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The relationship between sustainable innovation efficiency and economic growth in China

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ABSTRACT

China has taken sustainable development strategies seriously in recent years, aiming at reducing energy consumption and environmental pollutants emissions. This research empirically evaluates the sustainable innovation efficiency (SIE) in Chinafrom the perspective of energy and environmental constraints. Furthermore, the relationship between SIE and economic growth is tested through Granger causality test. The results indicate that SIE in China varies obviously in different regions. Granger causality runs only from economic growth to SIE and not the other way round. Economic growth is causative factor of sustainable innovation, indicating that China's sustainable innovation has not yet achieved coordinated development with the economy. Our findings also provide useful decision-supporting insights for Chinese policymakers to promote coordinated development of regional sustainable innovation and economic growth.

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sustainable innovation efficiency; energy and environmental constraints; economic growth; Granger causality test

1. Introduction

The sustainable growth of national and regional economic development now heavily depends on technological innovation (Nill and Kemp 2009; Wang et al. 2015). China's economic development has entered a new normal with the absence of the demographic dividend, and economic growth has also transitioned from high speed to medium-high growth (Chen and Groenewold 2019; Tung 2016; Zou 2018). China is in the midst of a significant economic transformation, and it is urgent to transform the mode of economic growth, optimise the industrial structure and improve the innovation capability of enterprises (Xiao, Pan, and Liu 2018). The Chinese government has recently placed a high value on the contribution that innovation makes to fostering economic growth. But now, China's innovation development largely depends on the massive investment in research and development (R&D) activities, while innovation efficiency is not high (Bai 2013; Kaihua and Mingting 2014). Innovation efficiency is the conversion rate between innovation inputs and outputs, which could reflect the quality and level of innovation (Barasa et al. 2019). However, the issue of input-output efficiency of technological resources is more worthy of attention (Cruz-Cázares, Bayona-Sáez, and García-Marco 2013; Guan and Zuo 2014).

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Since the reform and opening up, China's economy has expanded quickly, and its gross domestic product (GDP) has increased from 0.36 trillion Chinese yuan in 1978–121.02 trillion Chinese yuan (which equals 18 trillion U.S. dollars) in 2022, with higher average annual growth rate than the world average (Higgins, Zha, and Zhong 2016; Zheng and Walsh 2019). However, the rapid economic growth relies on the economic development model of high consumption and high pollution, which consumes a large amount of energy such as oil, coal, natural gas, etc., resulting in massive emissions of carbon dioxide, sulphur dioxide, causing increasingly serious resource and environmental problems (Wang and Jiang 2019; Zheng and Shi 2017; Zheng, Yi, and Li 2015). Sustainable innovation combines innovation drive and sustainable development, which helps to break through energy and environmental constraints (Hansen, Grosse-Dunker, and Reichwald 2011). Sustainable innovation is urgently needed to reduce the environmental undesirable outputs in the economic transition (Li and Lin 2017). Promoting regional sustainable development in China through coordinated development of economic, resource and environmental advantages is possible through sustainable innovation (Sun and Loh 2019).

There has been increasing interests in the study of innovation efficiency in China (Broekel 2012; Chen and Guan 2012; Fritsch and Slavtchev 2011), but there are relatively few studies based on the perspective of energy and environmental constraints, especially the lack of research to quantitatively assess the link between sustainable innovation efficiency and economic growth. The objective of this work is to fill up these knowledge gaps. This research emphasis on the research questions based on the energy and environmental constraints– 'What is the evolution of SIE in China?' and 'What is the causal relationship among SIE and economic growth in China?'.

This article is divided into six parts, the first of which serves as an introduction. The second section discusses relevant study regarding SIE and economic growth. The third section assesses and discusses the effectiveness of sustainable innovation. In Section 4, the Granger causality test is used to examine the causal relationships between SIE and economic growth. The contributions and limitations of this study are discussed in Section 5. In Section 6, the key results and implications for policy are presented.

