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Retraction

Retracted: A Model-Driven Analysis of the Relationship between Innovation and Growth in a Green Low-Carbon Economy Based on Open Public Data

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Wu, "A Model-Driven Analysis of the Relationship between Innovation and Growth in a Green Low-Carbon Economy Based on Open Public Data," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1553726, 12 pages, 2022.

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Research Article

A Model-Driven Analysis of the Relationship between Innovation and Growth in a Green Low-Carbon Economy Based on Open Public Data

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In the new era, China's economic development is in the offensive period of transforming the development mode, green development is an inevitable requirement to accelerate the transformation of economic development mode and optimize the industrial structure, and we should adhere to the concept of ecological priority and green development to promote high-quality economic development. The 19th Party Congress clearly proposed to "promote green development, establish a sound economic system of green low-carbon cycle development, and build a market-oriented green technology innovation system." Green technology is the technology to save resources, reduce pollution, and achieve sustainable development. Green technology innovation continues to promote green development, which will become an important support to promote the progress of ecological civilization, adhere to pollution prevention and control, and promote high-quality development. Promoting green technology innovation, taking the road of sustainable development, enhancing the awareness of environmental protection, and promoting high-quality economic development are also inevitable choices to promote the conversion of economic development mode. Carrying out research on the impact of green technological innovation on regional economic growth is of great significance to alleviate the shortage of innovation resources in China, guide enterprises to change to a green way of development, and promote the sustainable development of China's economy and population, resources, and environment. This paper provides publicly available data from 2015-2021, takes fixed asset investment as the variable, introduces control variables, and analyzes the relationship between technological innovation and economic growth using fixed-effects model and intermediate-effects model. The results show that innovation contributes significantly to regional economic growth and is influenced by the mediating role of fixed asset investment. In order to boost China's economic growth, specific policy recommendations are proposed in terms of optimizing the regional innovation layout, improving the intellectual property rights system, cultivating high-quality talents, optimizing the structure of fixed assets, and attracting the inflow of foreign capital.

1. Introduction

Innovation is the soul of a nation's progress and the driving force of a country's prosperity [1]. Innovation is the inexhaustible source to promote high-quality economic development and meet the growing needs of people for a better life. However, at present, China's industry is still not free from the "three high" development mode, with high consumption of resources and energy and prominent ecological and environmental problems, and it is urgent to accelerate the construction of a new model of green development with high technological content, low resource consumption, and low environmental pollution. In order to better implement the new development concept, the 19th Party Congress report clearly pointed out that "promoting green development and building a market-oriented low-carbon economic innovation system" [2]. Low-carbon economy innovation is to achieve green development as the goal, focusing on innovation to guide enterprises to carry out green innovation in products, technologies, processes and services, reduce resource consumption, improve resource utilization efficiency, and provide power and path reference for China to achieve high-quality economic development. Therefore, low-carbon economic innovation is indispensable for achieving coordinated economic, social, and environmental development, and it is of great theoretical and practical significance to study the dynamic interaction between low-carbon economic innovation and economic development.

General Secretary Xi Jinping put forward the new development concept for the problem of economic growth dynamics, and Xi Jinping's socialist thought of the new era with Chinese characteristics takes the five new economic development concepts of innovation, coordination, green, openness and sharing as the basic strategy of socialist construction [3]. Among them, innovation and green are two major elements of economic growth that cannot be ignored. The concept of innovative development provides endogenous power for economic growth, while the concept of green development provides sustainable power for economic growth.

The world has experienced the baptism of three technological revolutions, namely, the "mechanical age," "electrical age," and "information age," and is now ushering in the fourth wave of technological revolution [4]. The information technology represented by big data, blockchain, Internet of Things, and mobile communication is developing vigorously, and the intelligent technology represented by artificial intelligence, photoelectric chip, quantum information, and 5G communication is improving day by day, which injects the power of "wisdom" and adds new vitality to various industries such as industry, medical, city, finance, agriculture, and transportation. This has led to a new "intelligent era" [5]. In such an era of intelligence, countries around the world have been deploying core technology industrial strategies and devoting themselves to scientific research in science and technology innovation, hoping to seize the bull's eye of science and technology innovation industries such as artificial intelligence, blockchain, 5G communication, and big data to achieve autonomous control of science and technology and stand out in the competition of economic development [6]. The 2018 World Science and Technology Innovation Forum was held to exchange and discuss many topics such as artificial intelligence, new materials, space exploration, big data, cloud computing, smart cities, financial technology, and biotechnology; the Global Hard Technology Innovation Conference was based on the eight hard technology sectors of new energy, smart manufacturing, biotechnology, artificial intelligence, aerospace, optoelectronic chips, information technology, and new materials; the 2018 World Innovation Report clearly points out that the world is in the era of the explosion of science and technology innovation, where enterprises or countries should follow the pace of the times and seize the opportunity of the times; otherwise, it will certainly be eliminated by the times [7]. In 2019, in the seventh BRICS Ministerial Conference on Science and Technology Innovation, the heads of science and technology ministries believe that strengthening cooperation in science and technology innovation is a major mission that countries should undertake [8]. In 2016, the State Council issued the "Outline of Innovation-driven Development Strategy," proposing to drive economic growth through innovation, and since then, the Chinese government has been emphasizing the importance of innovation in driving economic development [9]. The report of the 19th Party Congress pointed out that "innovation is the first driving force leading development and is the strategic support for building a modern economic system" [10]. As one of the important economic policies in China, the role of science and technology innovation in boosting economic development is mainly manifested in the following aspects: First, scientific research papers, patent inventions, and intellectual property rights, as the final expression of the results of science and technology innovation, provide endogenous impetus to a certain extent for improving innovative thinking, promoting work efficiency, improving working methods, and forming new industrial chains, thus indirectly promoting economic growth; second, science and technology innovation strengthens the development capacity of real economy and science and technology service industry, which provides a new channel for the growth of real economy, and the development of science and technology further promotes the flourishing of technology development, technology transfer, and consulting services, which plays a decisive role in the development of tertiary industry and promotes the optimization and upgrading of industrial structure. Thirdly, scientific and technological innovation improves production efficiency and releases labor force, which in some ways alleviates the problem of aging population and eases social labor pressure [11]. Innovation plays a positive role in driving economic development, supporting economic growth, promoting the refinement of national economic and industrial division of labor, advanced industrial forms, bringing new economic and industrial development, new technologies, and new dynamics to further improve the quality of economic development, and helping China to cross the "middle-income trap."

