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Article

Digital Economy, Science and Technology Innovation and Carbon Emissions - A Dynamic Analysis of PVAR Based on Provincial Panel Data

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Abstract: This paper investigates the dynamic relationship between the digital economy, science and technology innovation and carbon emissions using a panel vector autoregressive model with data from 30 Chinese provinces from 2011 to 2019. The results show that: initial development of the digital economy will lead to an increase of carbon emissions, but the effect will be gradually weakened in later stages and become a reverse inhibitory effect; the growth of digital economy development level and the increase of carbon emissions intensity are mutually Granger causative; carbon emissions will inhibit the development of the digital economy in the short term, and will have a significant self-promoting effect; the improvement of science and technology innovation level on the growth of digital economy development level is the driving effect of the improvement of STI level on the growth of digital economy development level is not yet stable.

Keywords: Digital Economy; Science and Technology Innovation; Carbon Emission; PVAR Model

1. Introduction

The global climate problem is a huge challenge for all mankind, among which carbon emissions, mainly carbon dioxide, have brought a huge negative impact on human production and life. In the face of climate change challenges, China has put forward the goal of achieving peak carbon and carbon neutrality by 2030 and 2060. In October 2021, the Central Committee of the Communist Party of China (CPC) and the State Council issued the Opinions on Completely and Accurately Implementing the New Development Concept and Doing a Good Job of Peak Carbon and Carbon Neutrality, which specifies the goals of green low-carbon development and green transformation, aiming to implement the new development concept and achieve peak carbon and carbon neutrality. At present, China is in the stage of rapid development of its digital economy, with the continuous promotion of digital process, which relies on the wide application of digital technology in production and life. The digital economy is gradually becoming a strong support to achieve the goal of reduced carbon emissions, and the development of the digital economy is inseparable from the key factor of scientific and technological innovation, how to drive the development of digital economy through scientific and technological innovation to reduce carbon emissions is a key issue to be tested empirically.

Therefore, it is of great significance to use the digital economy as the main tool with science and technological innovation as the driving engine to reduce carbon emissions in order to achieve the strategic goal of carbon peaking and carbon neutrality. This paper uses the PVAR model to analyze the data of 30 provinces in China except Tibet, Hong Kong, Macao and Taiwan to investigate the interaction between the development level of the digital economy, the level of science and technology innovation and carbon emissions, which has important theoretical significance and practical value to improve the development of the digital economy, promote science and technology innovation and achieve peak carbon and carbon neutrality.

2. Literature Review and Theoretical Analysis

2.1. Digital Economy and Carbon Emission

In the context of the digital economy, many scholars have studied the relationship between the digital economy and carbon emissions (Miao et al., 2022) [1]. Xie et al. (2022) [2] have shown that the digital economy significantly suppresses carbon emissions through an empirical analysis of the mediating effect model, and the industrial structure upgrading plays an obvious mediating role in the transmission mechanism of the digital economy on carbon emissions. Li and Wang (2022) [3] conduct an empirical study on the development of digital economy and spatial carbon emission reduction through a dynamic spatial Durbin model, which shows that the digital economy has an inverted U-shaped local emission reduction effect of "promoting and then suppressing" and a U-shaped spatial spillover emission reduction effect of "suppressing and then promoting". Meanwhile, Xie (2022) [4] and Xu et al. (2022) [5] found that there is obvious spatial heterogeneity in the effect of digital economy on regional carbon emissions, and the emission reduction effect of digital economy is more significant in eastern regions.

2.2. Digital Economy and Science and Technology Innovation

Science and technology innovation provides an important driving force for the development of digital economy, and at the same time, the output of science and technology innovation is inseparable from the support of digital technology. Pu (2022) [6] and Lai et al. (2022) [7] found that the coupling and coordination degree of digital economy and science and technology innovation in China shows an overall development trend from low coupling to abrasion to high coupling, while there are obvious differences in the coupling degree between regions, overall, the eastern region is superior to other regions. Zhao and Li (2022) [8] conduct an empirical study on the relationship between science and technology innovation output and digital economy in the Yellow River Basin, and the research results shows that the development of the digital economy has a significant impact on technological innovation, and its spatial spillover effect is very significant. Wang et al. (2022) [9] investigate the driving effect of regional science and technology innovation level on digital economy development through panel quantile regression, and found that the influence of regional science and technology innovation level on digital economy development has a U-shaped pattern and a certain regional heterogeneity.

