whether there is a spatial relationship between variables and the type of spatial relationship. Then Wald test and LR test are carried out to determine whether the spatial Dubin model (SDM) will degenerate. LM test results are shown in the table below.

**Table 5.** LM test results

Test	Statistic	df	p-value
Spatial error			
Moran's I	5.771	1	0.000
Lagrange multiplier	24.226	1	0.000
Robust Lagrange multiplier	59.485	1	0.000
Spatial lag			
Lagrange multiplier	13.580	1	0.000
Robust Lagrange multiplier	48.839	1	0.000

The P values of both LM-error and LM-lag are 0.000, which is significant at 1% level. Therefore, the Robust Lagrange test is then adopted, and the P values of both Robust LM-error and Robust LM-lag are 0.000, which is significant at 1% level. Wald test and LR test were further used. Wald test and LR test results are as follows.

**Table 6.** Wald test and LR test results

Test Summary	Statistical value	P-value
Wald test of SEM model	39.48	0.0000
Wald test of SAR model	42.98	0.0000
LR Test (Assumption: SEM nested in SDM)	40.86	0.0000
LR Test (Assumption: SAR nested in SDM)	40.50	0.0000

It can be seen from the table that the P values of Wald test and LR test are both less than 0.01. Through the significance level test, it means that SDM model will not degenerate into SEM model and SAR model. Therefore, this paper uses SDM model to analyze the spatial spillover effect of green technology innovation in the Yangtze River Delta region.

### 5.2.2. Spatial spillover effect analysis

First, the Hausman test shows that the P value is less than 0.05, rejecting the null hypothesis and adopting the fixed-effect panel model. In order to analyze the impact of digital economy on the innovation and development of green technology in different spatial dimensions, this paper constructs a spatial Dubin model using the adjacency weight matrix and geographical distance matrix respectively, and conducts an empirical analysis using the panel data of 41 prefecture-level cities in the Yangtze River Delta from 2016 to 2020.

**Table 7.** Spatial Dubin model results

Variable	Adjacent-weight matrix	Geographic distance matrix	Variable	Adjacent-weight matrix	Geographic distance matrix
Main			W <sub>x</sub>		
del	818.9877*** (3.29)	719.4987*** (2.94)	w*del	-586.2566 (-0.94)	-2705.9042* (-1.88)
gi	5.2903** (2.35)	5.7152*** (2.59)	w*gi	3.5245 (0.74)	30.0718 (1.59)
open	138.7449*** (3.60)	122.4861*** (3.36)	w*open	-137.5089** (-2.00)	-517.5940* (-1.78)
lnurban	1.0701 (0.37)	1.0069 (0.38)	w*lnurban	-7.0666* (-1.70)	-34.7717** (-2.06)
tl	-382.1095*** (-3.40)	-402.4745*** (-3.70)	w*tl	-113.9167 (-0.42)	-768.0416 (-0.76)
tech	8.8044* (1.88)	14.8372*** (3.25)	w*tech	42.1945*** (4.21)	219.3178*** (5.58)

As can be seen from the table, the core explanatory variable digital economy index has passed the significance test. Four control variables of the spatial Dubin model constructed by the geographical distance matrix pass the significance test, and three control variables of the spatial Dubin model constructed by the adjacency weight matrix pass the significance test. In the geographical distance matrix, the digital economy has a negative spatial spillover value, indicating that the improvement of the digital economy level in a region may inhibit the development of green technology innovation in the surrounding region. The regression coefficient of digital economy is significantly positive, indicating that digital economy can promote the development of local green technology innovation.

Among the control variables, the improvement of the opening level of the foreign economy has a negative spillover effect on the green technology innovation and development of the surrounding areas, and the improvement of the urbanization level has a negative spillover effect on the green technology innovation and development of the surrounding areas, and the improvement of the scientific and technological level can promote the green technology innovation and development of the surrounding areas. In order to more accurately explore the spatial spillover effect of each variable, the spatial effect is divided into direct effect, indirect effect and total effect, and the spatial Dubin model constructed by geographical distance matrix is used to decompose the effect. The breakdown results are as follows.

