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Do technological innovation and environmental regulation reduce carbon dioxide emissions? evidence from China

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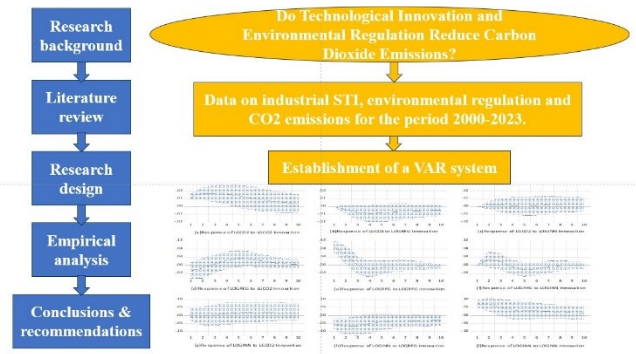
Graphical abstract



Abstract

The Chinese industry holds a significant position in the national economy. However, industrial carbon dioxide (CO_2) emissions account for a large proportion of the total CO_2 emissions, which has a negative impact on the environment. To identify the factors affecting industrial CO_2 emissions, a vector autoregressive (VAR) model system is established to empirically test the factors influencing industrial CO_2 emissions, using data on industrial technology innovation (TI), environmental regulation, and CO_2 emissions from 2000 to 2023 in China. The results show that there is a cointegration relationship between industrial technological innovation, environmental regulation and CO_2 emissions. Each unit increase in environmental regulation will reduce 2.132 units of CO_2 emissions. Meanwhile, each unit increase in technological innovation results in a decrease of 0.067 units of CO_2 emissions. Compared with TI, environmental regulation has a greater impact on CO_2 emission reduction. The effects of the impulses of the stochastic perturbation terms of industrial TI, environmental regulation, and CO_2 emissions on the current and future values of industrial TI, environmental regulation, and CO_2 emissions in the VAR system are depicted through the VAR impulse response function. The contribution of each new interest shock to the change of industrial TI, environmental regulation and CO_2 emissions is analyzed by variance decomposition. This paper enriches the application of institutional theory and technological innovation theory in CO_2 emission reduction and also provides a reference for relevant departments to formulate emission reduction policies and industrial technological innovation.

Keywords: Technology innovation, environmental regulation, carbon dioxide emission, industry, VAR

1. Introduction

China's industry plays an important role in the national economy. In 2022, the industrial added value accounted for 39.9% of the gross domestic product (GDP). However, according to relevant research data, industrial carbon dioxide (CO_2) emissions account for 84.5% of the total emission. Although industry has made a positive contribution to employment and economic growth, it has also brought a heavy burden on the environment (Ouyang & Lin, 2015; Lin,Zhang,Zou, & Peng, 2020). In recent years, extreme high temperature weather occurred in Western Europe, lead to wildfires in France and Spain frequently, unprecedented droughts comes to Italy and Portugal, and temperature in some parts of the United Kingdom once exceeded to 40 degrees Celsius. North America, the middle and lower reaches of the Yangtze River in China, South Korea and south-central Japan were also affected by high temperature. According to the prediction of the World Meteorological Organization (WMO), heat waves are occurring and will be more and more frequently, which is related to climate change. The root cause of extreme high temperature weather around the world is the increasing of carbon dioxide emissions and the enhancement of greenhouse gas effect, which lead to global warming. Among all kinds of greenhouse gases, carbon dioxide accounts for nearly three quarters of the total greenhouse gas emissions, so carbon dioxide emissions are often considered to be the key factor of global warming. China will strive to peak its carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. China's Interim Regulation on the Administration of Carbon Emission Trading came into effect on 1 May 2024 in order to regulate carbon emission rights trading and related activities, strengthen the control of greenhouse gas emissions, actively and steadily promote carbon peaking and carbon neutrality, promote green and low-carbon economic and social development, and advance the construction of an ecological civilisation. The Regulations, which contain a total of thirty-three articles, regulate the trading of carbon emission rights and related activities in the national carbon emission rights trading market.

Make efforts to reduce industrial carbon dioxide emissions, reduce fossil energy consumption, adopt clean energy and other measures are the guarantee to achieve the double carbon goal, while technological innovation and environmental regulation are the key factors to achieve these measures. At present, China's industry has achieved some results in curbing carbon dioxide emissions through technological transformation, strengthening the implementation of environmental policies and other measures, but there is still much space for improvement. This paper examines the impact of industrial science and technology innovation and environmental regulation on carbon dioxide emissions in China, and seeks to find an effective path to reduce carbon dioxide emissions.

2. Literature review

Technological innovation and environmental regulation are considered to be effective mechanisms to reduce carbon dioxide emissions and promote sustainable development. Mensah (2018) believed that technological innovation is a necessary condition for reducing carbon dioxide emissions, which plays a vital role in reducing emissions while also helping to save energy. Non-renewable energy accelerates emissions, while renewable energy reduces emissions. Dauda (2019) investigated the impact of innovation and economic growth of 18 developed and developing countries on carbon dioxide emissions during the period from 1990 to 2016, and the results showed that innovation reduced carbon dioxide emissions. Yu and Du (2019) concluded that compared with high-speed growth, independent innovation contributed more to the reduction of carbon dioxide emissions while the economy maintained slow-growth. Shahbaz (2020) believe that technological innovation has a negative impact on carbon dioxide emissions. Koçak and Ulucak (2019) investigated the relationship between R&D expenditure and carbon dioxide emissions among the 19 of OECD countries from 2003 to 2015, and found that R&D expenditure has a significant and positive impact on reducing carbon dioxide emissions. Erdogan (2021) used the panel data method to test the impact of technological innovation among the BRICS countries on carbon dioxide emissions in construction industry from 1992 to 2018, and the results showed that increasing technological innovation can reduce carbon dioxide emissions. Bilal (2021) discussed the relationship between technological innovation, globalization and carbon dioxide emissions. The results show that the relationship between technological innovation and carbon dioxide emissions is negative and has static significance in all regions (such as the the Belt and Road, South Asia, East and Southeast Asia, the Middle East and North Africa, Europe and Central Asia). Although many mathematicians believed that technological innovation played an important role in carbon emission reduction, the impact of technological innovation on carbon dioxide emissions may be different under different conditions. On the one hand, technological innovation provides huge potential for carbon dioxide emission reduction. On the other hand, improving energy efficiency through technological innovation means reducing costs, which in turn may lead to increased consumption due to the socalled “rebound effect” (Braungardt *et al.* 2016). Weina (2016) revealed that for Italy, green innovation improved environmental productivity, but did not play a significant role in reducing carbon dioxide emissions.

