The Digital Economy, Spatial Effects and Green Technology Innovation: Analysis Based on The Spatial Durbin Model

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Abstract: The way the economy operates in the digital era presents the characteristics of data-driven, interconnectedness of everything and innovation iteration, and the digital, networked and intelligent attributes of the digital economy have a profound impact on innovation activities. Based on the panel data of 30 provincial administrative units in China from 2007 to 2017, the spatial effect of digital economy on green innovation is empirically tested using the spatial Durbin model, and the following conclusions are drawn: Both digital economy and green technology innovation have significant positive spatial correlation in space, and there is a "spatial club There is a "spatial club" effect. The coefficients of the direct and indirect effects of the digital economy on green technology innovation are both significantly positive at the 1% level, and the digital economy not only has a significantly positive local green technology innovation effect, but also generates a greater neighbourhood green technology innovation effect. Based on this, policy recommendations for promoting green technology innovation are proposed.

Keywords: Digital economy; green technology innovation; spatial effect; Durbin model

1 INTRODUCTION

Green technology innovation, as a technological innovation activity aimed at promoting green technology development and improving the ecological environment, can effectively coordinate the relationship between economic growth and environmental protection by contributing to the construction of a green, low-carbon and circular production system, and is thus considered an important way to promote the green development of enterprises[1]. However, as green technology innovation is characterised by strong externalities, high investment and high risks, without external policy intervention and motivation sources, companies aiming to maximise profits usually lack the will to innovate green technology. 2018 saw China's share of green technology innovation at around 10% globally, compared to 22.4% in the US, 14.6% in Japan and 12.8% in Germany. there is a certain gap. Therefore, how to better drive green technology innovation in enterprises has become an important issue that needs to be studied and solved[2].

In recent years, the digital economy, as the most active area of China's economic development, has been expanding in breadth and depth of integration with all areas of the economy and society,

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playing an important role in stimulating consumption, boosting investment and creating employment. Relevant information from the China Academy of Information and Communication Technology shows that the size of China's digital economy was RMB 22.4 trillion in 2016 and reached RMB 35.8 trillion in 2019, accounting for 36.2% of GDP, with a year-on-year nominal growth of 15.6% on a comparable basis, much higher than the GDP growth rate. As the core force of the new round of industrial transformation, the digital economy is characterised by high technology, high growth, high integration and high synergy, etc. The innovation activities under the conditions of the digital economy are no longer purely technological innovation relying solely on the internal resources of enterprises, but more on the results of the interconnection and interaction between multiple innovation subjects and their environment. The innovation process involves not only the creation and industrialisation of new technologies, but also changes in the way resources are allocated, the way production is organised and the institutional arrangements that correspond to the new technological paradigm, providing a new source of power for total factor productivity improvement and opening up new space for economic growth. China's digital economy has gradually become an important part of the national economy and a growth driver, while maintaining high growth in scale.

As a convergent economy, the digital economy uses data as the core factor of production, permeating all production processes and gradually changing the types and proportions of factor inputs in the production process, breaking the shackles of traditional factor markets, thereby reducing resource mismatches and market distortions by intensifying market competition and optimising industrial division of labour (Yu and Wu Shiwei, 2020)[3]. Theoretically, the reduction of resource mismatch and market distortions can help increase total factor productivity through improved resource allocation efficiency. For example, Hsieh and Klenow (2009) incorporated product market distortions and factor market distortions into a monopolistic competition model to reveal the relationship between resource mismatch and total factor productivity and found that if the US is used as a benchmark, improvements in resource allocation efficiency would increase total factor productivity in China by 30%-50%[4].Brandt et al. (2013) found that factor market distortions increased China's total factor productivity loss in non-agricultural industries by an average of 20% over the period 1985-2007[5].