2.3. Science and Technology Innovation and Carbon Emission

In the process of achieving the strategic goals of carbon peaking and carbon neutral, it is always inseparable from the supporting role of science and technology innovation, which is an important tool to optimize the energy structure, improve the energy utilization rate and promote the upgrading and adjustment of industrial structure (Wang and Hu, 2022) [10]. Sun and Xue (2022) [11] used the improved STIRPAT model to analyze the impact of science and technology innovation on carbon emission efficiency, and found that science and technology innovation can significantly improve carbon emission efficiency by improving energy utilization efficiency. Cheng et al. (2019) [12] used the Gini coefficient, spatial autocorrelation and panel data to study the spatial and temporal variation characteristics of science and technology innovation and carbon emission efficiency in countries along the Belt and Road, and in general, science and technology innovation can effectively improve carbon emission efficiency in countries along the Belt and Road. Wang and Cheng (2020) [13] analyzed the impact of global science and technology innovation on carbon productivity in a global sample of 118 countries and showed that science and technology innovation has an important role in promoting carbon productivity mainly by promoting structural optimization, reducing energy consumption and improving energy efficiency.

2.4. Theoretical Analysis of Digital Economy to Promote Carbon Reduction

2.4.1. Promote Technological Innovation and Improve Energy Utilization Efficiency

At present, China's industrial structure is still dominated by energy-intensive industries, with a high degree of dependence on energy. First, China's energy consumption is mainly coal, which ranks first in the world. Secondly, China's energy utilization efficiency is not high and lacks energy technology innovation. Finally, fossil energy accounts for a large part of China's energy structure, and the degree of development of new and renewable energy is still insufficient. On the one hand, the digitalization of industry can help existing enterprises use digital technology to complete the transformation of production factors, reduce the dependence on traditional resources, improve the allocation efficiency of energy, and thus promote the reduction of carbon emissions. On the other hand, with the continuous promotion of digital industrialization, digital technologies such as big data and artificial intelligence can be used to realize the development of new energy and upgrade the existing energy structure, build a perfect and reasonable energy structure, and promote the sustainable development of new energy (Guo et al., 2022 [14]; Xu and Ma, 2022 [15]).

2.4.2. Improve the Level of Regulation of Carbon Emissions and Reduce the Negative Externalities of Carbon Emissions

The accounting and property rights of carbon emissions are complicated, so the government cannot effectively regulate the carbon emissions of enterprises, so enterprises are not willing to pay for the negative externalities caused by carbon emissions, which makes carbon emissions remain high. The negative externalities of carbon emissions can be reduced by clarifying property rights (Hu and Jin, 2022) [16]. In addition, digital technology can help to establish a carbon emission standard accounting system, through which government departments can calculate the carbon emission index of different enterprises, avoiding the validity of the accounting due to subjective judgment, and at the same time implementing corresponding rewards and penalties for enterprises according to the accounting situation, thus making the administrative control of carbon emission more professional and flexible. Through deep mining, big data and other digital technologies, government departments can effectively grasp the carbon emission information of enterprises and alleviate the information asymmetry between the government and enterprises, to regulate carbon emission at the macro level (Hu and Jin, 2022) [16].

