The Spatial Spillover of Digital Economy on Green Innovation: Evidence from China

Yuming Zhai, Ning Xie*

*206121158@mail.sit.edu.cn

School of Economics and Management, Shanghai Institute of Technology, Shanghai, China

Abstract: The Digital Economy Provides Fresh Blood For High-Quality Economic Development, And Has A Huge Impact On The Promotion Of Green Innovation. Based On The Date Of 282 Chinese Cities From 2011 To 2019, The Empirical Study Of Spatial Dobbin Model (SDM) Shows That Digital Economy Can Directly Improve The Level Of Local Green Innovation, And Drive The Surrounding Cities To Carry Out Green Innovation Activities Through Spatial Spillover Effect. The Robustness Test Enhances The Reliability Of This Result. The Heterogeneity Test Shows That The Big Cities Have Obtained Greater Digital Economy Spillover Dividends. The Research Conclusion Provides Important Policy Enlightenment For Giving Better Play To The Role Of Digital Economy In Green Innovation.

Keywords: Digital Economy, Green Innovation, Spatial Effect.

1 INTRODUCTION

As China has entered the era of Industry 4.0, the digital economy under the rapid development has now become the backbone of promoting the high-quality development of the domestic economy. This is conducive to helping enterprises transform the mode of economic development and promote the construction of ecological civilization [3]. Meanwhile, green development has become a new global development trend. China responded quickly and positively. It put forward the concept of high-quality economic development including green and innovation, and formulated a nationwide action plan for energy conservation and emission reduction. As the combination of innovation driven strategy and green development strategy, green innovation has become one of the core contents of promoting sustainable economic development and the key path of building a community with a shared future for mankind. Therefore, how to give full play to the power of digital economy to promote green innovation has gradually become the focus of all sectors of society and government.

Green innovation refers to the technological innovation of green products and processes to reduce the environmental burden or achieve the goal of ecological sustainability. The digital economy is an economic activity with data as its resource, which promotes profound changes in the production and operation modes of enterprises and society. Based on resource-based theory, the digital economy provides new digital resources, platforms and development space for green innovation [5].

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From the perspective of cost, the digital economy has the advantage of low cost, which improves the main body's green innovation willingness. The digital economy breaks through the restriction of geographical distance through efficient information transmission [4], reduces the daily operating costs of enterprises, and increases the investment in green innovation. Secondly, the construction of digital infrastructure has improved the level of regional informatization, it can effectively promote the integration of related industries, optimize regional industrial layout. It also provides a management medium for government supervision, and promote the industrial structure to digital, rational and green transformation and upgrading (Kohli & Melville, 2018).

From the perspective of resources, digital technology can promote resource matching and green transformation of enterprises. Digital technology provides an information platform for enterprises to grasp market trends more quickly, respond to market demands in time, and improve enterprise resource matching. In addition, more rapid information transmission and richer access to knowledge will make the market environment more open and transparent. Enterprises must ensure their own survival and development through innovation, and accelerate the innovation of green products and processes [6].

Because the digital economy can achieve efficient information transmission in different regions, promote close cooperation between supply chain enterprises, and promote green innovation activities among regions. Therefore, we propose the hypothesis as follows:

Digital economy can improve urban green innovation and drive the coordinated development of adjacant cities.

2 Materials and Methods

2.1 Model Settings

The following model is built for the spatial spillover effect of digital economy on green innovation (Formula 1), which is the spatial Doberman model (SDM).

$$Lngi_{i,t} = \alpha_0 + \rho WLngi_{i,t} + \varphi_1 WLnde_{i,t} + \alpha_1 Lnde_{i,t} + \varphi_2 C_{i,t} + \alpha_2 C_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

where W is the spatial weight matrix, ρ is the spatial autoregressive coefficient, and φ1 and φ2 is the coefficient of spatial interaction term.

2.2 Variables Description

2.2.1 Explanatory Variables

Digital economy (DE). Referring to the research of Zhao et al. (2020)[7], we selected five indicators: number of employees who engaged in software, mobile phone users number, the Internet broadband access users number, the telecom business income and the urban digital inclusive financial index. The five indexes are integrated into a comprehensive index through principal component analysis, which is recorded as De.

2.2.2 Explained Variable

Green innovation (Gi). Referring to the research of Liang et al. (2022)[2], we choose the green invention patent application number as the index to measure green innovation. Due to the uneven development level of green innovation among cities, the number of green creation applications in some regions is 0, which may affect the subsequent calculation. Thus, we use the logarithm of the urban green patents number plus 1 as the dependent variable, which is recorded as Gi.

3.2.3 Control Variables

Referring to relevant literature, we selected five control variables, which can reflect the regional economic, social and resource conditions to a certain extent.