So, is the digital economy driving green technology innovation in China? If the effect is confirmed, what is the mechanism of action behind it? Answering this question will not only help assess the innovation-driven effect of the digital economy, but also provide important insights into how China can leverage the opportunity of the development of the digital economy to vigorously promote green technological innovation and achieve green development. Based on this, this paper uses spatial econometric analysis based on provincial panel data from 2007-2017 in China to empirically test whether the development of China's digital economy drives green technological innovation, and to propose corresponding countermeasures. The main contributions of this paper are: first, the research perspective, based on the realistic background of the rapid development of the digital economy, assesses the green technological innovation driving effect of the digital economy, enriching the relevant theories of the digital economy and green technological innovation; second, the research methodology, taking into account the spatial economic correlation between regions, adopts a spatial econometric analysis method, providing richer empirical evidence, which can provide a reference for the relevant regional innovation Secondly, the research methodology takes into account the spatial economic linkages between regions and adopts a spatial econometric analysis, which provides richer empirical evidence and can provide reference for the formulation and coordinated development of relevant regional innovation policies.

2 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

2.1 The Driving Role of The Development of The Digital Economy on Green Technology Innovation

As the core force of the new round of industrial transformation, the digital economy, with data as a key factor of production, is characterized by high technology, high growth, high integration and high synergy, which has a direct role in promoting green technological innovation in the region. Firstly, the high technology and platform-based characteristics of the digital economy promote rapid improvement in total factor productivity. The digital economy is highly dependent on contemporary information technology, and as an important technological innovation, the digital economy itself requires a large amount of human and material resources for research and development and design[6]. At the same time, the digital economy has typical "platform-based" characteristics. On the one hand, it breaks through the division of information between consumers and researchers in traditional innovation, realising an effective match between supply and demand, enhancing the flexibility of forecasting, improving resilience in the face of threats and disruptions, reducing uncertainty in R&D caused by information asymmetry, and improving the efficiency of transformation of scientific and technological achievements On the other hand, the platform economy realises the diversification of innovation subjects, allowing innovation to shift from within closed organisations to open crowdsourcing spaces, enabling the sharing and integration of innovation resources in the industrial chain, which speeds up R&D and improves its success rate. Secondly, the convergence and synergistic characteristics of data elements drive up the production efficiency of traditional elements. Through the integration with capital, labour, entrepreneurial talent and other factors, new production factors with a higher degree of knowledge and intellectual intensity, such as information and data, can interact with and complement other factors, realising the reconstruction of traditional production factors with relatively weak mobility, promoting the improvement of the knowledge density of the traditional economy and enhancing the production efficiency of traditional factors[7]. Furthermore, the application of big data technology in the digital economy era has prompted changes in the organisational form, business processes, coordination mechanisms and participating subjects of enterprises, promoted the transformation of the organisational model of enterprises to networking, flattening and flexibility, improved the adaptability and flexibility of the supply structure to changes in demand, enhanced information communication and business cooperation within enterprises and between them and upstream and downstream enterprises, and improved the efficiency of factor allocation and use[8]. In particular, the realisation of personalised production models has increased product differentiation, and companies can achieve more effective price discrimination and reduce inter-company price competition through big data analysis of consumers. This change in the competitive environment will have different implications for the incentives to innovate at the production frontier and those at the non-production frontier, which in turn will also have different implications for technological efficiency and technological progress.

2.2 Spatial Spillover Effects of The Level of Development of The Digital Economy and Innovation Performance

From the perspective of resource factors, the low diffusion cost and high diffusion speed of data lead to its natural mobility property. This mobility is less restricted by geographic space, reflecting a strong geospatial spillover effect. In innovation activities, innovation agents in closer geographical proximity have more opportunities for exchange and cooperation, and increase the utilisation of data elements through sharing open data, thus enhancing the spatial spillover effect of regional innovation performance. A study conducted a questionnaire survey on 339 R&D personnel and middle and senior managers found that data spillover has a significant contribution to the formation of cluster innovation capability[9]. Therefore, data elements can not only improve the innovation performance of the region, but also improve the innovation performance of neighbouring regions through sharing and opening.