**Table 8.** Effect decomposition result

Explanatory variable	LR_Direct	LR_Indirect	LR_Total
del	795.5230*** (3.17)	-1878.6580* (-1.68)	-1083.1350 (-0.68)
gi	5.1349** (2.37)	13.7859 (1.28)	18.9208* (1.75)
open	138.5075*** (3.75)	-354.8683* (-1.87)	-216.3608 (-1.18)
lnurban	1.6651 (0.59)	-20.1435* (-1.69)	-18.4784* (-1.74)
tl	-399.1660*** (-3.67)	-258.0851 (-0.41)	-657.2511 (-1.06)
tech	10.9081** (2.43)	118.6796*** (3.68)	129.5877*** (3.93)

The direct effect coefficient of digital economy level is positive, and the indirect effect coefficient is negative, indicating that the improvement of digital economy level is conducive to the development of local green technology innovation, and the improvement of digital economy level will draw resources from surrounding areas and inhibit the development of green technology innovation in surrounding areas.

The direct effect coefficient and total effect coefficient of innovation greening level are positive, and the indirect effect coefficient fails to pass the test, indicating that the improvement of innovation greening level can promote the development of local green technology innovation, but has no spillover effect on the development of surrounding areas.

The direct effect coefficient of the level of foreign economic opening is positive, and the indirect effect coefficient is negative, indicating that the improvement of the level of foreign economic opening and the frequent foreign trade bring more advanced products are conducive to the development of local green technology innovation, but not conducive to the improvement of the level of green technology innovation in surrounding areas.

Both the indirect effect coefficient and the total effect coefficient of urbanization level are negative. The higher the level of regional urbanization, the negative impact on the development of green technology innovation in the surrounding areas. The direct effect did not pass the significance test, possibly because the influence of urbanization level on regional green technology innovation and development is non-linear.

The direct effect of the tertiary industry development level on the development of green technology innovation is positive, but the indirect effect has not passed the test, indicating that it is impossible to judge the impact of the improvement of the tertiary industry development level on the green technology innovation in the surrounding area.

The direct effect, indirect effect and total effect of the development level of science and technology are all positive, indicating that the improvement of the development level of science and technology will have a significant positive impact on both the local and surrounding areas. Improving the level of science and technology development in the Yangtze River Delta region is an effective means to improve the level of green technology innovation and development in the Yangtze River Delta region and give full play to its diffusion effect. It has provided scientific and technological support and talent support for green technology innovation and development in other regions.

## **6. CONCLUSIONS AND RECOMMENDATIONS**

### **6.1. Conclusion**

This paper takes 41 cities in the Yangtze River Delta region as the research object, and empirically analyzes the spatial correlation degree and the spillover effect of green technology innovation in 41 prefecture-level cities in the Yangtze River Delta region from 2016 to 2020 by constructing the spatial Dubin model. The main conclusions are as follows:

First, the digital economy has a strong positive impact on green technology innovation and development, and has an empowering effect on regional green technology innovation and development.

Second, the development of green technology innovation in the Yangtze River Delta showed a significant positive spatial autocorrelation, and the spatial autocorrelation decreased with the increase of years, and the trend of unbalanced development of green technology innovation increased.

Third, the development of green technology innovation in the Yangtze River Delta region shows the characteristics of high and high values or low values and low values. Some cities in Jiangsu Province and Shanghai showed high value aggregation, while most cities in Anhui province showed low value

aggregation. The agglomeration level of cities around the capital cities in the Yangtze River Delta region is high, but the spatial spillover effect is not obvious.

Fourth, among the factors affecting the development of green technology innovation in the Yangtze River Delta region, the level of digital economy, the level of green innovation, the level of economic opening to the outside world, the level of tertiary industry development and the level of scientific and technological development have a significant positive impact on the regional green technology innovation and development. Digital economy level, opening-up level and urbanization rate have negative spillover effects on green technology innovation and development in surrounding areas, while science and technology development level has positive spillover effects on green technology innovation and development in surrounding areas.

## 6.2. Suggestion

According to the above research conclusions, suggestions are put forward from the following three aspects.