(1) Economic development level (ECO): expressed as the logarithm of per capita GDP;

(2) Science and technology expenditure (ST): expressed by the proportion of science and technology expenditure in fiscal expenditure;

(3) Human capital (HUM): expressed as the proportion of the number of students in Colleges and universities to the total population;

(4) Foreign direct investment (FDI): expressed as the proportion of foreign direct investment in GDP ;

(5) Financial development (FIN): expressed as the proportion of the balance of deposits and loans of financial institutions in GDP (Ma & Wang, 2022);

(6) Environmental regulation (ER): expressed by the proportion of the frequency of environmental protection words in the work report of prefecture level municipal government.

The descriptive statistics of all variables are shown in Table 1.

Table 1 Descriptive statistics

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
GI	2,538	5.1888	1.652	0.693	10.454
DE	2,538	0.000	1.215	-1.476	12.541
ECO	2,538	7.369	0.917	4.903	10.550
ST	2,538	1.649	1.666	0.067	20.684
HUM	2,538	1.894	2.445	0.004	13.112
FDI	2,538	1.667	1.774	0.000	19.937
FIN	2,538	2.851	2.272	0.588	38.237
ER	2538	0.251	0.145	0.000	1.239

2.3 Data Source and Processing

Considering the availability of data, we finally used the data of 282 cities in China from 2011 to 2019 for empirical research. In particular, the digital inclusive finance index comes from the digital inclusive finance index system and index compilation, the green patent application data comes from Chinese Research Data Services (CNRDS) Platform, and other data come from

China Urban Statistics Yearbook, China Environmental Statistics Yearbook and China Information Industry Yearbook. Some missing data were obtained by linear interpolation.

3 Results & Discussion

3.1 Regression Analysis

First, we tested the global Moran index of digital economy and green innovation from 2011 to 2019, and the result is significantly positive, which indicating that between the two has a strong spatial correlation. And then, Hausman test, LR test, LM test and Wald test are all significant at the level of at least 5%, which indicates that choosing the spatial Dubin model (SDM) with spatiotemporal double fixed effects is appropriate.

Table 2 Estimation results of spatial effects

Variables	*W1*	*W2*	*W3*
DE	0.102*** (0.029)	0.114*** (0.029)	0.090** (0.029)
WxDE	0.253*** (0.115)	0.252*** (0.070)	0.100*** (0.046)
Direct effect	0.110*** (0.029)	0.117*** (0.029)	0.098*** (0.029)
Indirect effect	0.315*** (0.067)	0.279*** (0.071)	0.151** (0.052)
Total effect	0.425*** (0.070)	0.397*** (0.073)	0.249*** (0.056)
Control variables	YES	YES	YES
Observations	2538	2538	2538
R-squared	0.7658	0.7515	0.5404
Log-likelihood	-649.3888	-661.1476	-612.0804

Table 2 reports the SDM results under the economic geography nested matrix (W1), economic geography matrix (W2) and adjacency matrix (W3). In the first column of Table 2, the digital economy is significantly positively correlated with green innovation (α=0.102, p=0.000), and has significant spatial spillover effect (α=0.253, p=0.000). After further analysis of the test results, we find that the direct effect of digital economy on green innovation is significantly positive (α=0.110, p=0.000), the indirect effect is significantly positive (α=0.315, p=0.000), the total effect is also significantly positive (α=0.425, p=0.000). The results supports the research hypothesis, and the results of W2 and W3 also strengthen this conclusion.

3.2 Regional Heterogeneity Analysis

Due to digital economy in different regional resources and development stages may have differences, the impact on green innovation may also be heterogeneous. Referring to the division of the three economic zones, we divide 282 cities into three parts. Table 3 shows the SDM results of the eastern, central and western regions under W1.

Table 3 Urban scale heterogeneity analysis

Variables	Eastern region	Central region	Western region
DE	0.001 (0.047)	0.140** (0.054)	0.073 (0.054)
WxDE	0.139 (0.097)	0.670*** (0.134)	0.014 (0.104)
Direct effect	0.010 (0.049)	0.156** (0.055)	0.075 (0.055)
Indirect effect	0.173 (0.117)	0.787*** (0.146)	0.005 (0.094)
Total effect	0.183 (0.133)	0.942*** (0.148)	0.080 (0.105)
Control variables	YES	YES	YES
Observations	1017	972	549
R-squared	0.532	0. 784	0.041
Log-likelihood	-191.165	-261.849	-146.291

We can clearly know that the digital economy in central region cities has significantly promoted the development of green innovation at the level of 5%, but it is not significant in the other regions. The possible reason is that the central region has better digested and absorbed the cash knowledge and technology of the eastern region, seized the digital dividend generated by the digital economy, and thus showed a stronger willingness to green innovation.