3. Model Construction and Data Sources

3.1. Model Setting

The panel vector autoregressive model (PVAR model) was first proposed by Holtz-Eakin et al. in 1988, it inherits the advantages of the vector autoregressive (VAR model) model, treats each variable as an endogenous variable, and analyzes the interaction effects of each variable and it lags variables on other variables in the model. The PVAR model can effectively solve the problem of individual heterogeneity with the use of panel data. Based on this, the PVAR model is selected to study the dynamic relationship between digital economy, science and technology innovation and carbon emissions, and the PVAR model expression is as follows.

$$Y_{it} = \propto_t + \sum_{j=1}^{p} \rho_j Y_{i,t-j} + \varepsilon_{i,t} \tag{1}$$

Among them, $Y_{it} = [DEDI, TI, CEI]^T$ is a column vector, including the level of digital economy development (DEDI), scientific and technological innovation (TI) and carbon emissions (CEI). To ensure the stability of each variable, the first order difference method is used to deal with DEDI, TI and CEI; $\varepsilon_{i,t}$ represents a random disturbance term.

3.2. Data Sources and Descriptions

The three variables of digital economy development level, science and technology innovation level, and carbon emission are denoted as DEDI, TI and CEI, respectively. Descriptive statistics of each variable are shown in Table 1. To reduce the effect of heteroskedasticity, the three variables of digital economy development level, science and technology innovation level, and carbon emission are logarithmized.

Table 1. Descriptive statistics of each variable.

Variable Name	Variable Description	Sample Size	Average Value	Standard Deviation	Minimum Value	Maximum Value
Lndedi	Development level of digital economy	270	0.2873	0.0067	0.0745	0.6395
Lnti	Scientific and technological innovation level	270	0.1657	0.0085	0.0091	0.6116
Lncei	Carbon emissions	270	0.9912	0.0267	0.3014	2.6851

3.2.1. Development Level of Digital Economy

This paper measures the development level of digital economy from two dimensions: "digital industrialization" and "digitalization of industry", "digital industrialization" refers to the use of digital technology to bring about products and services, such as cloud photo albums, cloud disks, taxi software, digital TV, etc. "digitalization of industry" refers to the use of digital technology to bring about an increase in the quantity and efficiency of production in pre-existing industries, such as enterprises using industrial big data to help optimize their industrial structure, in which the digital financial inclusion index compiled by Guo Feng et al. (https://www.idf.pku.edu.cn/xz/272857.htm) is chosen to represent the digital financial inclusion index. This paper uses the entropy weight method to calculate the indicators of digital economy development, to measure the comprehensive indicators of digital economy development, and the corresponding indicators are shown in Table 2.

Table 2. Indicator system of digital economy development level.

Level I Indicators	Secondary Indicators	Third Level Indicators	Index Weights
Development level of digital economy	Digital industrialization	Internet penetration rate (positive)	0.079
		Number of Internet related employees (positive)	0.315
		Internet related output (positive)	0.423
		Number of mobile Internet users (positive)	0.091
	Industrial digitalization	Digital inclusive financial index (positive)	0.094

3.2.2. Science and Technology Innovation Level

Table 3. Index evaluation system of science and technology innovation level of each province in China.

Level I Indicators	Secondary Indicators	Third Level Indicators	Units	Indicator Weights
Science and Technology Innovation	Innovation input	R&D personnel full time equivalent	people	0.0790
		R&D expenditure intensity	%	0.0522
		Expenditure on technology acquisition and technological transformation of industrial enterprises above the scale	million yuan	0.0619
		Number of R&D project topics	item	0.0561
	Innovation Output	Number of domestic three kinds of patent applications authorized	piece	0.1087
		Main business income of high-tech industry	billion yuan	0.1287
		The number of new product research and development of high-tech enterprises	item	0.1198
		Technology Market Turnover	million yuan	0.1553
	Innovation Environment	Number of R&D institutions	piece	0.0287
		Ratio of local financial expenditure on science and technology to total financial expenditure	%	0.0503
		Average number of students enrolled in higher education institutions per 100,000 people	people	0.0191
		Number of enterprises in high technology industry	piece	0.1085
		GDP per capita	yuan	0.0317

Based on the study of Liu et al. (2022) [17] and Chen and Cai (2018) [18], this paper uses the entropy method to measure the science and technology innovation level of each province (city and autonomous region) in three dimensions: input, output and environment. The main indicators of innovation input are the elements of R&D personnel, R&D funding and the number of R&D projects; the main indicators of innovation output are the number of patent applications, new product development and sales and technology market turnover; the external conditions of science and technology innovation are the important indicators of innovation environment (See Table 3).