From the perspective of carrier platforms, digital platforms not only provide innovation subjects with the opportunity to collaboratively allocate innovation resources online, but also provide information access channels for innovation subjects to find partners and strengthen communication and docking. Innovation subjects can learn about potential innovation cooperation partners through the digital platform and further deepen their cooperation through field research, offline seminars and co-build physical platforms based on online communication. Han Pioneer et al. (2019) empirically analysed the impact of the comprehensive level of Internet development on innovation efficiency in 30 provinces in mainland China from 2006-2017, and the results showed that the Internet not only promoted regional innovation efficiency, but also showed significant innovation spillover effects. Thus, digital platforms help promote the geospatial clustering of innovation agents, which in turn provides resource support for matching innovation resources with innovation agents and for spatial clustering[10].

From the perspective of technological innovation, with the development of digital economy and digital technology, the digital transformation of internal innovation platforms of enterprises is also accelerating. For example, innovation platforms such as Alibaba AI Lab, Tencent AI Lab and Baidu AR Lab use digital tools or software for digital design, analysis, simulation and validation to achieve digital product definition, model data checking, mechatronic co-design, collaborative engineering calculation and digital simulation analysis, providing an integrated working environment for R&D personnel with virtual parallel co-design and simulation[11]. Digital technology improves the efficiency of physical innovation platforms in allocating innovation resources such as talent, technology and knowledge, enhances the clustering effect of physical innovation platforms on innovation resources, and promotes the flow of innovation resource elements and regional collaborative innovation.

3 STUDY DESIGN

3.1 Model Setting

Spatial econometrics is a tool used to identify spatially correlated effects and structural patterns between variables. Spatial panel models mainly include spatial lag (SAR), spatial error (SEM) and spatial Dubin model (SDM), among which, the spatial Dubin model can well analyse the effect relationship caused by the explanatory variables on the explanatory variables, and SAR and SEM are both special forms of SDM, which can be interconverted under certain conditions. In this paper, SDM is selected to empirically explore the effect of digital economy on green technology innovation, and its expression is shown as follows

$$\ln GI_{it} = \beta_0 + \beta_1 \ln DE + \beta_2 \ln X_{it} + \rho \sum_{j=1}^{n} w_{ij} \ln GI_{it} + \alpha_1 \sum_{j=1}^{n} w_{ij} \ln DE_{jt} + \alpha_2 \sum_{j=1}^{n} w_{ij} \ln X_{it} + \varepsilon_{it} \quad (1)$$

where i stands for city, t stands for year, GI stands for green technology innovation indicator, DE stands for digital economy indicator, X stands for control variable indicator, ρ stands for spatial spillover coefficient of the explanatory variable, α stands for spatial correlation coefficient, β stands for linear correlation coefficient, ε stands for random disturbance term and w stands for standardised spatial weight matrix. The first is a 0-1 spatial weight matrix (w1), which is set as wij=1 if city i is adjacent to city j and wij=0 if it is not. The second is a geographical distance weight matrix (w2), which is set as the inverse of the nearest road mile between city i and city j. The second is a spatial distance weight matrix (w2), which is set as the inverse of the nearest road mile between city i and city j. The second is a spatial distance weight matrix (w2), which is set as the inverse of the nearest road mile between city i and city j.

3.2 Variable Setting

Explanatory variable: green technology innovation (GI). Green technological innovation is difficult to be measured directly, and current measures of green technological innovation focus on two methods: one is to use R&D investment[12] or technology patents[13] as proxies for green technological innovation; the other is to use the green total factor productivity decomposition variable green technological progress, which takes into account environmental pollution, as a proxy[14] . The second approach is used in this paper. A hybrid function EBM (Epsilon-based Measure) model that combines both radial and non-radial distance functions proposed by Tone and Tsutsui[15] is used to measure green total factor productivity and obtain an adjusted green technological innovation index for the period 2007-2017.