2. Literature review

2.1. Sustainable innovation efficiency

In the pasted decades, scholars have paid attentions to the research of innovation efficiency taking environmental undesirable outputs into account. Broekel (2012) evaluated the regional innovation performance in Germany and examined the relationship between regions' innovation performance and the regional intensities and inter-regional collaboration. Wang et al. (2017) evaluated the sustainable innovation efficiency of manufacturing industry and found the backward environmental efficiency was the biggest barrier that restricted the sustainable performance. Broekel, Rogge, and Brenner (2017) measured the innovation efficiency of German regions through a shared-input DEA approach. Wang et al. (2018) studied the industrial eco-efficiency of Fujian province and found the obvious regional differences. By taking environmental pollutant emissions into undesirable outputs, Lin et al. (2018) evaluated the sustainable innovation efficiency of China's manufacturing industry and discovered the obvious gaps between industries. Luo et al. (2019) measured green innovation efficiency of strategic emerging industries and discovered that there has been an uptick in the efficiency of technological innovation in these sectors. Du, Liu, and Diao (2019) examined the effectiveness of regional green innovation and looked into regional variations. Liu et al. (2020) took environmental pollution and innovation failure as undesirable outputs and evaluated the sustainable innovation efficiency of high-tech industries, founding the regional differences of the factors. Taking environmental undesirable outputs into consideration, Xu, Loh, and Chen (2020) evaluated the SIE and examined influential factors. Min, Kim, and Sawng (2020) calculated the regional efficiencies of technology development and commercialisation in South Korea and examined the regional differences in innovation efficiency. Liu et al. (2021) evaluated the green innovation efficiency of China's intensive pollution sectors, taking industrial solid waste into account. Peng, Fan, and Liang (2021) measured the green innovation efficiency of technology-based SMEs, taking environmental pollution as the undesirable output. Fan et al. (2021) calculated green innovation efficiency of 235 cities and found large spatial imbalance. Yin and Wang (2021) assessed the effectiveness of patent-intensive industries, taking industrial wastes as undesirable outputs. Liu et al. (2021) assessed green innovation efficiency of industrial technology stage and achieving transition stage in China. In energy-intensive sectors, Zhu et al. (2021) evaluated the effectiveness of green technology innovation and its path to combinatorial enhancement. Xu, Mei, Sun et al. (2023) measured the sustainable innovation efficiency in European Union countries based on the perspective of energy and environmental constraints and found the obvious differences among the regions. Furthermore, the distinct convergence trends in regional sustainable innovation efficiency in European Union countries were observed (Xu, Mei, Liang, et al. 2023).

2.2. Innovation efficiency and economic growth

Economic growth is one of the most important issues in macroeconomics. By analysing the driving force, mechanism, path and process of economic growth, the long-term trend of economic development can be predicted. Economists have regarded innovation as a driver of economic growth. Schumpeter (1934) studied the connection between innovation and economic growth, believed that innovation was the main driver behind economic development, and established research framework of innovation economics. In Solow (1956) neoclassical economic growth model, technological progress and capital stock were the fundamental causes of economic growth. The new theory of economic growth believed that knowledge, human capital and technological innovation were the main driving forces for sustainable economic growth. Lucas (1988) studied economic growth from the perspective of capital decomposition, internalised productivity growth, established a human capital spillover model, and further explained that human capital accumulation was the source of economic growth, and knowledge was an important endogenous variable to promote economic growth. Romer (1990) regarded technological progress as the most important endogenous factor of economic development in the endogenous economic growth model, and believed that technological innovation could improve productivity and promote economic growth. Segerstrom (1991) established a dynamic general equilibrium model of economic growth and found that increasing innovation inputs could promote economic growth. R&D spillover effects have changed the structure of social production, and play a significant role in fostering economic growth (Bernstein and Nadiri 1989). The direct impact and spillover effects of industrial innovation activities on the production process are important determinants of economic growth (Stokey 1995). Regions and countries can increase total factor productivity by investing in R&D (Bayoumi, Coe, and Helpman 1999). The spillover effects of regional innovation translate innovation into higher economic growth rates (Capello and Lenzi 2014). Innovation activities play a central role in economic growth. Innovative activity not only directly affects economic productivity, but also promotes economic growth by encouraging the establishment of new firms (Wennekers and Thurik 1999). Innovation is transformed into the driving force of endogenous economic growth, helping innovation drive economic growth, and realising the synergy of knowledge innovation and technological innovation (Hasan and Tucci 2010). R&D investment, technological innovation and economic growth are mutually influential and dependent. Economy growth advances technological innovation activities, while technological innovation impacts economy growth through the multiplier effect.