3.2.3. Carbon Emissions

In view of the lack of carbon emission data for each province in China in various statistical yearbooks, this paper, with reference to existing research results, adopts the current internationally applicable measurement method to project CO_2 emissions according to the IPCC 2006 Guidelines for National Greenhouse Gas Inventories. The calculation method is as follows.

$$C = \sum_{i=1}^{7} C_i = \sum_{i=1}^{7} E_i \times \mu_i \times h_i \tag{2}$$

Where E_i denotes the total consumption of the ith type of energy source, and seven major energy sources, namely coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas, are selected for measurement in this paper; μ_i denotes the discounted standard coal coefficient; and h_i denotes the carbon emission coefficient. The specific values of μ_i and h_i are shown in Table 4.

Table 4. Conversion factor of standard coal and carbon emission factor of major energy species.

Energy Varieties	**Coal**	**Coke**	**Gasoline**	**Kerosene**	**Diesel**	**Fuel Oil**	**Natural Gas**
Discount factor for standard coal μ_i	0.7143	0.9714	1.4714	1.4714	1.4571	1.4286	1.2150
Carbon emission factor h_i	2.492	2.977	1.988	2.051	2.167	2.219	2.162

4. Analysis of the Empirical Results

4.1. Unit Root Test for Panel Data

Table 5. Unit root test results for Lndedi, Lnti and Lncei.

Test Method	**Statistic/P-value**	**lndedi**	**lnti**	**lncei**
LLC	t	-3.3118	-12.6116	-11.3495
	P-value	0.0005	0.0000	0.0000
IPS	Z	0.8637	-5.2908	-1.1664
	P-value	0.8061	0.0000	0.1217
ADF	Z	5.3419	-7.8935	1.7030
	P-value	1.0000	0.0000	0.9557
PP	Z	5.9173	-7.7164	1.4179
	P-value	1.0000	0.0000	0.9219
Test results		Non-smooth	Smooth	Non-smooth

Table 6. Unit root test results for d_lndedi, d_lnti and d_lncei.

Test Method	Statistic/P-value	d_lndedi	d_lnti	d_lncei
LLC	t	-16.9488	-10.0748	-15.3267
	P-value	0.0000	0.0000	0.0000
IPS	Z	-5.3205	-6.3469	-3.1305
	P-value	0.0000	0.0000	0.0009
ADF	Z	-3.7580	-7.4270	-4.9317
	P-value	0.0001	0.0000	0.0000
PP	Z	-7.6136	-12.7327	-6.6126
	P-value	0.0000	0.0000	0.0000
Test results		Smooth	Smooth	Smooth

Before using the PVAR model for estimation, it is necessary to ensure that all variables have smoothness, otherwise it will lead to the pseudo-regression phenomenon, so this paper uses four tests to check the smoothness of variables, and the test results are shown in Table 5 and Table 6.

From Table 5, the variable Lnti is smooth, but the variables lndedi and lncei both fail the IPS, ADF-Fisher and PP-Fisher tests. Therefore, in this paper, the three variables are treated as first-order differences, and as can be seen from Table 6, the variables d_lndedi, d_lnti and d_lncei all pass the four tests after first-order differences, so the three variables of digital economy development level, science and technology innovation level and carbon emission are all smooth after first-order differences.

4.2. Co-integration Test

From the perspective of test rigor, this paper adopts three methods to conduct cointegration tests. The results are shown in Table 7. The results show that the null hypothesis is rejected in all three tests at the 1% significance level, so it is concluded that there is a long-term cointegration relationship between the level of digital economy development, the level of science and technology innovation and carbon emissions.

Table 7. Results of co-integration relationship test.

Variables	Kao-ADF	Pedroni-PP	Westerlund-ADF
lnti、lncei、lndedi	4.7620*** (0.0000)	-1.9235*** (0.0272)	9.0429*** (0.0000)

Note: ***, **, * indicate significant at 1%, 5%, 10% confidence level, respectively.