First, pay attention to the regional balance of the level of green technology innovation and narrow the gap between cities. In recent years, the trend of uneven development of green technology innovation has increased. For cities with higher levels of development, they should further consolidate their dominant position and promote their sustainable and steady development. Provincial capitals and coastal cities should play a leading and exemplary role, and through their own successful experiences, lead cities with relatively low levels of development to achieve common progress and optimize the allocation of resources. Second, we need to promote green technology innovation and development through the digital economy. It can be concluded that the digital economy has an enabling effect on the level of green technology innovation, can effectively integrate resources, improve innovation efficiency, and promote the rapid development of green technology. Therefore, the government and enterprises should increase investment in digital technology and break through the key technologies of digital green integration. Third, we will strengthen regional science and technology development. It can be seen from the analysis results that the improvement of regional science and technology level can not only drive the local green technology innovation and development, but also radiate the surrounding areas and give full play to the spatial spillover effect. Local governments can cooperate with leading technology enterprises to build science and technology demonstration zones, drive the development of science and technology in surrounding areas, and increase the introduction of talents, so as to promote digital transformation and improve the level of green technology innovation.

## ACKNOWLEDGEMENTS

This article research was financially supported by the national college students innovation and entrepreneurship training program (Project approval number: 202210378178), Research on the Spatial Effect of Digital Economy Development Enabling Green Technology Innovation in Yangtze River Delta region.

## REFERENCES

- [1] TAPSCOTT D. The digital economy: Promise and peril in the age of networked intelligence [M]. New York: McGraw Hill, 1996.
- [2] Zhang Xinwei. Research on the evolution of innovation model under the condition of digital economy [J]. *Economist*, 2019(07):32-39.
- [3] Zhang Xuliang, Shi Jinchuan, Li Xiande, Zhang Haixia. The mechanism and effect of Internet on regional innovation in China [J]. *Economic Geography*, 2017, 37(12):129-137.
- [4] Zhao Binyuan. The impact of digital economy on regional innovation performance and its spatial spillover effect [J]. *Science and Technology Progress and Countermeasures*, 2019, 38(14):37-44.

- [5] Wen Jun, Yan Zhijun, Cheng Yu. Digital economy and improvement of regional innovation ability [J]. *Economic Issues Exploration*, 2019(11):112-124.
- [6] Xiong Li, CAI Xuilian. The impact of digital economy on the improvement of regional innovation capacity: An empirical study based on the Yangtze River Delta urban agglomeration [J]. *East China Economic Management*, 2019, 34(12):1-8.
- [7] Qi Shaozhou, Lin Shenbo, CUI Jingbo. Can the Environmental Rights Trading Market induce green innovation? -- Evidence based on green patent data of listed companies in China [J]. *Economic Research Journal*, 2018, 53(12):129-143.
- [8] Li Qingyuan, Xiao Zehua. Heterogeneous environmental regulation tools and corporate green innovation incentives: evidence from green patents of listed companies [J]. *Economic Research Journal*, 2019, 55(09):192-208.
- [9] Liu Chang, Tian Xiaoli. Regional environmental protection investment, urbanization and green technology innovation: An empirical study based on spatial Dubin model and intermediary effect [J]. *Science and Technology Management Research*, 2019, 40(15):236-243.
- [10] Si Lijuan. The impact of environmental regulation on green technology innovation: An empirical analysis based on urban panel data in the Yellow River Basin [J]. *Research on Finance and Economics*, 2020(07):41-49.
- [11] Chen Xiao, Li Meiling, Zhang Zhuangzhuang. Environmental regulation, government subsidies and green technology innovation: An empirical study based on the intermediary effect model [J]. *Industrial Technical Economics*, 2019, 38(09):18-25.
- [12] Xu Xianchun, Ren Xue, Chang Zihao. Big data and green development [J]. *China Industrial Economy*, 2019(04):5-22.
- [13] Guo Bingnan, Wang Yu, Li Ning. Has the digital economy boosted green technology innovation in China? [J]. *Journal of Guangxi University of Finance and Economics*, 2022, 35(02):1-19.
- [14] Yang Li, Sun Zhichun. Evaluation of development level of new urbanization in western China based on entropy value method [J]. *Economic Problems*, 2015(03):115-119.