2. Related Work

The current research on low-carbon economic innovation focuses on the connotation understanding of low-carbon economic innovation and its influencing factors. Among them, [12] summarized the connotation of low-carbon economic innovation from three perspectives: economic, environmental, and systemic, by combing through the existing domestic literature on low-carbon economic innovation. The empirical study focuses on the exploration of the influencing factors of low-carbon economic innovation. Palanisamy and others [13] discuss the impact on low-carbon economic innovation from environmental regulation. [14] discuss the influence of government support on firms' low-carbon economic innovation. [15] evaluated the efficiency of low carbon economic innovation of different types of enterprises. And not many studies have been conducted on the relationship between low-carbon economic innovation and economic growth. The available studies mainly focus on using time series data. The relationship between the two is discussed using cointegration theory, Granger causality test, and other econometric methods. Take Guangdong as an example to discuss the cointegration relationship between green innovation and economic growth [16]. Taking Henan as an example, the cointegration relationship between green innovation and economic growth is analyzed by constructing a VAR model, etc. [17]. The traditional innovation input-output indicators, such as personnel full-time equivalents and R&D internal funding expenditures, are still used in the selection of innovation measurement indicators for low carbon economy. These variables serve as an aggregate concept of innovation inputs, so there is a need to find new indicators that can objectively and scientifically represent the current status of innovation development in a low-carbon economy in a certain region [18].

Algalil and others put forward the neoclassical growth theory based on the Harold-Domar theory of economic growth [19]. The neoclassical growth theory criticizes the assumption of irreplaceability of labor and capital in Harold-Domar's economic growth theory and creatively incorporates technology as an exogenous factor of economic growth into the economic growth model and concludes that economic production can grow steadily. In addition, the neoclassical growth theory also broadened the form of the economic growth model. Algalil et al. suggested to include the internal structural factors of economic system, such as wages, prices, population growth, savings, and taxes, into the economic growth model. Neoclassical growth theory broadens the horizon of economic growth-related research by adding the internal dynamics of the economic system and expanding the research on the internal structural elements of the economic system. With the outbreak of the third technological revolution, more and more scholars realized the great role of scientific and technological progress in driving economic growth, and they also realized that it was wrong to consider science and technology as the exogenous driving force of economic growth. In 1985, researches represented by Romer and Lucas proposed the "new economic growth theory" [20]. In the early 1990s, Schumpeter put forward the new Schumpeterian growth theory, which takes scientific and technological progress and innovation as the endogenous driving force of economic growth [21]. Since then, science and technology innovation as the endogenous driving force of economic development has occupied a pivotal position in the research related to economic growth.

At the present stage, the research on economic growth and internal factors of economic system mainly focuses on the relationship between economic growth and scientific and technological innovation; [22] explained the relationship between economic growth and scientific and technological innovation from the perspective of theoretical analysis; [23] interpreted the relationship between scientific and technological innovation and economic growth from the perspective of policy and practice; [24] explored the relationship between scientific and technological innovation and economic growth from the perspective of empirical analysis. The six central provinces, which are the most important provinces in China, are the most important provinces in China. The six central provinces are important food production bases, raw material and energy bases, equipment manufacturing bases, and comprehensive transportation hubs in China [25]. Over the past decade or so since the deployment of the Central Rising, are there significant differences in low-carbon economic innovation among provinces? How to drive high-quality economic development through low-carbon economic innovation? These questions need to be addressed urgently. In summary, this paper will select low-carbon economic innovation proxy variables from a new perspective and construct a panel vector autoregressive model (PVAR) using panel data from six central provinces to explore the dynamic equilibrium relationship between low-carbon economic innovation and regional economic development and the driving mechanism. This study will have important theoretical and practical implications for the high-quality economic development of the central region.

3. Model

The mechanism of action between science and technology innovation and economic growth is shown in Figure 1. The interaction between science and technology, organizational and managerial innovation, and the regional environment promotes the development of regional science and technology innovation. Specific scientific and technological innovation is manifested as endogenous scientific and technological innovation elements such as technological innovation in production, upgrading of equipment and products, invention and creation on the one hand, and exogenous scientific and technological innovation elements such as innovation in management methods, innovation in organizational forms, and innovation in institutional environment on the other hand. At the same time, regional environmental differences also play an indelible role in the process of regional innovation development. The degree of regional science and technology innovation development is often influenced by many factors such as regional location, government policies, history and culture, and environmental resources. Therefore, the heterogeneity of time and space should be taken into account as much as possible when quantifying science and technology innovation.

The mechanism of green low carbon and economic growth is discussed in the context of China's time, and its mechanism of action is shown in Figure 2. The massive consumption of resources and energy has put a burden on the whole environment, resources, and energy system, manifested in environmental degradation, resource, and energy depletion, and even caused natural disasters and resource and energy crises. The abovementioned phenomenon is an early warning signal from the environment, resources, and energy system to the economy and society, so the government has changed its policy implementation and guided financial, information, and resource factors to the environmental protection, which has created a favorable production development environment and led to the increase of productivity. With the booming development of green low-carbon industries, the industry chain is getting closer and closer, and the production methods are becoming more and more perfect, leading to the expansion of the business scale of each green low-carbon industry. The great prospect of the development of green low-carbon industry makes the scientific community, business community, and the government to

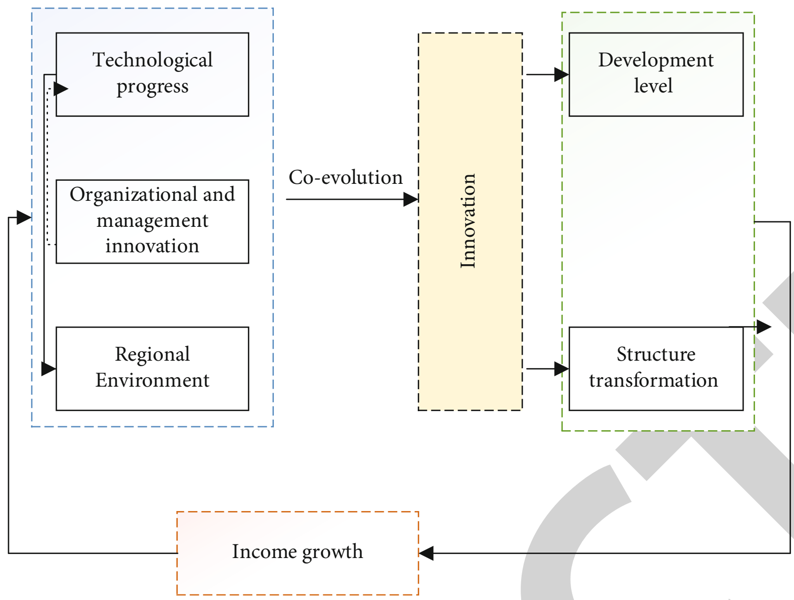

Figure 1: Mechanism of innovation and economic growth.