Table 8. PVAR optimal lag order selection.

LAG	AIC	BIC	HQIC
1	-6.59448*	-4.83836*	-5.88245*
2	-4.39204	-2.22438	-3.51139
3	-5.96296	-3.24515	-4.85925
4	-2.914	0.585737	-1.5027
5	-6.26354	-1.55127	-4.42031

4.3. Determining the Optimal Lag Order

Determining the optimal lag order of the model is a prerequisite for estimating the PVAR model. In this paper, the optimal lag order is determined by using the empirical results of the PVAR2 package (Lian Yujun), and the optimal lag order chosen according to the AIC, BIC, and HQIC information criteria can be found in Table 8.

4.4. Model Stability Test

In order to ensure the rationality of the subsequent impulse response function and ANOVA, the robustness of the model needs to be tested. If all the characteristic roots lie within the unit circle, it indicates that the robustness test is passed, so it can be seen from Figure 1 that the PVAR model constructed in this paper is robust.

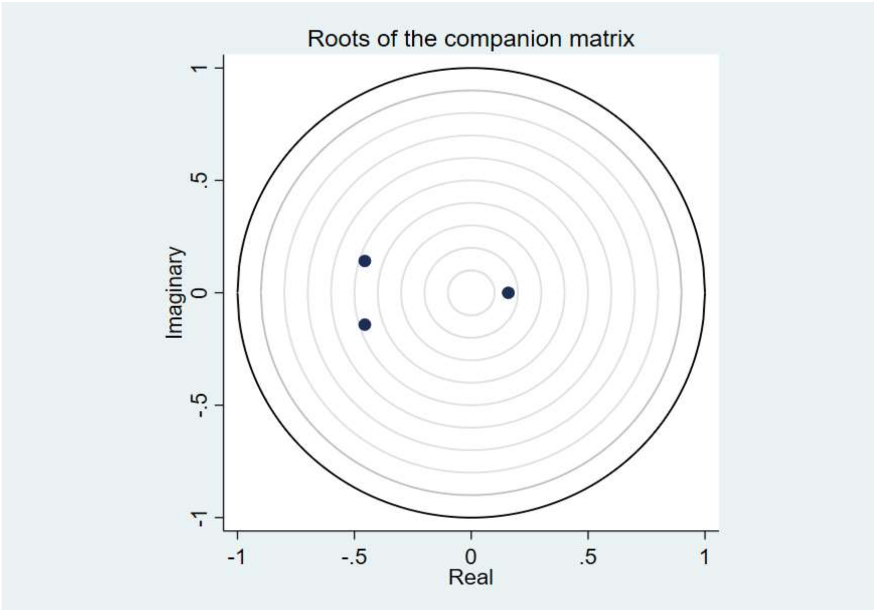

Figure 1. Unit root test.

Table 9. Granger causality test results.

Equation	Excluded	chi2	df	Prob>chi2
h_d_lnCEI	h_d_lnTI	0.45382	2	0.501
h_d_lnCEI	h_d_lnDEDI	4.49	1	0.034
h_d_lnCEI	ALL	5.8953	2	0.052
h_d_lnTI	h_d_lnCEI	0.07555	1	0.783
h_d_lnTI	h_d_lnDEDI	3.5528	1	0.059
h_d_lnTI	ALL	4.505	2	0.105
h_d_lnDEDI	h_d_lnCEI	8.9563	1	0.003
h_d_lnDEDI	h_d_lnTI	0.18943	1	0.663
h_d_lnDEDI	ALL	9.552	2	0.008

4.5. Granger Causality Test

The Granger causality test was used to determine the causal relationship of each variable and whether the explanatory variables can predict the explained variables. The test results are shown in Table 9. From Table 9, the d_lnCEI is the Granger cause of d_lnDEDI, d_lnCEI is not the Granger cause of d_lnTI; d_lnTI is not the Granger cause of d_lnCEI, d_lnTI is not the Granger cause of d_lnDEDI; d_lnDEDI is the Granger cause of d_lnCEI Granger cause of d_lnDEDI, d_lnDEDI is not Granger cause of d_lnTI.