3.3 Urban Scale Heterogeneity Analysis

Due to large differences in urban population, referring to the practices of He et al. (2020)[1], divide into small-medium sized cities and large cities according to whether the urban population is less than 5 million. Table 4 shows the analysis of urban scale heterogeneity.

Table 4 Urban scale heterogeneity analysis

Variables	Big	Small-medium
DE	0.156*** (0.046)	0.070** (0.036)
WxDE	0.304** (0.105)	0.202** (0.070)
Direct effect	0.161*** (0.047)	0.076** (0.037)
Indirect effect	0.322** (0.102)	0.239*** (0.075)
Total effect	0.483*** (0.102)	0.315*** (0.079)
Control variables	YES	YES
Observations	819	1719
R-squared	0.7662	0.6883
Log-likelihood	-85.8086	-533.9603

The impact in large cities is positive and significant (α=0.156, p=0.000), while the impact on small-medium sized cities is also positive and significant (α=0.070, p=0.007). However, the impact of big cities is stronger in terms of value and significance. This may because big cities have a good foundation in R&D foundation, digital technology and industrial agglomeration, forming the characteristics of coordinated evolution of digital economy and green innovation.

3.4 Robustness and endogenous text

3.4.1 Robustness Check

We conducted a series of robustness tests to further enhance the rebustness of the results. Firstly, we use the authorized number of urban green innovation patents as the new explained variable (α = 0.118, p = 0.000). The SDM results based on W1 are shown in column (1) of Table 5. It is found that the conclusion is still supported. Secondly, due to the low administrative levels in terms of political resources and innovation ability, we exclude cities with high administrative levels (municipalities and provincial capitals), and only 247 general cities are regtained as samoles for regression. The SDM results under W1 are shown in column (2) of Table 5. The research conclusions and are still robust (α=0.083, p = 0.000).

Table 5 Robustness check

Variables	Green patents authorized number	Ordinary prefecture level city
DE	0.118*** (0.028)	0.083** (0.032)
WxDE	0.143** (0.060)	0.175** (0.065)
Direct effect	0.123*** (0.028)	0.089** (0.033)
Indirect effect	0.184** (0.065)	0.213** (0.071)
Total effect	0.307*** (0.067)	0.302*** (0.075)
Control variables	YES	YES
Observations	2538	2223
R-squared	0.698	0.714
Log-likelihood	-591.964	-633.981

3.4.2 Endogenous Text

Since the two-way causality will affect the accuracy of the research results, we select the digital economic variables lag for one period (GI1) as the instrumental variable, and use the two-stage least square method for regression. The endogenous text results are shown in Table 6. After considering endogeneity, the positive impact of digital economy on green innovation is still significant. Meanwhile, Kleibergen-Paap rk LM statistics p value is 0.000 (α = 442.156), which indicates that the instrumental variables can confirm the research hypothesis; in the test of weak identification of instrumental variables, the Kleibergen-Paap rk Wald F statistic is greater than the critical value at the 10% level of Stock-Yogo weak identification test. Overall, it is reasonable to choose GI1 as the tool variable of digital economy.

Table 6 Robustness check

Variables	2sls
	GI1
DE	2,284** (0.058)
Control variables	YES
Kleibergen-Paap rk LM statistic	442.156***
Kleibergen-Paap rk Wald F statistic	4311.507
Observations	2256
R-squared	0.782

4 Conclusion

Based on the data of 282 Chinese cities in 9 years, this study verifies the impact mechanism between digital economy and green innovation by using SDM. The results show that the digital economy can promote the development of green innovation through space spillover effect. Further research found that the digital economy of center regions and large cities can promote the development of green innovation.

This study has the following policy significance. (1) Clarify the important role of digital economy in promoting the development of urban green innovation. Further promote the full coverage of 5G, big data and other digital infrastructure as soon as possible to lay a solid material foundation for the release of digital dividends. At the same time, increase the investment in digital industry, build a platform for digital technology and industry integration, and enabe the development of industries from multiple angles and in all directions. (2) Fully consider the spatial spillover effect of digital economy, and implement the regional difference strategy. There are differences in the promotion role of digital economy in cities in different sizes and different regions, use digital technology to build a sharing mechanism of technology, information, talent and other resource elements between different regions, and make full use of the "diffusion effect" of big cities to drive the development of surrounding cities.

However, our research still has some limitations. (1) Although the study surveyed most cities in China, due to the availability of data, we have no way to analyze all cities in China. In addition, due to the restrictions of COVID-19, our research period is up to 2019. Future research can further expand the research sample and interval. (2) The connotation of digital economy may change with the passage of time. Therefore, future research can further expand the comprehensive index of digital economy. (3) The study only takes cities in China as an example. If cities in other countries are compared, new findings may be made.

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