Previous studies revealed that China's technological innovation and economic growth do not yet have a strong cyclical relationship (Liu and Xia 2018). Due to the differences in the selection of innovation indicators, the research results on relationship between innovation and economic growth vary greatly (Rodríguez-Pose and Crescenzi 2008). Sustainable economic growth depends not only on increasing innovation investments, but also on the relationship between innovation efficiency and economic growth. Scholars have studied the relationship between innovation efficiency and economic growth. Baek and Pagan (2002) studied the innovation efficiency of SMEs and found that innovation efficiency was the most critical factor affecting the growth of enterprise income. Ma and Cheng (2014) analysed the impact of innovation efficiency on economic growth, and found that technological innovation efficiency was the most significant factor affecting economic growth. Li and Li (2017) found that the current technological innovation efficiency in China had not significantly improved regional economic growth. Through a spatial econometric model, Zhang (2019) found that although innovation efficiency had a positive effect in promoting economic growth, innovation was not the primary driver of China's regional economic growth. Firsova and Chernyshova (2020) found that innovative development is mainly derived from the economy of scale, and the effectiveness of regional innovation systems was increased through broader resource bases. The relationship between innovation efficiency and economic growth remained ambiguous up to this point (Wang, Wang, and Fan 2021). Further, there lacks the research on the casual relationship between sustainable innovation efficiency and economic growth based on energy and environmental constraints.

3. Regional sustainable efficiency evaluation

3.1. Methods and models

A common non-parametric approach frequently used in efficiency research across a wide range of fields is data envelopment analysis (DEA). Charnes, Cooper, and Rhodes (1978) presented comparing the relative efficacy among several units. The characteristics of the assessment object could be objectively reflected by DEA methods, which are also well suited to handle situations with many inputs and outputs. Traditional DEA approaches are either input- or output-oriented and cannot manage problems with undesirable outputs if input and output slacks are not taken into account. Tone (2001) proposed slack-based measurement (SBM) model to deal with the slack variables and then extended the model by adding slacks to the constraints on undesirable outputs. This model can better reflect the essence of efficiency evaluation and is more in line with reality. This paper evaluates SIE through DEA-SBM model (Equation 1).

$$\min \theta^* = \frac{1 - \dfrac{1}{m}\sum_{i=1}^{n}(s_i^-/x_{i0})}{1 + \dfrac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}(s_r^g/y_{r0}^g) + \sum_{r=1}^{s_2}(s_r^b/y_{r0}^b)\right)}$$
$$s.t.\begin{cases} x_0 = X\lambda + s_i^- \\ y_0^g = y^g\lambda - s^g \\ y_0^b = y^b\lambda + s^b \\ \lambda, s^-, s^g, s^b \geq 0 \end{cases} \tag{1}$$

The vectors s^-, s^g and s^b are the inputs, desirable outputs and undesirable outputs slack variables. λ refers to the weight vector. If $\theta^* = 1$ and $s^- = s^g = s^b = 0$, the DMU is efficient. If $\theta^* < 1$, the DMU is not optimally efficient.

3.2. Indicator and data

Since technological innovation activities are highly dependent on investments in R&D activities, increasing R&D investments can improve innovation capability. Innovation input indicators usually includes R&D personnel input and R&D expenditure (Evangelista et al. 2001). This study selects the R&D personnel full-time equivalent and internal R&D expenditure as the input indicators.

Patents and new product sales are the most used indicators to reflect innovation outputs (Hong et al. 2015; Li 2009). This study selects patent applications and new product sales as desirable outputs. In view of the harmfulness of environmental undesirable outputs, industrial sulphur dioxide (SO_2) (Yang et al. 2018) and carbon dioxide (CO_2) emissions (Feng et al. 2018) are chosen to represent the undesirable output indicators.

Mainland China contains 31 provinces, which are typically divided into eastern, central and western China. Tibet was excluded in our study due to the lack of available data. The original data come from China Science and Technology Statistical Yearbook, China Statistical Yearbook, China Energy Statistical Yearbook and China Statistical Yearbook on Environment. The data on R&D expenditures are obtained by calculating the capital stock of R&D expenditures by perpetual inventory method (Griliches 1986). By multiplying the consumption by the associated carbon emission coefficients, regional CO_2 emissions could be calculated (Li et al. 2012). In addition, this paper sets the innovation time lag as 1 year (Chen, Liu, and Zhu 2018). Due to the lack of data in some years, we selected input data for 2008–2016 and output data for 2009–2017. Table 1 details the variables of the innovation input and output variables in 30 provinces.

3.3. Evaluation analysis

SIE of 30 provinces from 2008 to 2016 was calculated through the DEA-SBM. The outcomes are displayed in Table 2. The higher value indicates higher efficiency. 8 provinces in 2008 had an efficiency value of 1, and 9 provinces had a value that was less than 0.4. In 2016, the number of provinces with efficiency value '1' increased to 12, and there were only 3 provinces below 0.4.