4.6. GMM Estimation of PVAR Model

After completing the unit root test and determining the optimal lag order, the helmert transformation was used to eliminate the time effect and fixed effect of the data, and GMM estimation was performed for the three variables, and the results are shown in Table 10.

Table 10. GMM estimation results of PVAR model.

Variables	GMM	h_d_lndedi	h_d_lncei	h_d_lnti
L.h_d_lndedi	b_GMM	-0.7368	-0.8945	-6.4703
	se_GMM	0.4114	0.4221	3.4327
	t_GMM	-1.7908	-2.119	-1.8849
L.h_d_lncei	b_GMM	0.3016***	0.3878***	0.1875
	se_GMM	0.1008	0.1403	0.6822
	t_GMM	2.9927	2.7642	0.2749
L.h_d_lnti	b_GMM	0.0051	-0.0081	-0.4086
	se_GMM	0.0118	0.0121	0.0957
	t_GMM	0.4352	-0.6737	-4.2678

From the estimation results, it can be seen that when digital economic development growth (d_lndedi) is used as the explanatory variable, the current year's digital economic development growth is negatively affected by the lagged period's digital economic development growth, but this effect is only significant in the national region; the lagged period's carbon emission intensity growth has a significant positive effect on the current period's digital economic development growth, but the effect is not significant in the central region. The positive impact of the increase in the level of science and technology innovation in the lagging period on the growth of the digital economy in the current period is insignificant both nationally and in the eastern, central and western regions.

When carbon emissions intensity growth (d_lncei) is used as the explanatory variable, its one-period lagged value has a significant positive effect on the current period, but this effect is not significant in the western region; the one-period lagged growth in the level of digital economic development has a negative effect on the current period carbon emissions intensity growth, but this effect is not significant; the one-period lagged increase in the level of science and technology innovation has a non-significant negative effect on the current period carbon emissions intensity growth, but there is a certain degree of negative effect in the central region.

When using the increase in the level of science and technology innovation (d_lnti) as the explanatory variable, its one-period lagged value has a significant negative effect on the current period, and this effect is significant in the whole country and in the eastern, central and western regions; the one-period lagged increase in the level of digital economic development has a negative effect on the increase in the level of science and technology innovation in the current period, but this effect is not significant; the negative effect of the one-period lagged increase in the intensity of carbon emissions on the increase in the level of science and technology innovation in the current period is significant in the whole country and in the western region.

According to the model GMM estimation results, the explanatory power of the growth of digital economy development level and carbon emission growth on the increase of science and technology innovation level is not strong, so this paper focuses on the dynamic influence of carbon emission on the development of digital economy and itself. The paper then goes on to use impulse response and variance decomposition methods to provide an in-depth analysis of the above effects.

4.7. Impulse Response and Variance Decomposition

The above GMM estimation is a static analysis of the model, and in order to further study the dynamic interaction between the variables, the impulse response plot with a lag of 6 periods is obtained by 200 simulations with the help of Monte Carlo experiments in this paper, the first to third columns of Figure 2 reflect the changes when the growth in the level of development of the digital economy, the increase in the intensity of carbon emissions and the increase in the level of science and technology innovation are hit respectively, the first to third rows show the impact of the increased level of development of the digital economy, the increased intensity of carbon emissions and the increased level of science, technology and innovation, respectively, as shown in Figure 2. When the number of lags gradually increases, the impulse response functions of each variable are close to 0, indicating that it is meaningful to study the model.