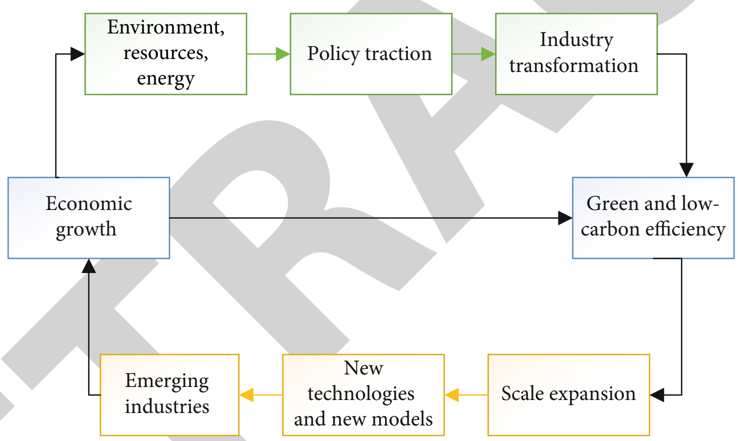

Figure 2: Mechanism of green low carbon and economic growth.

be eager to continuously transfer the development factors to the green low-carbon industry. New technologies and new models have emerged and are being improved. New production models and new production technologies have led to the birth of new industries associated with the green low-carbon industry, which has injected new vitality into economic growth.

Based on the theoretical study of science and technology innovation, it is found that science and technology innovation brings big advantages to industrial development, namely, profitability, clean production, and energy consumption reduction. Scientific and technological innovation is conducive to industrial production efficiency, and the improvement of production efficiency enables enterprises to gain a competitive advantage in an industry or industry, which eventually manifests itself as strong profitability. The new technology provides a clean production environment for enterprises. At the same time, new energy technologies and green production technologies greatly reduce energy consumption and improve energy efficiency. This is crucial for industries, especially green and low-carbon industries, as shown in Figure 3.

The three main advantages of science and technology innovation determine the market's superiority and the government's preference. For the green low-carbon industry, the more an enterprise can grasp the core technology, the more profitable the enterprise will be, and the more market resources it can obtain. When the market allocates resources, it will tilt the resources to the enterprises with strong scientific and technological innovation ability, and more and more enterprises will realize the importance of scientific and technological innovation to the development of enterprises and gradually increase the investment in scientific and technological innovation.

The mechanism of science and technology innovation, green low carbon, and economic growth are shown in Figure 4. Under the role of the "technology-organization-region" trinity of science and technology innovation, science

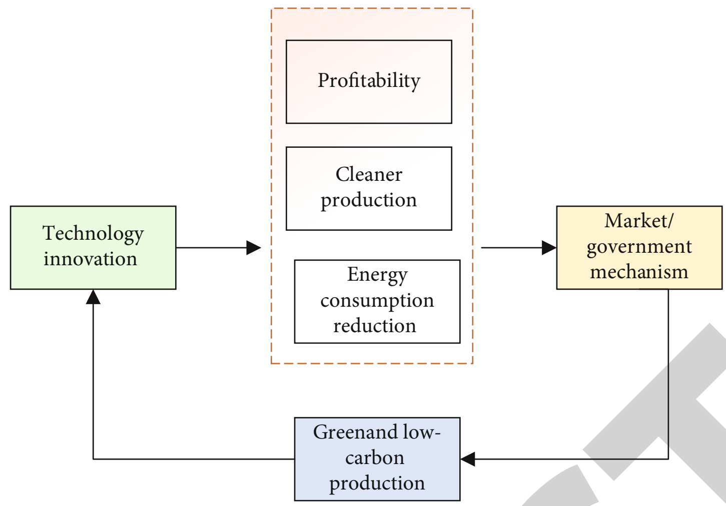

FIGURE 3: Mechanism of action of green low carbon and innovation.

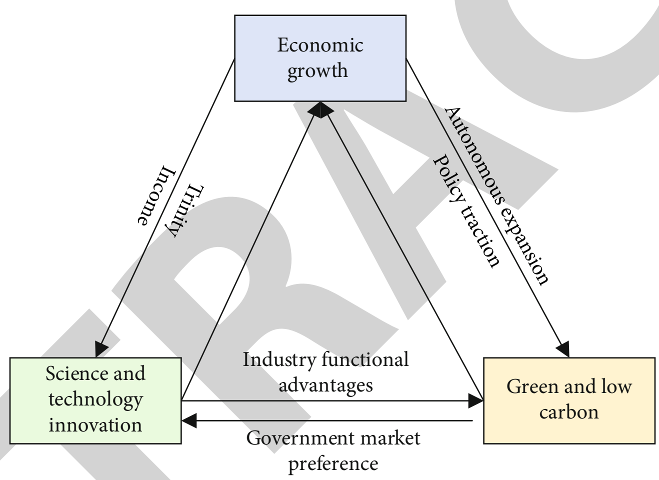

FIGURE 4: Mechanism of the role of science and technology innovation, green low carbon, and economic growth.

and technology innovation has become the driving force for economic growth. At the same time, it should be noted that for different economies; there are differences in organizational and industrial forms and regional states, which cause heterogeneity in the development path of regional science and technology innovation. For different subjects, economic growth has different forms of expression, such as for the government means the increase of tax revenue and for industry means the increase of output value. From the viewpoint of "human nature" hypothesis, the increase of income is the most important expression of economic growth, which will give full play to the subjective initiative of scientific and technological research and development personnel and bring positive incentive to the development of scientific and technological innovation, further stimulating the improvement of scientific and technological innovation level.