On the relationship between environmental regulation and carbon dioxide emissions, scholars have two main views: green paradox and mandatory emission reduction (Wang *et al.* 2022). Scholars who hold the view of green paradox believe that environmental regulation cannot effectively control carbon dioxide emissions. Countries that have ratified the Kyoto Protocol promise to limit global warming by reducing the demand for fossil fuels, but if suppliers feel that greening policies will harm their future prices, they will accelerate development faster, thus accelerating global warming (Sinn, 2008). Albulescu (2020）focusing on 12 EU countries, the panel data from 1990 to 2017 were analyzed. The results showed that the increase in the share of renewable energy had a negative impact on carbon dioxide emissions, but there was no clear evidence to show the role of environmental regulations, and the ratification of the Kyoto Protocol by EU countries had no significant impact. Scholars who support mandatory emission reduction believe that environmental regulation has become one of the key measures to prevent further energy consumption and environmental degradation, and has been widely used in the economic activities of countries around the world (Zhou *et al.* 2017). Neves, Marques and Patrício (2020) studied the impact of environmental regulation on carbon dioxide emissions based on the annual data of 17 EU countries from 1995 to 2017,The results show that environmental regulation is effective in reducing carbon dioxide emissions in the long run, and policies supporting renewable energy sources tend to reduce carbon dioxide emissions in the short and long run. Ouyang et al (2020) believed that the implementation of mandatory emission reduction policies can reduce the carbon dioxide emissions of heavy industry. Zhang et al (2020) using panel data from 30 provincial administrative regions in China, this paper empirically analyzes the impact of environmental regulation on carbon dioxide emissions and intensity. The results show that there is a significant inverted U-shaped relationship between environmental regulation and carbon dioxide emissions. With the continuous improvement of environmental regulation, the positive role of environmental regulation in reducing carbon dioxide emissions and intensity is more obvious.

Danish et al (2020) made analyse based on the data of Brazil, Russia, India, China and South Africa from 1995 to 2016,the results confirmed the positive role of environmental regulations in reducing carbon dioxide emissions. The mitigation of climate change is not only related to economic development, but also driven by effective environmental regulations.

The simultaneous role of technological innovation and environmental regulation is crucial to carbon dioxide emission reduction ((Huisingh *et al.* 2015). Technological innovation is the main factor affecting carbon dioxide emissions, while environmental regulation is another important factor. However, due to the existence of "rebound effect" and "Green Paradox", the impact of the two on carbon dioxide emissions reduction varies between countries ((Wang *et al.* 2020). Porter and Van der Linde (1995) believed that strict and properly designed environmental regulations can stimulate enterprises' innovation activities, and the resulting "compensation effect" can partially or completely offset the cost of environmental regulation, and help improve productivity. Yin, Zheng and Chen (2015) established a panel data model with environmental regulation and technological innovation as the adjusting variables. The results show that environmental regulation has a significant regulatory effect on carbon dioxide emissions, and technological innovation is conducive to carbon dioxide emissions reduction. Ma, Murshed and Khan (2021) found that the use of renewable energy, technological innovation, R&D expenditure and carbon emission tax can reduce carbon dioxide emissions, and the joint use of carbon emission tax, R&D expenditure, technological innovation and renewable energy can further reduce carbon dioxide emissions. Hashmi and Alam (2019) examined the impact of environmental regulation and technological innovation on carbon emission reduction in OECD countries from 1999 to 2014. The results showed that the increase of environmental protection patents and per capita environmental taxes could reduce carbon emissions in OECD countries.

The existing literature has made a useful discussion on the impact of technological innovation and environmental regulation on carbon dioxide emissions, but there is no unified view. There is not much attention to the carbon dioxide emissions of all sectors of the national economy, especially the mechanism of technological innovation and environmental regulation affecting the carbon dioxide emissions of China's industrial system at the same time. Based on the above analysis, this paper raises two basic questions: Has China's industrial technological innovation promoted carbon dioxide emission reduction? Can environmental regulation effectively control industrial carbon dioxide emission reduction? In this paper, we will use the vector autoregressive (VAR) model to test the above two problems.

3. Research design

3.1. Theoretical analysis

Most scholars believe that technological innovation can help reduce carbon dioxide emissions and improve environmental quality (Yang *et al.* 2017). Technological innovation has effectively promoted the application of new technologies, thus directly improving energy efficiency and reducing energy consumption. Carbon dioxide emissions are generated from almost all activities in the industrial sector. If the new carbon dioxide emission reduction technology is effectively applied to the whole industry, it will help alleviate the increasingly serious climate change crisis (Slowak *et al.* 2015). Technological innovation can inhibit energy consumption, reduce pollutant emissions and improve environmental quality, which is a powerful means to mitigate carbon dioxide emissions and achieve long term sustainable development (Ben *et al.* 2018). In addition, technological innovation can help promote the development of renewable energy and help countries optimize the use of renewable resources, thereby reducing carbon dioxide emissions ((Danish, 2021). The agency variables of technological innovation mainly include R&D expenditure and the number of R&D personnel, but it is doubtful whether R&D expenditure and the number of R&D personnel can accurately measure technological innovation (Wang *et al.* 2018). The purpose of the patent is to protect the invention or technology, which is characterized by openness, objectivity, authority and timeliness. The technological innovation research based on the analysis of patent literature in-formation is more convincing. At present, scholars have adopted different proxy variables to measure technological innovation. For example, Chen and Lee (2020) used R&D expenditure as the proxy variable of technological innovation, while Zhao (2021) used the number of patent applications as the proxy variable of technological innovation.

In addition to technological innovation, environmental regulation is also considered as an important mechanism to reduce carbon dioxide emissions. Environmental regulation is an important part of social regulation. The government regulates manufacturers' production and business activities through administrative orders, emission permits, administrative penalties and emission taxes to achieve sustainable economic and environmental development. Environmental regulation can indirectly affect carbon dioxide emissions through technological innovation, which has both positive and negative compensation effects. The two effects mainly depend on the compensation effect or the dominant role of the offset effect. Strict environmental regulations increase the environmental costs of energy intensive enterprises, and enterprises are forced to carry out environmental protection technology innovation to achieve sustainable development, thus promoting the optimization and upgrading of industrial structure and carbon dioxide emission reduction. In the long run, environmental regulation is effective in reducing CO_2 emissions. Scholars have classified environmental regulations from different perspectives, mainly from two perspectives: one is based on formal and informal perspectives; The other perspective is based on cost and performance. According to the research of Neves, Marques and Patrício (2020), environmental regulation can be divided into formal regulation and informal regulation. Formal regulation includes market tools and non-market tools. Market tools refer to market-oriented environmental policy tools (taxes, trade plans, feed-in tariffs, insurance premiums and deposit and refund plans). Non-market instruments include greenhouse gas emission standards and government expenditure on renewable energy research and development, which are mainly implemented by government organizations. Informal regulation mainly depends on social environmental awareness, such as the influence of news media. According to Wu (2020), environmental regulation can be divided into cost-based and performance-based environmental regulation indicators. From the perspective of cost, the degree of environmental regulation is mainly measured from the perspective of pollution control expenditure (investment), which is positively correlated with the intensity of environmental regulation. Therefore, pollution control expenditure (investment) can well reflect environmental regulations. From the perspective of performance, the effect or performance of environmental pollution control can better reflect the level of environmental regulation. The removal rate and utilization rate of different pollutants are regarded as important indicators to measure the level of environmental regulation. As mentioned above, many documents have carefully studied environmental regulations and used different variables to study their impact on carbon dioxide emissions, but no consensus has been reached.