Explanatory variable: digital economy (DE). Referring to Xu Xianchun and Zhang Meihui (2020), the evaluation system of digital economy was constructed from three dimensions: digital infrastructure, digital application and digital development potential[16]. Among them, digital infrastructure mainly includes four indicators: Internet penetration rate, total telecommunication services, number of mobile phone users, and revenue of software and information technology service industry; digital application includes four indicators: e-commerce transaction volume, number of digital platforms, number of enterprises engaged in e-commerce transaction activities, and percentage of digital payment of enterprises; digital development potential includes: R&D investment in ICT industry, information The digital development potential includes four indicators: R&D investment in the ICT industry, the number of ICT patents granted, the number of employees in the ICT industry, and the revenue of the ICT industry. Finally, the entropy value method was used to calculate the weights of the indicators and the composite index.

Control variables: Some control variables were selected to reflect the characteristics of the city and to influence green technology innovation. These include industrial structure (IND), economic development level (PGDP), government intervention (TE), information technology level (TC), and financial development (FD). Among them, industrial structure is expressed using the share of tertiary industry output in GDP of each province: economic development level is expressed using GDP per capita of each province: government intervention is expressed using the share of fixed asset investment in GDP of each province; informationization level is expressed using the number of Internet users of each province; financial development is expressed using the loan balance of financial institutions at the end of the year of each province.

3.3 Data Description

The data used in this paper are the inter-provincial panel data of China from 2007-2017. Among them, gross regional product, gross regional product index, total fixed capital formation, fixed asset investment price index, total number of employed persons, technology market turnover, general local fiscal budget expenditure, urban population, urban population density per capita, urban road area per capita, total import and export, and total investment by foreign-invested enterprises are from the National Bureau of Statistics; years of education per capita, year-end urban population The data used for the years of education per capita and the year-end urban population ratio were obtained from the China Statistical Yearbook; the data on the balance of RMB loans of financial institutions were obtained from the China Regional Statistical Yearbook. In addition, this paper uses the annual average price of the RMB to USD exchange rate from the National Bureau of Statistics to adjust the total investment of foreign invested enterprises and the total import and export.

4 ANALYSIS OF EMPIRICAL RESULTS

4.1 Spatial Durbin Model Estimation

As green technological progress has significant spatial autocorrelation, this paper uses a spatial econometric model for estimation. Before conducting the panel model estimation, the form of estimation of the econometric model needs to be selected, firstly with the help of LM test and Robust LM test to determine the form of existence of spatial correlation between variables. LM(lag), LM(error) and Robust LM(error) all passed the test at the 1% significance level, while Robust LM(lag) was not significant, indicating that the spatial lag model (SAR) is more suitable than the spatial error (SEM); secondly, the correlation between the spatial effect and the explanatory variables was analysed according to the Hausman test, as can be seen from the table below The Hausman statistic is 211.72 (p=0.000), indicating that the fixed effect is considered better than the random effect at the 1% significance level; the spatial and temporal fixed effects and the spatial and temporal double fixed effects are put into the spatial Dubin model respectively, and the model is tested separately using the maximum likelihood estimation, and it is found that the model fits best when the temporal fixed effect is added and Finally, according to the results of the LR and Wald tests, the results of LR(lag), LR(error), Wald(lag) and Wald(error) all passed the test at the 1% significance level, rejecting the original hypothesis that the SDM model would degenerate into SEM and SLM. LeSage (2009) pointed out that for endogeneity problems, the use of SDM models yields estimates that are not biased by amplification[17]. Therefore, the spatial Durbin model is chosen for estimation in this paper.

Table 1 also gives the spatial spillover coefficient of 0.208 for green technology innovation, which passes the test at the 1% significance level, indicating that there is a significant positive spatial spillover effect of green technology innovation, with each 1% increase in green technology innovation in the region driving a corresponding 0.208% increase in green technology innovation in neighbouring regions, which is consistent with the results of the spatial autocorrelation test in the previous paper. Since the coefficient of the spatial spillover effect of green technology innovation under the neighbouring spatial weight matrix is not zero and significant, the regression results cannot be used directly to explain the economic implications of each variable, so further effect decomposition is needed to analyse the effect of each variable on green technology innovation according to the decomposition results[18].