Next, we proceed to analyze the relationship between innovation and growth of low-carbon economy based on the data model.

3.1. Extended Implicit Variable Method. Considering the economic production activities of different regions over a period of time, i.e., for different time periods $t = 1, 2, \cdots, T$, the regional GDP, labor, and capital stock of region $i = 1, 2, \cdots, n$ can be expressed as Y_{it}, L_{it}, K_{it}, respectively. In most cases, the production function of each region satisfies the Cobb Douglas production function of the form

$$Y_{it} = A_i K_{it}^{\alpha_{it}} L_{it}^{\beta_{it}} e^{u_{it}}. \tag{1}$$

In (1), α_{it} represents the capital elasticity, β_{it} represents the labor elasticity, u_{it} is the disturbance term of the model, and A_i is the comprehensive technology level of different regions,

$$\ln Y_{it} = \ln A_i + \alpha_{it} \ln + \beta_{it} \ln L_{it} + u_{it}. \tag{2}$$

This is different from the traditional Cobb Douglas function, mainly in the following ways: First, equation (2) takes into account the spatial and temporal heterogeneity; that is, the elasticity of labor and capital is different for different regions at different times. Second, it relaxes the assumptions about the payoffs of scale, which is usually based on the assumption of constant payoffs of scale. In equation (2), both variable and constant returns to scale are allowed, and there is no restriction on $\alpha_{it} + \beta_{it}$; i.e., the case of returns to scale can be different for different regions.

In this paper, a panel state-space model is used to estimate α_{it}, β_{it} and then measure the change in total factor productivity. On the one hand, we consider the variation of scale payoffs, whereby a state space model is developed as

$$\ln Y_{it} = \ln A_i + \alpha_{it} \ln K_{it} + \beta_{it} \ln L_{it} + u_{it}^1, \tag{3}$$

$$\alpha_{it} = \phi_i \alpha_{it-1} + \nu_{it}, \tag{4}$$

$$\beta_{it} = \theta_i \beta_{it-1} + w_{it}, \tag{5}$$

where equation (3) is the measurement equation, equations (4) and (5) are the state equations, and α_{it}, β_{it} are the hidden variables, also known as state variables, which are usually assumed to follow a first-order autoregressive process. The Kalman filter is used to estimate equations (3) to (5), and the Akira pool information criterion, the Schwarz criterion, and the Hannan-Quinn criterion are computed to evaluate the effect of model fit on data with changing returns to scale $\mathrm{AIC}_1, \mathrm{SC}_1, \mathrm{HQC}_1$. Similarly, considering the case of constant returns to scale, the state space model is transformed into

$$\ln Y_{it} = \ln A_i' + \alpha_{it}' \ln K_{it} + \left(1 - \alpha_{it}'\right) \ln L_{it} + u_{it}^2, \tag{6}$$

$$\alpha_{it}' = \phi_i' \alpha_{it-1}' + \nu_{it}', \tag{7}$$

$$\beta_{it}' = 1 - \alpha_{it}'. \tag{8}$$

The Kalman filter method is used to estimate equations (6) and (7) to evaluate the model fit effect of each type of criterion, which is noted $\mathrm{AIC}_2, \mathrm{SC}_2, \mathrm{HQC}_2$. By comparing the information criterion obtained in the two cases to determine the payoff of scale in the region. In other words, if $AIC_1 < AIC_2, SC_1 < SC_2$ and $HQC_1 < HQC_2$ are satisfied, model (3)-(5) should be selected, and the scale payoff is considered to be variable, and the increasing or decreasing scale payoff of the region is further determined by calculation; if $\mathrm{AIC}_1 > \mathrm{AIC}_2, \mathrm{SC}_1 > \mathrm{SC}_2$ and $\mathrm{HQC}_1 > \mathrm{HQC}_2$ is satisfied, models (6)–(8) should be selected, and the scale payoff is considered to be constant. In order to make the estimation results of the Kalman filter method converge quickly, a two-step estimation method is used according to the suggestion of Tie-Mei Gao. In the first step, a panel random effects model with regional dummy variables is estimated, and the estimated intercept term is actually the average STI level of the region at the time period. The logarithmic values of the variance of the variable intercept, the disturbance term, and the random effect term are estimated, and the initial values of the corresponding parameters of the panel state space model are used. In the second step, after determining the initial values of the intercept term and the logarithm of the residual variance of the two types of state space models, the Kalman filter method is applied to estimate the state space models to obtain fast convergence of the estimation results.

Once the capital and labor elasticities are estimated for each region at different time periods, the changes in total factor productivity can be calculated by (9) to reflect the changes in STI.

$$\mathrm{TFPC}_{it} = \begin{cases} \dfrac{\Delta Y_{it}}{Y_{it}} - \widehat{\alpha}_{it}' \dfrac{\Delta K_{it}}{K_{it}} - \widehat{\beta}_{it}' \dfrac{\Delta L_{it}}{L_{it}}, & \text{region } i \text{ is constant payoff to scale,} \\ \dfrac{\Delta Y_{it}}{Y_{it}} - \widehat{\alpha}_{it} \dfrac{\Delta K_{it}}{K_{it}} - \widehat{\beta}_{it} \dfrac{\Delta L_{it}}{L_{it}}, & \text{variable payoffs to scale for region } i. \end{cases} \tag{9}$$

3.2. Description of Science and Technology Innovation Measurement. The study population includes 30 provincial administrative regions in mainland China except for the Tibet Autonomous Region, and the study period is from 2000 to 2018. Output is measured by regional GDP and converted to GDP in comparable prices in 2000 using the GDP index of each region. The capital stock is accounted for using the perpetual inventory method, based on the year 2000. All the above data are obtained from the statistical yearbooks of each region and the statistical bulletin data published.

To avoid pseudoregressions, panel unit root tests and panel cointegration tests were conducted for $\ln Y_{it}, \ln K_{it}, \ln L_{it}$ and their difference variables. The CADF, ipshin, Fisher, and methods were used for the panel unit root test, and the Kao, Pedroni, and Westerlund tests were used for the panel cointegration test. The results show strong evidence of a significant cointegration relationship between the three. Following the idea of the two-step estimation method described above, the logarithm of the residual variance of the intercept estimated by the panel random effects model is used as the initial value of the corresponding parameters of the panel state space model, and the Kalman filter method is applied to the state space model in both cases of scale payoffs. The parameters of the state space model are all significant in most of the regions, in both the case of variable and constant payoffs of scale. In addition, the information criterion of the state space model in four regions, namely, Shanghai, Beijing, Tianjin, and Guangdong, was found to be smaller than that of the constant scale payoff case, while the other regions were found to be the opposite. Therefore, the economic production in Shanghai, Beijing, Tianjin, and Guangdong is in the state of variable payoffs to scale; the economic production in other regions is in the state of constant payoffs to scale.