From the relevant theoretical analysis, it can be seen that technological innovation and environmental regulation have had an impact on carbon dioxide emissions, but there is no unified understanding of how and how much impact they have. This paper will further explore the impact of technological innovation and environmental regulation on carbon dioxide emissions on the basis of previous scholars' research.

3.2. Variable selection

3.2.1. Technological innovation

Innovation is the transformation of an idea into a new/improved product, service or process, and it involves a series of activities from idea generation to the commercialisation of products and services that benefit the end user (Baregheh, Rowley, & Sambrook, 2009). The innovation process consists of three main phases (Bahoo, Cucculelli,& Qamar, 2023): idea generation; development of an idea programme; and idea implementation to deliver products or services that may change the business model of the firm.Technological innovation is defined as the development and application of new production methods, new patents and technologies. On the one hand, technological innovation helps to produce high value-added products. On the other hand, technological progress has a positive impact on economic and social welfare. Some scholars regard patents as the agent variables of technological innovation. The China National Intellectual Property Administration classifies patents into three types: invention, utility model and design. Among them, invention patents refer to new technical solutions proposed for products, methods or improvements, which are most innovative. When the National Bureau of Statistics makes statistics on the number of patents, it also makes statistics according to the number of patent applications and the number of patent licenses. Generally speaking, although the number of patent licenses is less than the number of patent applications, its innovative value and practical value may be higher due to the strict examination process. Although universities and scientific research institutions also have invention patents, the number of them is not as large as that of enterprises, and the invention patents of enterprises may be more directly applied to production practice. Therefore, this paper selects the number of enterprise invention patents authorized as the proxy variable for technological innovation.

3.2.2. Environmental regulation

Environmental regulation is an important factor affecting carbon dioxide emissions. Because it is difficult to directly measure the intensity of environmental regulation, scholars have adopted different proxy variables for environmental regulation, such as Zhang (2020) chose environmental pollution control investment to measure environmental regulation, including investment in urban environmental infrastructure, investment in the control of old industrial pollution sources and "three simultaneities" investment in construction projects. Ouyang et al. (2020) argued that the higher the intensity of environmental pollution, the greater the urgency of environmental governance and the more stringent the corresponding government environmental regulations. According to previous scholars' research, this paper establishes environmental regulation indicators based on the perspective of cost. Its advantages are as follows: First, pollution control expenditure (investment) reflects the intensity of environmental regulation. The higher the pollution control expenditure (investment) is, the more urgent the demand for pollution control is, and the greater the intensity of environmental regulation is. Secondly, the investment in the treatment of industrial pollution sources is released by the National Bureau of Statistics, and the data can be reliably available. Therefore, this paper chooses industrial pollution source treatment investment to measure environmental regulation, including wastewater treatment, waste gas treatment, solid waste treatment, noise treatment and other pollution treatment investment, which can better reflect the intensity of environmental regulation.

3.2.3. CO_2 emissions

At present, China's industrial carbon dioxide emissions mainly come from the combustion of fossil fuels and industrial production processes. Fossil fuels mainly include coal, coke, petroleum (can be divided into fuel oil, gasoline, kerosene, diesel) and natural gas. The carbon dioxide emissions in industrial production mainly include carbon dioxide generated in the production processes of water sludge, lime, calcium carbide, etc (Wu *et al.* 2020).

Guan (2021), according to the guidelines of the United Nations Intergovernmental Panel on Climate Change (IPCC), gave the accounting formula for the industry's carbon dioxide emissions:

$$CE_{ij} = CE_{iJ} \times \frac{SI_{ij}}{SI_{iJ}} \tag{1}$$

Where SI stands for industry statistical indicators, including industry energy consumption, industry energy intensity, industry value added, industry output, etc. j refers to industries defined by national official statistics, and j is the matching industry in the list of 47 industries in the subsectoral accounting carbon dioxide emission inventory in the China Carbon Accounting Databases (CEADs). In this paper, we use industrial CO_2 emission data provided by the China Carbon Accounting Database (CEADs).

3.3. Model setting

This paper uses the vector autoregressive (VAR) model in econometrics to explore the impact of industrial technological innovation and environmental regulation on carbon dioxide emissions. Vector autoregressive (VAR) model is a model widely used in multi-variate time series analysis, which is composed of regression equations. The VAR model is estimated by regressing the lag value of each model variable itself and the lag value of other model variables to some pre-specified maximum lag p-order. The VAR model with p-order autoregressive lag value is called VAR (p) model ((Kilian *et al.* 2017). The general simplified VAR (p) mathematical expression can be expressed by the following formula:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \mu_t \tag{2}$$

Where y_t is a K×1 order vector of the observed time series data (I = 1,2 … p) K × K is Order parameter matrix, $v = A(L)\mu_0 = A(1)\mu_0 = (I_K - \sum_{j=1}^{p} A_j)\mu_0$ is a constant term. Error term. $\mu_t = (\mu_{1t}, \cdots, \mu_{Kt})'$ is a covariance matrix, $\mathrm{E}(\mu_t \mu_t') = \Sigma_\mu$, K-dimensional zero mean white noise process， $\mu_t \sim (0, \Sigma_\mu)$.

The VAR modelling steps are usually (1) Variable selection. Identify which variables are related to each other and include these variables in the VAR model. (2) Lag order determination. Determine the lag order of the model by criteria such as AIC, SC, HQ, LogL, or likelihood ratio (LR) test. (3) Model estimation. The model is estimated using the least squares method (OLS) to obtain the estimated values of each parameter. (4) Model testing. Unit root test, residual autocorrelation test, etc. to ensure the stability and applicability of the model. (5) Result analysis. The model results are analysed through impulse response analysis and variance decomposition to reveal the dynamic relationship between variables.In this study, $y_t = \begin{bmatrix} LOG(co_2)_t \\ LOG(regulation)_t \\ LOG(innovation)_t \end{bmatrix}$ stands for the carbon dioxide emission in t period, $LOG(innovation)_t$ stands for environmental regulation in t perior, $LOG(innovation)_t$ stands for technological innovation in the t period. In order to facilitate calculation, $LOG(co_2)_t$ is abbreviated as LGCO2 $LOG(regulation)_t$ .is abbreviated as LGinn.

3.4. Data source

According to the research of scholars Obobisa et al (2022) industrial technology innovation uses invention patents as proxy variables, and the data is sourced from the China Science and Technology Statistical Yearbook from 2000 to 2023. Because it is difficult to directly obtain the number of invention patents granted by industrial enterprises, This paper calculates according to the relevant data published by the National Bureau of Statistics (for example, 268366 invention patents were granted to all enterprises in 2020, and 446069 invention patents were applied to industrial enterprises above the designated size. According to the estimation that the invention patent authorization rate published by the China National Intellectual Property Administration in the 2020 annual report is 47.3%, the number of invention patents granted to industrial enterprises above the designated size is about 210990, accounting for 78.6% of all enterprises, and the data of industrial enterprises below the designated size is not included here). The number of invention patents granted by industrial enterprises accounts for the majority of the number of invention pa-tents granted by all enterprises, so it is reasonable and reliable to choose the number of invention patents granted by all enterprises to replace the number of invention patents granted by industrial enterprises. According to the research of scholars Zhang et al. (2020), this article selects industrial environmental pollution control investment as the proxy variable for environmental regulation. The data is sourced from the *China Environmental Statistical Yearbook* from 2000 to 2023. The data of industrial carbon dioxide emissions are from 2000 to 2023 (Due to the fact that the database only provides data up to 2021, trend analysis is used to calculate the data for 2022 and 2023) provided by China Carbon Ac-counting Database (CEADs), which mainly includes coking products, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery gas, other petroleum products, natural gas, heating, electricity and other energy sources. In order to reduce the fluctuation of data, the above data are calculated after taking logarithms. All data in this paper were processed using EViews 13.0.