Table 1 Estimation Results of The Spatial Durbin Model

VARIABLES	OLS	DURBIN MODEL
$lnDE$	0.278^{***}	0.004^{***}
$lnIND$	0.027^{***}	-0.017
$lnPGDP$	0.004	-0.017^{**}
$lnTE$	-0.045^{**}	-0.004
$lnTC$	0.005	-0.005^{*}
$lnFD$	0.013^{***}	0.002
ρ		0.181^{***}
$W \times lnDE$		-0.055^{***}
$W \times lnIND$		0.005
$W \times lnPGDP$		0.008
$W \times lnTE$		-0.007
$W \times lnTC$		-0.008
$W \times lnFD$		-0.016
$R2$	0.171	0.228
$Hausman$		211.72^{***}

Note: ***, **, * denote significant at the 1%, 5% and 10% levels respectively, with standard errors in parentheses, as in the table below.

4.2 Estimation of Effect Decomposition Results

Table 2 presents the results of the effect decomposition based on the estimated form of the spatial Durbin model set out in the previous section, and also gives the results of the estimation in the geospatial weight matrix as a robustness check. From the regression results of the direct effects, the impact of the digital economy on green technology innovation is positive and significant at the 1% level, with an impact coefficient of 0.031. Every 1% increase in the development of the digital economy will correspondingly promote 0.031% increase in green technology innovation in the region; this indicates that with the development of the digital economy, the driving force of the digital economy to drive innovation is increasing, and the green effect is constantly emerging, thus promoting the Green technological innovation. The effect of government intervention on green technology innovation is negative and significant at the 1% level, indicating that government intervention plays a hindering role in the improvement of green technology innovation in the region, and cannot rely solely on the increase of government investment in fixed assets to improve the level of green technology innovation; the effect of financial development on green technology innovation is positive and significant at the 1% level, indicating that with the improvement of the level of financial development will play a role in promoting the level of green This may be due to the fact that financial development has increased enterprises' investment in innovation through developing capital markets and improving direct financing channels for enterprises. The industrial structure, the level of economic development and the level of information technology all have a promotional effect on green technological innovation, but they do not pass the test at the 10% significance level, indicating that their promotional effect on green technological innovation in the region is not significant.

In terms of the indirect effect coefficient, the impact of the digital economy on green technology innovation is positive and significant at the 1% level, with an impact coefficient of 0.081. Every 1% increase in the digital economy of a region will lead to a 0.081 increase in green technology innovation in neighbouring regions. This is mainly related to the difference in the digital economy gradient between the two regions; the effects of industrial structure and information technology on green technology innovation are positive and significant at the 10% level, indicating that they can significantly promote the level of green technology innovation in neighbouring regions; the effects of economic development and financial development on green technology innovation are negative, but do not pass the test at the 10% significance level. The negative effects of economic development and financial development on green technology innovation did not pass the test at the 10% significance level, indicating that their effects on green technology innovation in neighbouring regions are not significant at this stage.

In terms of the coefficient of influence of the total effect, the impact of the digital economy on green technology innovation is positive and significant at the 1% level, with an impact coefficient of 0.112 From the perspective of the city as a whole, the digital economy has a catalytic effect on green technology innovation, and the digital economy policy implemented at this stage can indeed significantly improve the level of green technology innovation; the impact of industrial structure and information technology level on green technology innovation is positive and significant at the The impact of industrial structure and information technology on green technology innovation is positive and significant at the 5% level. The increase in the proportion of tertiary industries, mainly service industries and other new industries, will reduce pollution emissions and increase enterprises' investment in R&D and innovation, thus increasing the level of green technology innovation. The impact of government intervention on green technology innovation is negative and significant at the 1% level, and government intervention has a negative impact on green technology innovation from the overall city unit. The coefficients of economic development and financial development on green technology innovation do not pass the test at the 10% level of significance, and their effects on green technology innovation are not significant in the context of the overall city unit.