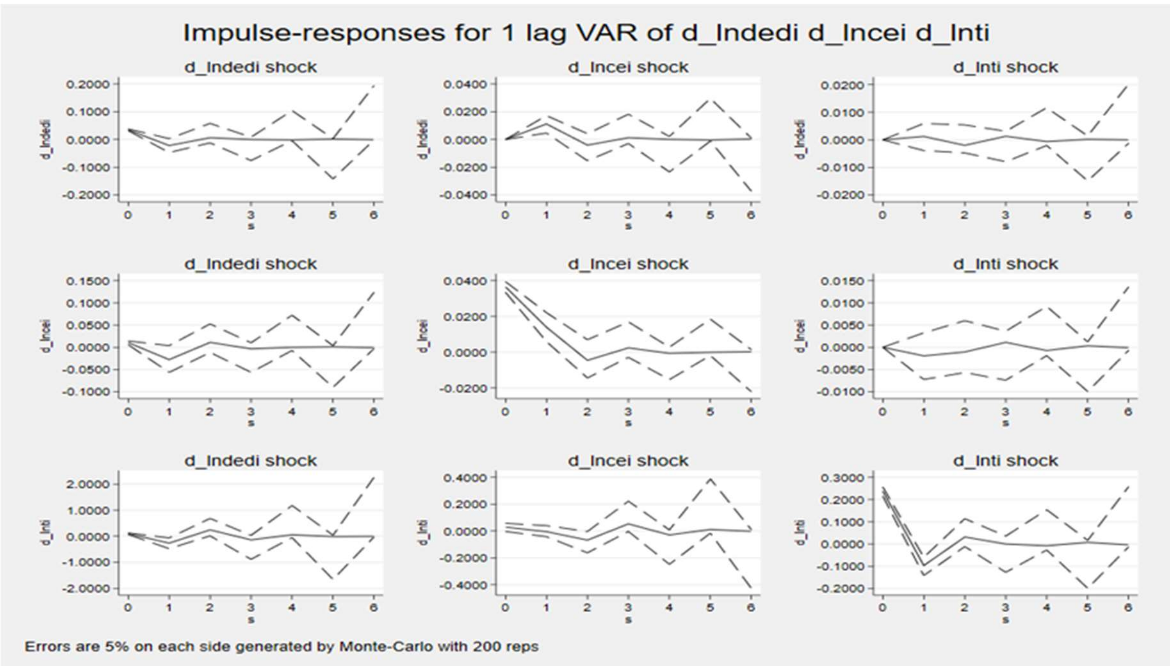

Figure 2. Graph of impulse response function.

The following conclusions can be drawn from the impulse response plots in Figure 2. Firstly, when the growth of digital economic development level, the increase of science and technology innovation level and the increase of carbon emission intensity by its own shock effect will reach a positive maximum in the current period, and then drop sharply to a negative minimum in periods 1 to 2, with the negative effect gradually decreasing until it disappears, indicating that the increase of these three variables has a significant shock effect on itself especially the science and technology innovation level and carbon emission, indicating that these The increase in the intensity of the current period of these variables is likely to lead to a higher intensity level in the next period.

Secondly, when the growth of the development level of digital economy faces the impact of the increase of carbon emission intensity, the impact is 0 in the current period, and then there is a negative impact, which indicates that there is a certain lag effect of the growth of the development level of digital economy on the increase of carbon emission intensity, and this impact gradually decreases in the later period until it falls to 0. It indicates that in the short term, the increase of carbon emission intensity will crowd out the development of digital economy to a certain extent, but as the digital economy grows, the impact of the increase of carbon emission intensity will be more significant. However, with the continuous improvement and maturity of the digital economy, this inhibiting effect gradually disappears. On the contrary, when the carbon emission intensity increases in the face of the impact of the growth of the digital economy, the impact remains zero in the current period, then the positive impact starts to appear in the first period, but becomes negative in the second period, and then gradually tends to zero until the fluctuation disappears, indicating that at the early stage of the development of the digital economy, it is necessary to purchase industries by increasing the exploitation of resources and energy consumption, thus promoting the increase of carbon emission intensity. However, with the development of digital economy, the optimization and adjustment of the industrial structure of digital economy, digital technology can effectively improve the utilization rate of resources and alleviate the problem of information asymmetry, which has a restraining effect on the increase of carbon emission intensity.