4. Empirical analysis

4.1. Unit root test

Because many time series data in reality show nonstationarity, direct regression can easily lead to false regression, so it is necessary to test the stationarity of time series. Unit root test is a special method used in time series analysis to test the smoothness of the series, unit root test methods are varied, the following are several major unit root test methods: (1) ADF test (Augmented Dickey-Fuller test). ADF test is an augmented form of the Dickey-Fuller test for dealing with time series data that contain higher-order lag terms. lagged terms in the time series data. It controls for disturbances in serial correlation by including a differential lag term in the regression model to determine whether a unit root exists in the series. If the series is smooth, there is no unit root; otherwise, there is a unit root. (2) PP test (Phillips-Perron test) The PP test is similar to the ADF test, but uses a non-parametric approach to correct for serial correlation, which is an improvement on the small sample nature. The principle is similar to the ADF test, but a different approach is used to correct for serial correlation. (3) KPSS test (Kwiatkowski-Phillips-Schmidt-Shin test) The KPSS test is a test based on a smooth series, where the original assumption is that the series is smooth and the alternative assumption is that the series has a unit root. (4) ERS test (Elliott-Rothenberg-Stock test).ERS test is a unit root test based on an error correction model for non-stationary time series where there is a long-run equilibrium relationship. (5) NP test (Nelson-Plosser test): NP test is a method specially used to test whether there is a unit root in macroeconomic time series. The test is mainly designed for the characteristics of macroeconomic data, with high relevance and practicality. (6) DF-GLS test (Dickey-Fuller Generalized Least Squares test): DF-GLS test is a kind of improved Dickey-Fuller test, which uses the generalized least squares method to estimate the parameters of the model in order to improve the efficacy of the test. The principle is to optimise the estimation of model parameters by generalised least squares to improve the accuracy and stability of the test.

Table 1. ADF unit root test

Variables	Test Type	Significance	t-values	Critical values	Conclusion
	(c， t， k)	p-value	t-Statistic	1% level	
$LGCO_2$	(c， t， 0)	0.301	-2.557	-4.441	Nonstationary
LGreg	(c， t， 0)	0.618	-1.908	-4.416	Nonstationary
LGinn	(c， t， 2)	0.350	-2.441	-4.468	Nonstationary
D($LGCO_2$)	(c， t， 0)	0.246	-2.700	-4.441	Nonstationary
D(LGreg)	(c， t， 3)	0.013	-4.312	-4.441	Nonstationary
D(LGinn)	(c， t， 1)	0.000	-6.638	-4.468	Nonstationary
D($LGCO_2$,2)	(c， t， 0)	0.001	-5.716	-4.468	Steady
D(LGreg,2)	(c， t， 0)	0.009	-4.580	-4.498	Steady
D(LGinn,2)	(c， t， 3)	0.004	-5.127	-4.572	Steady

Table 2. Results of hysteresis exclusion test

Variables	$LGCO_2$	LGreg	LGinn	Joint
Lag 1	36.03745	12.94758	20.74633	90.50345
	[0.0000]	[0.0048]	[0.0001]	[0.0000]
Lag 2	4.432877	6.875701	1.526730	20.12477
	[0.2184]	[0.0760]	[0.6761]	[0.0172]
df	3	3	3	9

Table 3. Calculation results of lag length criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	30.860	NA	1.78e-05	-2.423	-2.275	-2.385
1	114.209	137.706*	2.80e-08*	-8.888*	-8.295*	-8.739*

*Note: *, ** and *** are significant levels of 10%, 5% and 1% respectively.*

In this paper, the ADF unit root test is performed on the logarithmized data. The results are shown in Table 1. All sequences are stable in the second order difference, so the original sequence is a second order single integer sequence.

Note: c refers to the intercept item; T is the trend item included; K is the order of lag difference automatically selected. According to the rounding principle, three digits are reserved after the decimal point of all figures in this paper.

4.2. Determination of VAR model hysteresis

4.2.1. Lag elimination test

The hysteresis exclusion test is used to test the hysteresis of each variable in the VAR system. The test results are shown in Table 2. For lag 1, each equation of all endogenous variables is significant at 1% significant level, and for lag 2, LGreg variables are significant at 1% significant level.

4.2.2. Hysteresis length criterion

The calculation results of lag length criterion are shown in Table 3. FPE, AIC and HQ criteria all point to the second order hysteresis, so VAR (1) is selected for subsequent analysis.

4.3. Stability test

The stability of VAR system is a prerequisite for impulse response and variance decomposition. According to Figure 1, the reciprocal of the moduli of all AR roots are located in the unit circle, so it can be judged that the VAR system is stable.

4.4. Cointegration inspection

Many economic variables show a continuous upward or downward movement, which can be generated by the random trend in the integrated variables. If the same random trend drives a group of integrated variables together, it is called cointegration. In this case, some linear combinations of integrated variables are stable. This linear combination that links variables with common trend path is called cointegration relationship (Kilian *et al.* 2017). Cointegration can be achieved by re-parameterizing VAR model into vector error correction model (VECM) (Aghabalayev,2022). Cointegration analysis is mainly applied to economic systems in which short-term dynamic relations are subject to significant effects of random disturbances, while long term relations are subject to equilibrium relations.

Table 4. Estimation of VAR model coefficients

Variables	**$LGCO_2$**	**LGreg**	**LGinn**
$LGCO_2$ (-1)	1.228318	0.250079	-1.051837
Standard Deviation	(0.21596)	(1.58077)	(1.49033)
T Statistics	[5.68770]	[0.15820]	[-0.70577]
$LGCO_2$ (-2)	-0.306123	0.537724	1.638087
Standard Deviation	(0.23861)	(1.74655)	(1.64662)
T Statistics	[-1.28295]	[0.30788]	[0.99482]
LGreg (-1)	-0.024654	0.774739	-0.170918
Standard Deviation	(0.03022)	(0.22121)	(0.20855)
T Statistics	[-0.81579]	[3.50226]	[-0.81953]
LGreg (-2)	-0.010702	-0.379722	-0.011863
Standard Deviation	(0.03155)	(0.23094)	(0.21772)
T Statistics	[-0.33922]	[-1.64426]	[-0.05449]
LGinn (-1)	0.026639	0.404243	0.974882
Standard Deviation	(0.03585)	(0.26239)	(0.24738)
T Statistics	[0.74313]	[1.54063]	[3.94088]
LGinn (-2)	-0.020158	-0.463381	-0.152813
Standard Deviation	(0.03396)	(0.24854)	(0.23433)
T Statistics	[-0.59367]	[-1.86438]	[-0.65214]
C	0.374092	-1.115031	-0.763387
Standard Deviation	(0.21980)	(1.60887)	(1.51683)
T Statistics	[1.70197]	[-0.69305]	[-0.50328]

If the time series $y_{1t},y_{2t},\cdots,y_{nt}$ are single integers of order d, i.e., I(d), and there exists a vector $k=(k_1,k_2,\cdots,kn)$ such that $ky'_t \sim I(d-b)$, where $y_t=(y_{1t},y_{2t},\cdots,y_{nt})$, and $d\geq b\geq 0$, the series $y_{1t},y_{2t},\cdots,y_{nt}$ is said to be cointegrating of order (d,b), denoted as $y_t \sim CI(d,b)$, k is the cointegration vector.