3.3. Root Test. The panel root test was performed on the TFPC and DPCC panel data to check the smoothness of the data, as shown in Table 1. The CADF in Table 1 indicates that the Pesaran CADF test was performed on the series, the constant term indicates that the test equation contains a constant term, the trend term indicates that the trend term was added to the constant term, and the outlier treatment indicates that the outlier treatment was applied to the abnormal data based on the addition of the constant and trend terms (except for the Hadri test, which is similar

Table 1: Panel unit root test for science and technology innovation, green, and low carbon growth.

Variables	Test name	Test setting	Statistical quantity
TFPC	CADF	Constant terms	−4.489***
		Trend terms	−1.896***
		Outlier processing	−3.702***
	Ipshin	Constant terms	−8.639***
		Trend terms	−7.654***
	Fisher	Constant terms	285.508***
		Trend terms	309.897***
	Levinlin	Constant terms	−13.303***
		Trend terms	−11.803***
	Hadri	Homo	-0.696
		Hetero	-0.455
		SerDep	17.082***
EFFC	CADF	Constant terms	−11.439***
		Trend terms	−8.212***
		Outlier processing	−8.349***
	Ipshin	Constant terms	−15.936***
		Trend terms	−12.184***
	Fisher	Constant terms	343.555***
		Trend terms	241.302***
	Levinlin	Constant terms	−11.856***
		Trend terms	−7.732***
	Hadri	Homo	-2.816
		Hetero	-2.718
		SerDep	16.718***
DIPCC	CADF	Constant terms	−6.522***
		Trend terms	−5.743***
		Outlier processing	−5.867***
	Ipshin	Constant terms	−9.344***
		Trend terms	−8.428***
	Fisher	Constant terms	109.432***
		Trend terms	216.368***
	Levinlin	Constant terms	−9.485***
		Trend terms	−9.647***
	Hadri	Homo	8.795
		Hetero	8.240
		SerDep	13.714***

to the other tests). The original hypothesis of Hadri test is that all time series in the panel are smooth, while the original hypothesis of CADF, ipshin, Fisher, and levinlin case tests is that all time series corresponding to cross sections in the panel are nonsmooth. The Hadri test includes Homo, Hetero, and SerDep settings: Homo indicates the assumption of homogeneity based on cross-sections, Hetero indicates the assumption of heterogeneity based on cross-sections, and SerDep indicates the assumption of serial correlation based on disturbance terms.

Table 2: Statistical description of the variables.

Aar	N	Ave	Sd	Min	Max
Lnp-GDP	210	10.88448	0.410156	10.04978	12.00895
Lnp-PAT	210	-6.604783	0.938030	-8.517192	-4.55639
p-Invest	210	43352.8	14169.0	15283	81815
p-FDI	210	30452.85	4552.52	1562	2721846
p	210	0.253525	0.102276	0.13	0.62

3.3.1. Introduction to the Panel Smoothed Transfer Regression Model. The panel smoothed transfer regression model (PSTR) is a fixed effects model with exogenous regressors. Equation (10) defines the underlying PSTR model with one transformation variable included.

$$y_{it} = \mu_i + \lambda_t + \beta_1' x_{it} + \beta_2' x_{it} g(q_{it}\,; \gamma, c) + u_{it}. \tag{10}$$

In equation (10), $i = 1, \cdots, N, t = 1, \cdots, T$. The explanatory variable y_{it} is a scalar, μ_i represents a fixed individual effect, λ_t represents a time effect, and x_{it} is a k-dimensional vector, which is an exogenous explanatory variable and whose parameters vary over time. q_{it} is an observable transformation variable, u_{it} is an error term, and Chamberlain et al. refer to the PSTR model as essentially a fixed effects model, so that exogenous explanatory variables are not allowed to include lagged terms of the explanatory variables.

The main feature of the panel smoothed transfer regression model is the inclusion of a transformation function $g(q_{it}\,; \gamma, \mathbf{c})$, which is a continuous bounded function on the transformed variables, which enables the smoothed variation of the coefficients of the explanatory variables in the nonlinear part of the model, and therefore, the parameters of the model include both linear and nonlinear components. Granger and Terasvirta, Terasvirta and Jansen, and Terasvirta in their papers considered equation (11) as the most suitable function to achieve this function.

$$g(q_{it}\,; \gamma, \mathbf{c}) = \left(1 + \exp\left(-\gamma \prod_{j=1}^{m} (q_{it} - c_j)\right)\right)^{-1}, \quad \gamma > 0, c_1 \leq, \cdots, \leq c_m. \tag{11}$$

In equation (11), $\mathbf{c} = (c_1, \cdots, c_1)'$ is the m-dimensional vector of the off number, and $\gamma \geq 0, c_1 \leq, \cdots, \leq c_m$ is the parameter constraint on the transformation function. The slope parameter γ defines the slope of the transition function. When $m = 1$ and $\gamma \longrightarrow \infty$, equations (10) and (11) degenerate into a two-institution panel threshold regression model; when $m > 1$ and $\gamma \longrightarrow \infty$, the transition function will smoothly transition from 0 to 1 after multiple transition parameters $c_1, \cdots, c_m$; when $\gamma \longrightarrow \infty$, the transition function becomes a constant, and then, the panel smooth transfer regression model degenerates into a standard regression model with fixed effects. The panel smoothed transfer

Table 3: Matrix of correlation coefficients of variables.

	Lnp-GDP	Lnp-PAT	p-FDI	p-lnvest	p
Lnp-GDP	1				
Lnp-PAT	0.802***	1			
p-FDI	0.774***	0.667***	1		
p-lnvest	0.465***	0.318***	0.053	1	
p	-0.482***	-0.538***	-0.231***	-0.122*	1

regression model degenerates to a standard linear model with fixed effects.