Thirdly, when the growth of digital economy development level faces the impact of the improvement of science and technology innovation level, the impact is 0 in the current period, then there is a negative impact in the first period, after which the positive and negative impacts occur alternately, and the degree of impact is very small, and finally tends to 0. This indicates that the impact of the improvement of science and technology innovation level on the development level of digital economy is non-linear, and the degree of impact is not significant, indicating that the current science and technology innovation fails to effectively promote the development of digital economy.

In order to better reflect the degree of influence of the endogenous variables on the random disturbance term in the model and analyze the relative contribution degree of the structural variables to the changes of other variables in the model, this paper performs variance decomposition, and the results of variance decomposition are shown in Table 11. The variance decomposition results are shown in Table 11. According to Table 11, its own contribution to the growth in the level of development of the digital economy is the highest at 92.0%, followed by the contribution of science, technology and innovation at 67.9% and finally carbon emissions at 39.4%; the contribution to the increase in the intensity of carbon emissions comes mainly from itself, at 60.3%, with the level of development of the digital economy contributing 7.6% and science, technology and innovation contributing 3.9%; for the increase in the level of science and technology innovation, its own contribution is 28.2%, the level of development of the digital economy contributes 4.0% and carbon emissions contribute 3.0%.

Table 11. Results of variance decomposition of each variable.

Variables	s	d_lndedi	d_lncei	d_lnti
d_lndedi	10	0.920	0.076	0.004
d_lncei	10	0.394	0.603	0.003
d_lnti	10	0.678	0.039	0.282
d_lndedi	20	0.920	0.076	0.004
d_lncei	20	0.394	0.603	0.003
d_lnti	20	0.679	0.039	0.282
d_lndedi	30	0.920	0.076	0.004
d_lncei	30	0.394	0.603	0.003
d_lnti	30	0.679	0.039	0.282

5. Conclusion and Policy Implications

This paper constructs a PVAR model using provincial panel data from 2011-2019 to empirically study the interaction between digital economy, science and technology innovation and carbon emissions, and the findings show that:

1) the digital economy leads to an increase in carbon emissions at the early stage of development, but changes to a suppressive effect at a later stage.

2) The increase in the level of development of digital economy and the increase in the intensity of carbon emissions are Granger causal.

3) Carbon emissions will inhibit the development of digital economy in the short term, and will have a significant self-promoting effect.

Based on the above research, this paper draws the following insights:

1) Strengthen the foundation of digital economy development and enhance digital technology research and development. According to the empirical study in this paper, the digital economy cannot suppress the increase of carbon emissions at the early stage of development, so it is necessary to improve the speed and quality of the development of the digital economy and give full play to the key role of digital technology in energy saving and emission reduction. Promote a new round of digital infrastructure construction, accelerate the construction of new infrastructure with 5G base stations, big data centers and artificial intelligence platforms as the core, and improve the level of digital infrastructure. Accelerate the construction of digital technologies such as big data, cloud computing, Internet of Things, block chain and artificial intelligence, and use digital technologies to help enterprises achieve green transformation.

2) Strengthen digital science and technology innovation and improve the support of science and technology innovation. On the one hand, it is necessary to increase the intensity of investment in scientific and technological research and development, overcome the difficulties at the digital technology level, use digital technology to help enterprises achieve scientific planning and efficient

allocation of resources, and alleviate the mismatch between innovation input and output. On the other hand, the government level needs to play a good regulatory and control function to create a fair competitive link from multiple directions and angles to motivate enterprises to carry out digital technology innovation.

3) Improve the speed and quality of digital economy development, and promote the digital economy to empower carbon emission reduction. Avoid the digital economy falling into the traditional way of rough development, focus on low-carbon control of digital economy infrastructure, and promote the transformation of smart city development with developed cities that have a solid digital economy foundation as the first. Give full play to the role model of digital economy enterprises in the field of energy saving and emission reduction, promote the continuous improvement of carbon emission information disclosure system, and at the same time implement effective carbon emission incentives and penalties for enterprises to fill the loopholes for enterprises to make use of information asymmetry and gain.

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