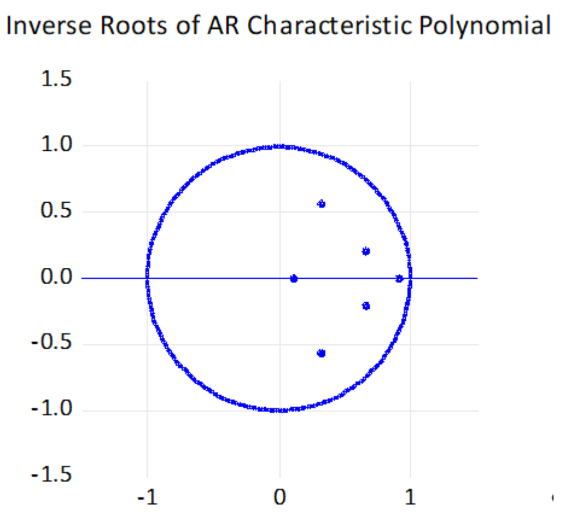


Figure 1. AR root diagram

The main methods of cointegration test are EG two-step method and Johansen test.EG two-step method is applicable to the cointegration test between two variables, and requires the variables to have the same number of single integer order.Johansen test is a multivariate cointegration test method, which can test the cointegration relationship between multiple time series at the same time.In this paper, Johansen test is used to conduct cointegration test on industrial technological innovation, environmental regulation and carbon dioxide emissions, which is a maximum likelihood method for testing.

(1) The VAR system is established, and the results are shown in Table 4.

According to the output results in Table 4, the estimated results of VAR model can be written:

$$\begin{bmatrix} LGCO_2 \\ LGreg \\ LGinn \end{bmatrix}_t = \begin{bmatrix} 0.374 \\ -1.115 \\ -0.763 \end{bmatrix} + \begin{bmatrix} 1.228 & -0.025 & 0.027 \\ 0.250 & 0.775 & 0.404 \\ -1.052 & -0.171 & 0.975 \end{bmatrix} \begin{bmatrix} LGCO_2 \\ LGreg \\ LGinn \end{bmatrix}_{t-1} + \begin{bmatrix} -0.306 & -0.011 & -0.020 \\ 0.538 & -0.380 & -0.463 \\ 1.638 & -0.012 & -0.153 \end{bmatrix} \begin{bmatrix} LGCO_2 \\ LGreg \\ LGinn \end{bmatrix}_{t-2} + \begin{bmatrix} \hat{\varepsilon}_0 \\ \hat{\varepsilon}_1 \\ \hat{\varepsilon}_2 \end{bmatrix}_t$$

(2) Test the validity of the model. First, test whether the residuals obey the normal distribution, and the results are shown in Table 5. From the output results, we can accept the original assumption that the residual is subject to normal distribution.

Table 5. Test results of residual normal distribution

Component	Skewness	Chi-sq	df	Prob.*
1	-0.117335	0.050481	1	0.8222
2	-0.005247	0.000101	1	0.9920
3	0.229766	0.193572	1	0.6600
Joint		0.244154	3	0.9702
Component	Kurtosis	Chi-sq	df	Prob.
1	2.144869	0.670312	1	0.4129
2	2.108706	0.728205	1	0.3935
3	2.105734	0.733070	1	0.3919
Joint		2.131587	3	0.5455
Component	Jarque-Bera	df	Prob.	
1	0.720793	2	0.6974	
2	0.728306	2	0.6948	
3	0.926642	2	0.6292	
Joint	2.375741	6	0.8821	

Table 6. Residual autocorrelation test

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	25.11111	9	0.0029	3.952773	(9, 24.5)	0.0032
2	10.73581	9	0.2943	1.272119	(9, 24.5)	0.3006
3	8.171979	9	0.5169	0.922594	(9, 24.5)	0.5227

Table 7. Huai specific variance test

Chi-sq	df	Prob.
82.99292	72	0.1767

Table 8. Unlimited cointegration rank test (Trace)

Hypothesized No. of CE(s)	characteristic value	Trace Statistic	0.05critical value	Prob.**
None *	0.903834	60.95261	29.79707	0.0000
At most 1	0.321976	11.77743	15.49471	0.1679
At most 2	0.158238	3.617411	3.841465	0.0572

Table 9. Normalized cointegration coefficient (standard error in brackets)

$LGCO_2$	LGreg	LGinn
1.000000	2.131580	0.067066
	(0.34351)	(0.06186)

Secondly, the residual autocorrelation is tested, and the test results are shown in Table 6. It can be seen from the test results that the original hypothesis is accepted at the significance level of 1%, that is, there is no autocorrelation in the residual sequence.

Third, carry out White heteroscedasticity test on the residual, and the results are shown in Table 7. It can be seen from the test results that the original hypothesis is accepted at the significance level of 1%, that is, there is no heteroscedasticity.

Therefore, after the above analysis, there are sufficient reasons to believe that the setting of VAR model is not biased and stable.

4.4.3 Cointegration analysis

After the VAR system is established, the cointegration test is performed next. The test results are shown in Table 8 and Table 9. The results from Table 8 show that there is a cointegration relationship among logarithmic technological innovation (Lginn), environmental regulation (LGreg) and carbon dioxide emissions ($LGCO_2$), and there is one specific cointegration relationship. It can be seen from Table 9 that the standardized cointegration vector with cointegration relationship can be written as:

$$LGCO_2=-2.132LGreg-0.067\ LGinn \quad (4)$$

It can be seen from the cointegration equation that each additional unit of environmental regulation will reduce 2.132 units of carbon dioxide emissions; At the same time, each additional unit of technological innovation will reduce 0.067 units of carbon dioxide emissions.

Trace test shows that there are three cointegration equations at 0.05 level* Denotes rejection of assumptions at 0.05 level

4.5 VAR impulse response and variance decomposition

4.5.1 Pulse response

The impulse response function describes the response process of other variables in the condition that the t period and the previous periods remain unchanged, and the standard error of the impulse response function is calculated by using the progressive analytical method.

Figure 2 shows the synthesis of nine impulse response functions. The horizontal axis is the number of periods, the vertical axis is the size of the impulse response function, and the upper and lower dashed lines represent the standard deviation of plus or minus two times.