By allowing different types of parameter variations in the case of $m = 1$ or $m = 2$, the transformation function is already a very flexible parameter procedure. For example, if $m = 2, c_1 = c_2 = c$, it shows that only the Euclidean distance between the transformed variable q_{it} and c has an effect on the explained variable. Furthermore, if $\gamma \longrightarrow \infty$, the transformation function defines a three-institution model with the same external regime and different intermediate regimes. Finally, when $m = 1$, the transition function achieves a monotonically smooth transition controlled by c_1.

A generalized version of the panel smoothed transfer regression model is the generalized additive PSTR model, whose model is given in

$$y_{it} = \mu_i + \lambda_t + \beta_0' x_{it} + \sum_{j=1}^{r} \beta_j' x_{it} g_j\left(q_{it}^{(j)}; \gamma_j, c_j\right) + u_{it}. \quad (12)$$

The transformation function of equation (12) takes the form of equation (11). For $g_j, j = 1, \cdots, r$, if $m_j = 1, q_{it}^{(j)} \equiv q_{it}$ and $\gamma_j \longrightarrow \infty$, equation (12) degenerates to a panel threshold regression in the $r + 1$ regime. Thus, the generalized addable panel smoothed transfer regression model is an extended form of the multi-institution panel threshold regression model.

3.3.2. Panel Smoothing Transfer. The regression model is set to test whether there is a nonlinear effect between STI growth, green low carbon efficiency growth, and economic growth and to examine the nonlinear dynamic change relationship between the three, which will be tested and modeled in this paper as follows.

$$\mathrm{TFPC}_{it} = \beta_{01}\mathrm{EFFC}_{it} + \beta_{11}\mathrm{DIPCC}_{it} + \sum_{j=1}^{2} g_{j1}\left(\beta_{j1}'\mathrm{EFFC}_{it} + \beta_{j1}'{}'\mathrm{DIPCC}_{it}\right) + \tilde{u}_{it1}, \quad (13)$$

$$\mathrm{EFFC}_{it} = \beta_{02}\mathrm{TFPC}_{it} + \beta_{12}\mathrm{DIPCC}_{it} + \sum_{j=1}^{2} g_{j2}\left(\beta_{j2}'\mathrm{TFPC}_{it} + \beta_{j2}'{}'\mathrm{DIPCC}_{it}\right) + \tilde{u}_{it2}, \quad (14)$$

$$\mathrm{DIPCC}_{it} = \beta_{03}\mathrm{TFPC}_{it} + \beta_{13}\mathrm{EFFC}_{it} + \sum_{j=1}^{2} g_{j3}\left(\beta_{j3}'\mathrm{TFPC}_{it} + \beta_{j3}'{}'\mathrm{EFFC}_{it}\right) + \tilde{u}_{it3}. \quad (15)$$

In the above three models, g_1, g_{21} denote the conversion functions with green low carbon efficiency growth rate and economic growth rate as the conversion variables, respectively; g_{12}, g_2 denote the conversion functions with STI growth rate and economic growth rate as the conversion variables, respectively; g_{13}, g_3 denote the conversion functions with STI growth rate as the conversion variables, respectively. The formula of the conversion function is shown in equation (11), and for different models, the conversion function has different position parameters and slope parameters. $\tilde{u}_{it1}, \tilde{u}_{it2}, \tilde{u}_{it3}$ can be expressed as the sum of three modal disturbance terms, time effects, and individual effects, respectively. Model (13) tests whether the two can bring nonlinear shocks to the STI growth rate under the effect of green low carbon efficiency and economic growth rate; model (14) tests whether the two can bring nonlinear shocks to the green low carbon efficiency growth rate under the effect of STI growth rate and economic growth rate; model (15) tests whether the two can bring nonlinear shocks to the economic growth rate under the effect of STI growth rate and green low carbon efficiency growth rate. Model (15) examines whether the two can bring nonlinear shocks to the economic growth rate under the effect of STI growth rate.

4. Case Study

We start with the number of patents granted to explore the relationship between economic innovation and growth, to analyze the rules of variation.

4.1. Descriptive Analysis of Variables. According to Table 2, the sample size of all variables is 210. Due to the variability of regional economic levels and the nonsynchronous nature of regional development in China, the maximum and minimum values of the main variables differ significantly. The logarithm of the variables makes the values smaller and reduces the difference between the values, but the maximum and minimum values of the variables still differ greatly. The standard deviations of fixed asset investment and foreign direct investment are 43352.8 and 30452.85, respectively, which means that the difference in the values is large; that is, the difference in the level of economy leads to the large difference in fixed asset investment and foreign direct investment as well; the mean value of government involvement is 0.25, while the difference between the maximum and minimum value is as high as 0.51; that is, there is a large difference in the degree of government intervention in economy.

4.1.1. Correlation Analysis. According to Table 3, the impact of technological innovation on variable interpretation on economic growth is significantly correlated with 1% confidence level, and the correlation coefficient is 0.802, indicating that technological innovation can promote economic growth. The relevant ratios of fixed asset investment and foreign direct investment to economic growth are 0.465 and 0.774, respectively, which are conducive to economic growth. The ratio of government participation in the process of economic growth and economic growth is -0.482, which

Table 4: Model regression results.

	Model I	Model II	Model III	Model IV
Explained variables	Lnp-GDP	Lnp-GDP	p-lnvest	Lnp-GDP
Lnp-PAT	0.335*** (14.77)	0.343*** (15.78)	15680.78*** (7.95)	0.245*** (11.8)
p-lnvest				6.22e-06*** (9.01)
p-FDI		2.22e-06*** (5.77)	0.0065 (0.18)	2.16e-06*** (6.85)
p		-2.688*** (-8.72)	-100545*** (-3.62)	-2.062*** (-7.7)

Table 5: PVAR lag order test of innovation and economic growth in low carbon economy.

Hysteresis order	PVAR(1)	PVAR(2)	PVAR(3)	PVAR(4)	PVAR(5)
AIC	-2.857	-2.987	-3.122792	-3.095	-3.097
SC	-2.617536	-2.565	-2.520	-2.312	-2.133
HQ	-2.762	-2.816	-2.878166	-2.777	-2.705

means a reverse development; that is, the government participation rate in the process of economic growth is -0.482.

4.1.2. Regression Analysis. The time dimension (T) of the article data is 7, and the cross-sectional dimension (N) is 30. Since T is smaller than N, which is a short panel, a static panel model is used. To analyze it accurately, it is necessary to determine the type of model to which the data belongs first. The article uses Stata16 statistical software to analyze the data to determine its type.