Comparing the coefficients of the variables in the geographic distance weight matrix in Table 2, the coefficients of the direct, indirect and total effects of the main explanatory variables of this paper, the digital economy, remain unchanged in sign and significance despite the difference in magnitude, indicating that the above findings are robust.

Table 2 Estimated results of the decomposition of the effects of the spatial Durbin model

Effect	Variable	(w1)	(w2)
Direct ffect	$lnDE$	0.031***	0.033***
Indirect fect	$lnDE$	0.081***	1.321***
Total Effect	$lnDE$	0.112***	1.353***

5 CONCLUSIONS AND POLICY RECOMMENDATIONS

Based on the spatial panel data of 30 provincial regions in China from 2007 to 2017, the spatial effect of digital economy on green technology innovation was empirically tested by constructing a spatial Durbin model, and the following conclusions were drawn:(1) All provinces have significant positive spatial correlation between digital economy and green technology innovation in space, and there is a "spatial (1) All provinces have significant positive spatial correlation between digital economy and green technology innovation, and there is a "spatial club" effect, with most provinces showing "high-high" and "low-low" clustering characteristics. (2) The coefficients of the direct and indirect effects of the digital economy on green technology innovation are all significantly positive at the 1% level, and the digital economy not only has a significant effect on local green technology innovation, but also generates a greater effect on green technology innovation in neighbouring areas, and the robustness test results also support this conclusion. (3) Industrial structure, informationization level, government intervention, economic development and financial development can all influence green technology innovation to a certain extent; specifically, industrial structure and informationization level can effectively enhance green technology innovation, while government intervention will have a negative impact on green technology innovation; in addition, economic development level and financial development can also influence green technology innovation to a certain extent but not In addition, the level of economic development and financial development can also affect green technology innovation to some extent but not significantly.

Based on the above findings, we can draw the following insights: (1) to give full play to the demonstration effect of regions with advantages in green technology innovation, and to form a "multi-centre" synergistic development pattern of green technology innovation in each province. As there is a significant positive spatial spillover effect of green technology innovation, the improvement of green technology innovation in this region will have a catalytic effect on its neighbouring regions, so for those cities with a high level of green technology innovation, they need to give full play to their leading demonstration role to drive the development of green technology innovation in their neighbouring cities, forming a "win-win" development pattern of green technology innovation in all provinces. "(2) Increase the development of the digital economy (2) Increase the intensity of the digital economy, and at the same time increase the participation of neighbouring city governments in the process of formulating and implementing digital economy policies in the region, so as to give full play to the "innovation compensation effect" of the digital economy. Theory and facts have proven that market regulation alone does not promote green technology innovation and that government regulation is essential. Therefore, provincial governments need to strengthen the regulation of green technology innovation activities carried out by enterprises, formulate appropriate digital economy policies, and effectively implement them; at the same time, due to the spatial spillover effect of the digital economy, the formulation of relevant digital economy policies needs to increase the participation of governments of neighbouring cities, so as to guide the benign competition of the digital economy in various regions and promote the conversion of "bottom-up competition" to "bottom-up competition". (3) Focus on other factors (3) Focus on the impact of other factors on green technology innovation. While developing the economy at a rapid pace, we should also make good use of economic instruments to promote the production of clean enterprises and identify effective measures to reduce the inflection point of the "EKC" curve, so that the rising phase of the inverted "U" curve can be slowed down as much as possible. The rising phase of the inverted "U" curve should be slowed down as much as possible, and the falling phase should be accelerated as much as possible. At the same time, it is important to reduce government investment in fixed assets and make it moderate, and to improve the level of information technology and the speed of financial development in order to promote green technology innovation to a greater extent.

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