It can be seen from Figure 2(a) that the carbon dioxide emissions ($LGCO_2$) immediately responded to its own standard deviation update. In the first phase, the response of the carbon dioxide emissions was about 0.015, and then the impact of this impact on the carbon dioxide emissions continued to increase, reaching the peak in the second phase, and then decreased slowly. At the same time, the impact of the disturbance impact of carbon dioxide emissions on carbon dioxide emissions lasts for a long time, and the change of carbon dioxide emissions is not stable until after 10 periods.

It can be seen from Figure 2(b) that carbon dioxide emissions ($LGCO_2$) did not respond immediately to the disturbance from environmental regulation. The response of carbon dioxide emissions in the first phase was 0, and then the response of carbon dioxide emissions to the disturbance from environmental regulation increased slowly and in a negative direction. After reaching the maximum value in the fourth period, it decreased slowly until it stabilized to zero around the tenth period.

It can be seen from Figure 2(c) that carbon dioxide emissions ($LGCO_2$) did not respond immediately to the disturbance from technological innovation. The response of carbon dioxide emissions in the first phase was 0, and then the response of carbon dioxide emissions to the disturbance from technological innovation increased slowly and in a positive direction. After reaching the maximum value in the second period, it decreases slowly until it reaches zero around the tenth period.

It can be seen from Figure 2(d) that the environmental regulation (LGreg) did not respond immediately to the disturbance from carbon dioxide emissions. The response of the environmental regulation in the second phase was close to zero, and then the response of environmental regulations to carbon dioxide emissions disturbance increased and showed a positive direction. After reaching its peak in the 5.5 period, it slowly decreased until it stabilized towards zero around the tenth period.

It can be seen from Figure 2(e) that the environmental regulation (LGreg) immediately responded to a standard deviation new information from itself. The response of the environmental regulation in the first phase was about 0.10, and then the impact of this shock on environmental regulations gradually decreased, with the response of environmental regulations decreasing to 0 in the 2.5th period. Afterwards, the response of environmental regulations to their own disturbances increased and had a negative direction. After reaching its peak in the 3.5th period, it slowly decreased until it stabilized towards 0 around the 6th period.

It can be seen from Figure 2(f) that environmental regulation (LGreg) did not respond immediately to the disturbance from technological innovation. The response of environmental regulation in the first phase was 0, and then the impact of this impact on environmental regulation increased slowly. The response of environmental regulation reached a peak in the 1.5 phases, and then the response of environmental regulation to technological innovation decreased. The response of environmental regulation to technological innovation in the 3 phases was 0, and then increased slowly and the direction was negative, It reached the maximum value in the 4.5 period, and then decreased slowly until it stabilized to zero around the eighth period.

It can be seen from Figure 2(g), that technological innovation (Lginn) did not immediately respond to disturbances from carbon dioxide emissions. The response of technological innovation in the first phase was close to 0, and then the response of technological innovation to disturbances from carbon dioxide emissions slowly increased and the direction was negative. Starting from the second phase, the response of technological innovation to the disturbance of carbon dioxide emissions has increased in a positive direction, and tends to stabilize around the eighth phase.

It can be seen from Figure 2(h) that technological innovation (Lginn) responded immediately to the disturbance from environmental regulation and the direction was negative. The response of technological innovation in the first phase was close to -0.07, and then the response of technological innovation to the disturbance from environmental regulation decreased slowly. In the second period, the response was the smallest, after which the technological innovation made a slow increase in the disturbance of environmental regulation, and the direction was negative, until it stabilized around the eighth period.

It can be seen from Figure 2(i) that technological innovation (Lginn) responds immediately to its own disturbance. The response of technological innovation in the first phase is about 0.07, and this response level continues to the second phase. Then the response of technological innovation to its own disturbance slowly decreased, until it stabilized around the ninth period, close to zero.

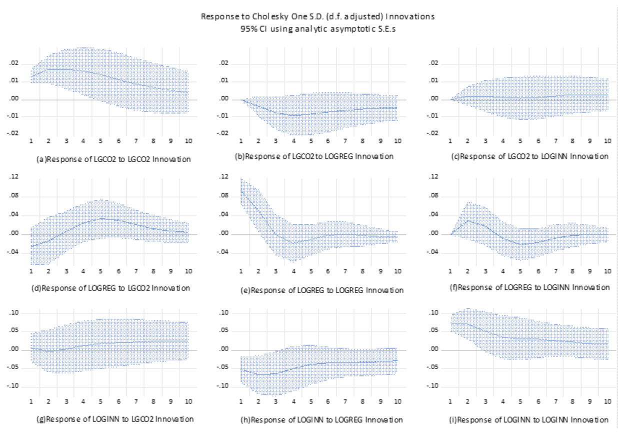


Figure 2. Pulse response function distribution

4.5.2 Variance decomposition

The impulse response function can capture the dynamic impact path of one variable's impact factor on another variable, and the variance decomposition can decompose the variance of one variable in the VAR system to each disturbance term. Therefore, variance decomposition provides the relative degree of each disturbance factor affecting each variable in the VAR model. In this paper, Monte Carlo method is used to calculate the standard error, and the results are shown in Tables 10, 11 and 12.

Table 10. $LGCO_2$ variance decomposition results

Response variable				
$LGCO_2$	**Standard error**			
S.E.	**Impulse variable**			
		$LGCO_2$	**LGreg**	**LGinn**
1	0.013166	100.0000	0.000000	0.000000
		(0.00000)	(0.00000)	(0.00000)
2	0.021909	96.37513	2.810377	0.814490
		(6.86238)	(5.38941)	(2.88069)
3	0.028946	90.68727	8.309577	1.003148
		(12.1841)	(10.8104)	(4.55660)
4	0.034323	86.42978	12.74529	0.824926
		(16.1690)	(14.9097)	(6.17560)
5	0.038017	84.06183	15.23241	0.705757
		(18.4882)	(17.0912)	(7.78791)
6	0.040349	82.66594	16.61972	0.714341
		(20.0303)	(18.1689)	(8.79946)
7	0.041810	81.46529	17.62820	0.906507
		(20.7862)	(18.4807)	(9.47694)
8	0.042788	80.23546	18.52058	1.243961
		(20.8225)	(18.6659)	(9.81369)
9	0.043490	79.07784	19.31412	1.608049
		(20.8886)	(18.9502)	(9.99836)
10	0.044012	78.10796	19.96569	1.926346
		(21.0889)	(19.1863)	(10.3149)

Table 11. LGreg variance decomposition results

Response variable LGinn	**Standard error S.E.**	**Impulse variable**		
		$LGCO_2$	**LGreg**	**LGinn**
1	0.096371	6.820684	93.17932	0.000000
		(9.19599)	(9.19599)	(0.00000)
2	0.113889	6.176351	86.88288	6.940765
		(8.91918)	(11.6836)	(7.71052)
3	0.115578	6.307688	84.36395	9.328357
		(9.30877)	(12.5265)	(9.93370)
4	0.119898	10.37922	80.51779	9.102983
		(10.2092)	(12.4789)	(9.69752)
5	0.126847	16.46256	72.70199	10.83545
		(12.2045)	(14.7378)	(9.90925)
6	0.131558	20.70063	67.60067	11.69870
		(13.3065)	(15.9206)	(10.2643)
7	0.133463	22.67124	65.69082	11.63793
		(13.8145)	(16.5731)	(10.5339)
8	0.134089	23.37455	65.09333	11.53212
		(14.2082)	(17.0244)	(10.5646)
9	0.134361	23.59157	64.92102	11.48741
		(14.4424)	(17.3005)	(10.6054)
10	0.134506	23.66185	64.87524	11.46290
		(14.3866)	(17.5384)	(10.7623)