As shown in Table 4, model I includes the explanatory variables economic growth and technological innovation that explain the main variables, but does not include any control variables. According to model I, the prequalification index of technological innovation is 0.335, which shows that the significant contribution rate of technological innovation variables to economic growth is 1%. For every logarithmic technological innovation, 3335 units will be added, regardless of the impact of other variables. However, economic growth is affected by many factors. If other variables are not considered, the impact of technological innovation on economic growth will be underestimated. After, two regulatory variables related to government participation and foreign direct investment are included in model I, which indicates that one unit is added to the logarithm of technological innovation, while the others remain unchanged, which indicates that the increase in the proportion of logarithmic innovation variables leads to an increase of 0.343 in the number of logarithmic indicators of economic growth, while other variables remain unchanged.

4.1.3. Selection of Lag Order. In this paper, the AIC, SC, and HQIC statistics are used to determine the optimal autoregressive lag order, and the optimal lag order of the model is determined based on the order where AIC, SC, or HQIC takes the maximum value. The results are shown in Table 5.

As can be seen from Table 5, when LGDP, LPG, and LAU build the PVAR model with lag order chosen as 3, the AIC and HQ statistics are the smallest, so it is more appropriate to build the PVAR(3) model.

4.1.4. Estimation of PVAR Model. In estimating the PVAR model, it is usually necessary to eliminate the fixed effects in the sample first, but the PVAR model structure makes the independent variables correlated with the fixed effects, and thus, the mean difference method usually used may lead to bias. Therefore, in this paper, the Helmef process is used to eliminate the fixed effects. Since the parameters of the vector autoregressive model are not practically meaningful, it generally focuses only on the impulse response function and variance decomposition induced by the variables to analyze the effect of a unit standardized new interest of a random perturbation on the endogenous variables and the contribution of structural shocks to the fluctuations of the endogenous variables. Therefore, the parameters estimated by the PVAR(3) model are not detailed here.

4.2. Function Analysis. In this paper, by {LGDP, LPG, LAU} a standard deviation shock, the orthogonal impulse response function plots are obtained using Monte Carlo simulation 100 times and 95% confidence intervals are given. This is shown in Figures 5 and 6.

Figure 5 shows the shock response of LGDP to LAU. When a positive new interest shock is given to LAU in period l, the impulse response value of LGDP rises rapidly. The rate of increase starts to slow down from period 2. The maximum value is reached in period 4 and then starts to decline. This indicates that utility model licensing has a lag on economic growth. There is a positive effect at the beginning, and the effect decreases over time.

Figure 6 shows the shock response of LPG to LGDP. When a positive new interest shock of LGDP is followed by an impulse response impact on LPG, the first 7 periods produce a negative shock, where periods 1, 2, and 3 show a downward trend and the negative response reaches a maximum in period 3, after which an upward trend begins. After the 7th period, a positive shock is generated. This indicates that the rapid economic development is accompanied by a gradual increase in the demand for invention patents.

4.3. Variance Decomposition. In order to examine more precisely the mutual influence relationship between low carbon economic innovation and economic growth, this is shown in Figures 7–9.

Figure 7 shows that under the response shock of LGDP, economic growth initially explains itself to a degree of 100%, and as the number of periods increases, the contribution of

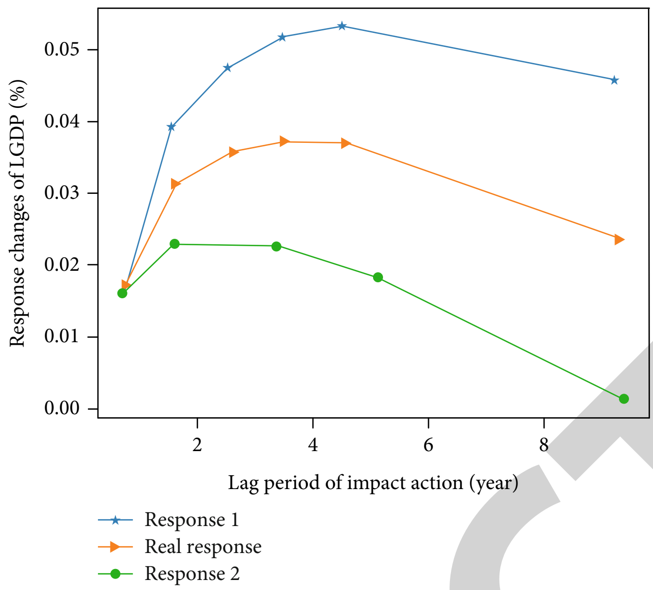

Figure 5: Response function of economic growth (LGDP) due to utility authorization (LAU) shock.

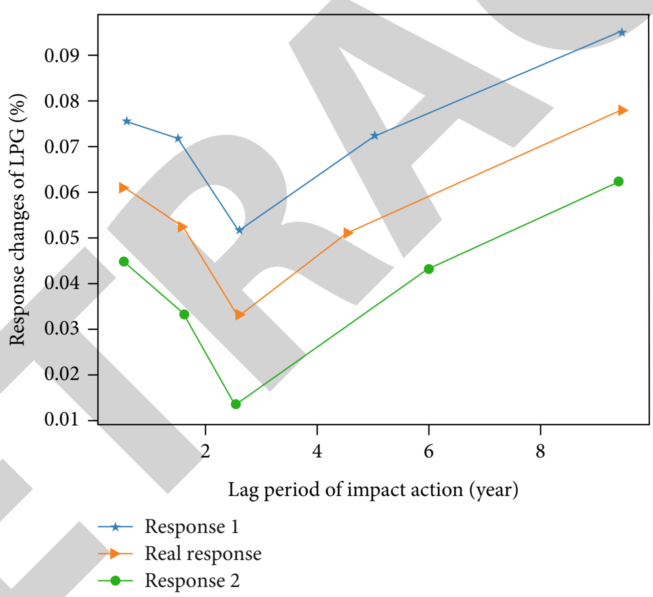

Figure 6: Response function of economic growth (LGDP) shock-induced patent licensing (LPG).

its own variance begins to decrease. It reaches 75% in the 10th period. It goes to 60% in period 20. The contribution of invention patent grant to the variance of economic growth shows an increasing trend from period 2. It rises to 35% in the 20th period. This indicates that invention patent grant has strong explanatory power for economic growth. It decreases to 5% in period 20. Overall, in the process of promoting economic development, invention patents play a greater role than utility model patents.

Figure 8 shows that, under the response shock of LPG, at period 1, invention patent grant, utility model grant, and GDP all explain the degree of variance of invention patent grant, of which the degree of its own explanation is about 80%. As the number of periods increases, the contribution of its own variance begins to decline, rises slightly from the 5th period, and then begins to decline again in the 16th period, but the decline is not obvious, to 70% in the 20th period. The contribution of GDP to the variance of invention patent grant shows an upward trend from the 1st period. The rate of increase is fast in the first two periods. Then, it gradually slows down and rises to 15% in the 20th period. The contribution of utility model grant to the variance of invention grant starts to rise from period 2, reaches the maximum in period 4, and then starts to decline slowly.

Figure 9 shows that under the response shock of LAU, the degree of explanation of utility model licensing, GDP

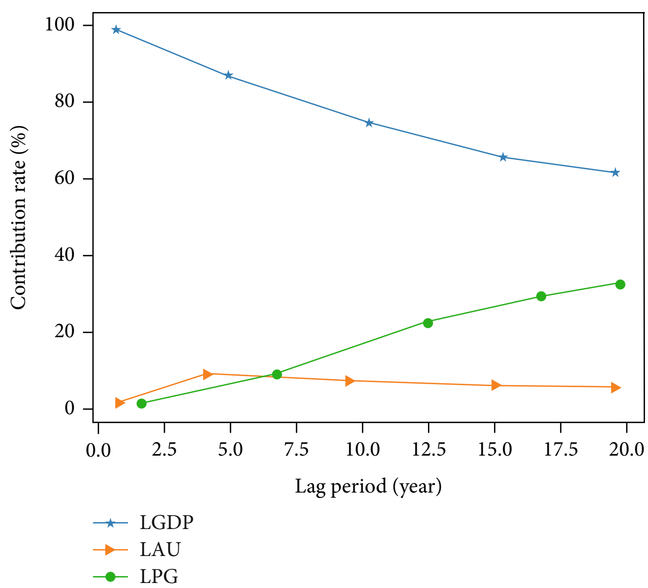

Figure 7: Variance decomposition of economic growth (LGDP).

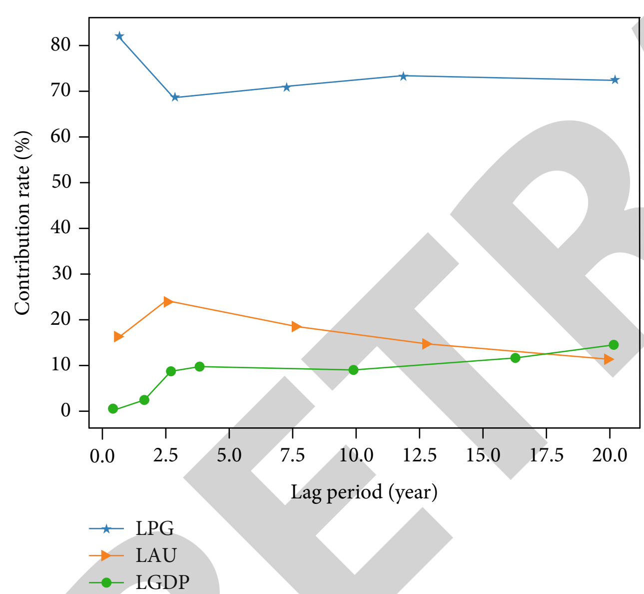

Figure 8: Variance decomposition of invention patent grant (LPG).

on utility model licensing variance at period 1. The degree of explanation of itself accounts for about 90%. As the number of periods increases, the contribution of its own variance starts to decrease. The contribution of GDP to the variance of utility model grant shows a slowly increasing trend from the first period. The contribution of invention patent grant to the variance of utility model grant starts to rise slowly from the 2nd period. The contribution of both GDP and invention patent grant to the variance of utility model grant stays at about 25%. This indicates that the development of the times leads to more utility model patents for economic development. Invention patents also lead to a number of utility model patents granted.

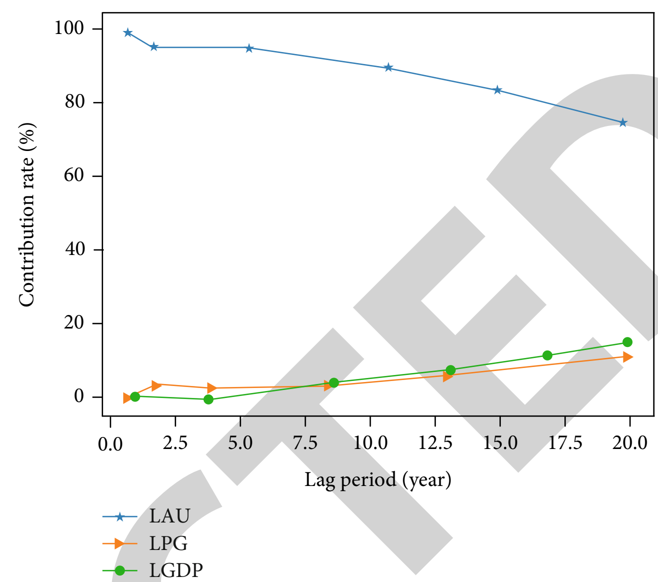

Figure 9: Variance decomposition of utility model authorization (LAU).

5. Conclusion

This paper takes economic development into a new stage as the background and takes technological innovation as the core variable to study the impact of technological innovation on regional green economic growth. By summarizing the relevant literature on green economic growth theory, technology innovation theory, the impact of technological innovation on green economic growth, and empirical studies at home and abroad, we identify the areas not covered in the current research and consider the research framework of this paper. The level of technological innovation and the level of green economic growth in each province of China are accounted for and evaluated comprehensively, and then, panel data are constructed to study and compare the impact and differences of technological innovation on green economic growth in different regions of China and finally to reflect on the problems arising from the research and to propose relevant countermeasures. Studying the impact of innovation level on the economic growth of Chinese provinces not only helps to understand its mechanism but also helps to find ways to ensure the sustainable and harmonious development of regional economies.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared that there are no conflicts of interest regarding this work.

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