It can be seen from Table 10 that the standard deviation of the first phase forecast of carbon dioxide emissions ($LGCO_2$) is equal to 0.013, the standard deviation of the second phase forecast is 0.022, and the standard deviation of the second phase forecast is larger than that of the first phase, because the second phase forecast includes the uncertainty impact of environmental regulation and technological innovation in the first phase forecast. With the passage of the forecast period, the standard deviation of carbon dioxide emissions forecast increases slowly. In the first forecast, the forecast variance of carbon dioxide emissions is all caused by the disturbance of carbon dioxide emissions. In the second forecast, 96.375% of the forecast variance of carbon dioxide emissions is caused by the disturbance of carbon dioxide emissions, 2.810% is caused by the disturbance of environmental regulations, and 0.814% is caused by the disturbance of technological innovation. With the passage of time, the part of carbon dioxide emission forecast variance caused by the disturbance of non-carbon dioxide emission variables increases, while the part caused by the disturbance of carbon dioxide emission itself decreases, but its proportion is still large. Around the 9 period, the decomposition results of carbon dioxide emissions were basically stable. The predicted variance of carbon dioxide emissions was 79.078% caused by the disturbance of carbon dioxide emissions, 19.966% caused by the disturbance of environmental regulations, and 1.608% caused by the disturbance of technological innovation.

It can be seen from Table 11 that the standard deviation of the first phase of the LGreg forecast is equal to 0.096, the standard deviation of the second phase is 0.114, and the standard deviation of the second phase is larger than that of the first phase, because the second phase of the forecast includes the uncertainty impact of carbon dioxide emissions and technological innovation in the first phase of the forecast. With the passage of the forecast period, the standard deviation of environmental regulation forecast increases slowly. In the first forecast, the forecast variance of environmental regulation is 93.179% caused by the disturbance of environmental regulation itself, and 6.821% caused by the disturbance of carbon dioxide emissions. In the second forecast, 86.883% of the forecast variance of environmental regulation is caused by the disturbance of environmental regulation itself, 6.176% is caused by the disturbance of carbon dioxide emissions, and 6.941% is caused by the disturbance of technological innovation. With the passage of time, the part of environmental regulation forecast variance caused by the disturbance of non-environmental regulation variables increases, while the part caused by the disturbance of environmental regulation itself decreases, but its proportion is still large. Around the eighth period, the decomposition result of environmental regulation was basically stable. 65.093% of the predicted variance of environmental regulation was caused by the disturbance of environmental regulation itself, 23.375% was caused by the disturbance of carbon dioxide emissions, and 11.532% was caused by the disturbance of technological innovation.

Table 12. LGinn variance decomposition results

Response variable				
LGinn	**Standard error S.E.**	**Impulse variable**		
		$LGCO_2$	**LGreg**	**LGinn**
1	0.090858	0.787217	32.47642	66.73636
		(6.87543)	(16.2532)	(16.8015)
2	0.133790	0.378966	39.59220	60.02883
		(8.24472)	(17.4587)	(17.2069)
3	0.156701	0.320939	44.91179	54.76727
		(9.29854)	(18.7482)	(18.6335)
4	0.169031	0.802292	47.31114	51.88657
		(10.1636)	(19.3073)	(19.8536)
5	0.177262	1.801610	47.83570	50.36269
		(11.7544)	(19.4448)	(20.6783)
6	0.184237	3.026764	47.70680	49.26644
		(13.5710)	(19.6193)	(21.1869)
7	0.190634	4.340418	47.58216	48.07743
		(14.6820)	(19.6538)	(21.4309)
8	0.196373	5.712421	47.57211	46.71547
		(15.0773)	(19.6002)	(21.4532)
9	0.201323	7.076369	47.55659	45.36704
		(15.6280)	(19.5801)	(21.5034)
10	0.205485	8.323443	47.47765	44.19891
		(16.4915)	(19.7041)	(21.5962)

It can be seen from Table 12 that the standard deviation of the first phase of the forecast of LGinn is equal to 0.091, the standard deviation of the second phase is 0.134, and the standard deviation of the second phase is larger than that of the first phase, because the second phase of the forecast includes the uncertainty impact of carbon dioxide emissions and environmental regulation in the first phase of the forecast. With the passage of the prediction period, the standard deviation of technological innovation prediction increases slowly. In the first forecast, the variance of technological innovation forecast is 66.736% caused by the disturbance of technological innovation itself, 0.787% caused by the disturbance of carbon dioxide emissions and 32.476% caused by the disturbance of environmental regulations. In the second forecast, 60.029% of the forecast variance of technological innovation is caused by the disturbance of technological innovation itself, 0.379% is caused by the disturbance of carbon dioxide emissions, and 39.592% is caused by the disturbance of environmental regulations. With the passage of time, the part of the forecast variance of technological innovation caused by the disturbance of non-technical innovation variables increases, while the part caused by the disturbance of technological innovation itself decreases. Around the tenth period, the decomposition results of technological innovation gradually stabilized. 44.199% of the predicted variance of technological innovation was caused by the disturbance of technological innovation itself, 8.323% by the disturbance of carbon dioxide emissions, and 47.478% by the disturbance of environmental regulations.

5. Conclusions and policy implications

5.1 New Finding and Discussion

Based on the relevant data of China's industrial technological innovation, environmental regulation and carbon dioxide emissions from 2000 to 2019, this paper establishes a VAR system to test the cointegration relationship between industrial technological innovation, environmental regulation and carbon dioxide emissions; The impulse response function of VAR is used to describe the impact of the impulse of the random perturbation term of three endogenous variables of the VAR system on the current and future values of all endogenous variables in the VAR system; Through variance decomposition, the contribution of each innovation shock to the change of endogenous variables is analyzed, and the relative importance of each innovation to the three endogenous variables of the VAR system, industrial technological innovation, environmental regulation and carbon dioxide emissions, is found. The conclusions are as follows:

(1) There is a cointegration relationship among industrial technological innovation, environmental regulation and carbon dioxide emissions. In recent years, research on mitigating the greenhouse effect has been continuously deepening, and discussions on the influencing factors of carbon dioxide emissions reduction have been expanding (Awan *et al.* 2022; Chang *et al.* 2023). When studying the driving factors of carbon dioxide emissions, it is mainly studied from the perspectives of technological innovation (Xie *et al.* 2023), digital economy (Qiu *et al.* 2023) and renewable energy (Ahmed *et al.* 2022). However, there is still limited literature considering the impact of technological innovation and environmental regulations on carbon emissions. Qiu, Wang, and Lian (2023) used econometric methods and found that macroeconomic policies can reduce carbon emissions. Different from the research of Qiu and Wang, and Lian (2023), this paper not only considers environmental regulation, but also adds technological innovation factors to the VAR system, comprehensively considering the impact of the combination of environmental regulation and technological innovation on carbon emissions. With the innovation of industrial science and technology and the improvement of environmental regulations, carbon dioxide emissions are restrained. Specifically, each additional unit of environmental regulation will reduce 2.132 units of carbon dioxide emissions; At the same time, each additional unit of technological innovation will reduce 0.067 units of carbon dioxide emissions. Compared with technological innovation, environmental regulation has a greater impact on carbon dioxide emission reduction.

(2) The impact of the pulse of the stochastic perturbation term of the three endogenous variables of industrial technological innovation, environmental regulation and carbon dioxide emissions in the VAR system on the current and future values of all endogenous variables is relatively complex, and varies in the short, medium and long term. Previous studies have focused on the long-term effects of financial risks and technological innovation, population, wealth, regulation and technology, environmental regulation and renewable energy R & D expenditure on carbon dioxide emissions. This paper not only studies the long-term impact, but also describes the short-and medium-term effects of industrial scientific and technological innovation and environmental regulation on carbon dioxide emissions. In the short term, carbon dioxide emissions responded immediately to its own standard deviation, but did not respond immediately to the disturbance from environmental regulation and technological innovation. The environmental regulation responded immediately to a standard deviation from itself, but did not respond immediately to the disturbance from carbon dioxide emissions and technological innovation. Technological innovation responded immediately to the disturbance from itself, did not respond immediately to the disturbance from carbon dioxide emissions, and responded immediately to the disturbance from environmental regulations with a negative direction. There are some fluctuations in the medium term, but they all reach stability in the long term (the tenth term).

(3) Through variance decomposition, the relative degree of each disturbance factor affecting industrial technological innovation, environmental regulation and carbon dioxide emissions in the VAR model is understood. Based on the provincial panel data in China, it is found that except for the variable itself, carbon pressure level has the greatest contribution to the long-term variance of renewable energy technological innovation, renewable energy technological innovation has the highest contribution to the variance of environmental regulation intensity, and environmental regulation intensity has the highest contribution to the variance of carbon pressure level. In the past, most of the research objects are regional. This paper takes Chinese industry as the research object and expands the scope of the research object. In the short term, it is found that the predicted variance of industrial carbon dioxide emissions is all caused by the self-disturbance of carbon dioxide emissions, the part of the forecast variance of environmental regulation caused

by the self-disturbance of environmental regulation is 93.179%, and the part of the forecast variance of technological innovation caused by the self-disturbance of technological innovation is 66.736%. In the long run, the decomposition results of carbon dioxide emissions are basically stable. 79.078% of the predicted variance of carbon dioxide emissions is caused by the disturbance of carbon dioxide emissions itself, 19.966% is caused by the disturbance of environmental regulations, and 1.608% is caused by the disturbance of technological innovation; 65.093% of the forecast variance of environmental regulation is caused by the disturbance of environmental regulation itself, 23.375% is caused by the disturbance of carbon dioxide emissions, and 11.532% is caused by the disturbance of technological innovation; The forecast variance of technological innovation is 44.199% caused by the disturbance of technological innovation itself, 8.323% caused by the disturbance of carbon dioxide emissions, and 47.478% caused by the disturbance of environmental regulations.

5.2 Countermeasures and suggestions

(1) We will continue to strengthen industrial technological innovation and improve the level of technological innovation. From the research results, China's industrial technological innovation has a certain role in promoting carbon dioxide emission reduction, but the strength is not strong enough and the effect is not outstanding enough. Therefore, it is necessary to accelerate the increase of technological innovation to improve the benefits of carbon dioxide emission reduction. Targeted technological innovation can be made in the development and application of clean energy and technological innovation in industrial production process. The development and application of clean energy can replace fossil fuels and reduce carbon dioxide emissions. Technological innovation in industrial production process can reduce energy consumption and save costs, especially the application of artificial intelligence and digital technology to achieve the effect of energy conservation and emission reduction. Industrial technological innovation should be persistent, especially the key technology of "stuck neck", so as to promote industrial carbon dioxide emissions in the long term.

(2) Continue to increase investment in environmental pollution control and improve the efficiency of environmental regulation. The investment in environmental pollution control plays a significant role in reducing carbon dioxide emissions, indicating that environmental regulation is an important measure for reducing carbon dioxide emissions. Whether in the short term or in the long term, environmental regulation contributes a lot to carbon dioxide emission reduction, so it is necessary to maintain the continuity and sustainability of environmental regulation. We will continue to promote the emission reduction of carbon dioxide by means of funds, policies and other means in the industrial field. All kinds of emission reduction policies should be timely evaluated and constantly introduced; According to local conditions, appropriate subsidies will be given to all kinds of investment in environmental pollution control, with awards instead of subsidies, and a small amount of government subsidies will be used to stimulate the continuous investment of industrial enterprises in environmental pollution control. At the same time, industrial enterprises should arrange a certain budget every year to ensure the continuous development of environmental pollution control.

(3) In promoting the construction of a mechanism to reduce carbon dioxide emissions in China's industry, the concept of green development should be deeply integrated. It is necessary to strengthen the innovation and application of green technology, encourage enterprises to research and develop low-carbon technologies, improve energy efficiency and clean up the production process. Optimise the industrial structure, guide resources towards low-carbon and environmentally friendly areas, and eliminate high-energy-consuming and high-emission production capacity. Establish a sound carbon trading market, and encourage enterprises to take the initiative to reduce emissions through the market mechanism, so as to achieve a win-win situation in terms of economic and ecological benefits. Strengthen policy guidance and supervision, formulate stricter emission standards, and implement punitive measures for enterprises that exceed emission standards. Finally, to enhance public awareness of environmental protection, advocate a green lifestyle, the formation of the whole society to participate in the atmosphere of emission reduction, and jointly promote China's industrial green low-carbon transformation.

5.3. Limitations and future research

This study has made some contributions to the research methods and policy recommendations, but there are still some limitations. This study links environmental regulation, technological innovation and industrial carbon emissions, but does not examine the impact of industrial segments, such as environmental regulation and technological innovation, on heavy industry and light industry may be different. Environmental regulation is mostly government behavior, including regulations and policies related to carbon dioxide emission permits, emission standards, emissions and so on, so it is difficult to measure directly. It is feasible to use industrial pollution source treatment investment as a proxy variable in this study, but there may be deficiencies. In addition, this study does not subdivide the impact of technological innovation, such as green innovation and subversive innovation, on carbon dioxide emissions, which are all issues that future researchers should pay attention to.

Looking ahead, with the continuous advancement of technology and the continued improvement of policies, the application of innovative technologies for emission reduction should be further promoted, and the greening and intelligent development of industry should be facilitated. At the same time, international cooperation and exchanges will be further strengthened to jointly address the challenges of global climate change. In addition, the public's awareness of environmental protection will continue to be raised, and a wider trend of green consumption and low-carbon living will be formed. Through sustained efforts, China's industry will achieve more efficient, cleaner and sustainable development, contributing Chinese wisdom and strength to global climate governance.

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