Figure 1 shows the average SIE. There are six provinces have the average efficiency value '1'. Except for Chongqing, which locates in the western region, the others are situated in the eastern. Most of these provinces have developed economies, excellent environmental protection and technological innovation. Beijing, Shanghai, Zhejiang, Guangdong, and Chongqing are located in China's economically developed and technologically innovative regions such as the Beijing-Tianjin-Hebei Urban Agglomeration, Yangtze River Delta, Pearl River Delta and Chengdu-Chongqing Economic Circle, with many technological innovation centres. Zhejiang, Guangdong and Hainan rank among the top performers in low-carbon environmental protection of the whole country.

The average efficiency values range from 0.8 to 1 across seven provinces. Most of them locate in the central and eastern regions. Among them, Anhui, Jiangsu and Shandong have comparatively advanced economies, a large number of scientific research universities and institutions, and relatively high scientific and technological innovation levels. Hunan, Tianjin, Jilin and Qinghai are greatly influenced by the government's coordinated development strategy and environmental protection policies, and have high sustainable innovation efficiencies.

There are 13 provinces with a value among 0.4 and 0.8. Most of them locate in the relatively backward central and western regions, undergoing urbanisation and industrialisation. At the same time, these provinces are underdeveloped economy with low scientific and technological innovation levels, which restrict the improvement of SIE.

Also, there are four provinces have efficiency below 0.4. These are the provinces where fossil fuels are traditionally produced and used in China, with a large proportion of resource-intensive

Table 1. Descriptive statistics of innovation input and output variables.

Inputs and outputs	Variable	Unit	Mean	Std.dev.	Min	Max
Inputs	R&D personnel full-time equivalent	10,000 man-year	7.05	9.36	0.06	45.19
	R&D expenditure	100 million yuan	630.93	844.78	2.05	4733.82
Desirable outputs	Patent application	10,000 pieces	1.79	2.8	0.01	19.93
	New product sales	trillion yuan	0.36	0.48	0.00	2.73
Undesirable outputs	SO_2 emission	10,000 tons	61.43	40.06	1.43	182.74
	CO_2 emission	100 million tons	4.13	2.90	0.35	13.23

Table 2. 2008–2016 SIE evaluation results.

Province/Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	Mean
Beijing	1	1	1	1	1	1	1	1	1	1
Tianjin	0.8635	1	1	1	1	1	0.9926	0.8262	0.5395	0.9135
Hebei	0.3468	0.3836	0.3840	0.4909	0.6016	0.5328	0.4553	0.4626	0.5231	0.4645
Liaoning	0.3593	0.4133	0.3970	0.5321	0.6805	0.5444	0.3883	0.4423	0.4925	0.4722
Shanghai	1	1	1	1	1	1	1	1	1	1
Jiangsu	1	1	1	1	1	1	1	0.9308	0.7804	0.9679
Zhejiang	1	1	1	1	1	1	1	1	1	1
Fujian	0.6296	0.7031	0.6754	0.6495	0.5963	0.5308	0.4853	0.6102	0.5936	0.6082
Shandong	0.9979	1	1	1	1	0.7994	0.7224	0.7257	0.7277	0.8859
Guangdong	1	1	1	1	1	1	1	1	1	1
Hainan	1	1	1	1	1	1	1	1	1	1
Shanxi	0.1868	0.2216	0.2377	0.2935	0.3737	0.3117	0.2398	0.3208	0.4317	0.2908
Jilin	1	1	1	1	0.3859	0.7890	0.7755	1	1	0.8834
Heilongjiang	0.1759	0.2041	0.1856	0.1852	0.2374	0.2330	0.2352	0.2394	0.2336	0.2144
Anhui	0.8161	1	1	1	1	1	1	1	1	0.9796
Jiangxi	0.2218	0.2801	0.3072	0.4463	0.7192	0.5949	0.6318	0.8772	1	0.5643
Henan	0.4847	0.4320	0.3871	0.3792	0.6302	0.5772	0.5397	0.5330	0.6037	0.5074
Hubei	0.6176	0.5786	0.5249	0.6401	0.7465	0.7154	0.6295	0.7510	0.7578	0.6624
Hunan	0.7524	0.8775	0.8655	1	1	1	1	1	1	0.9439
Inner Mongolia	0.2561	0.2776	0.2564	0.2951	0.3351	0.2452	0.2725	0.2810	0.3569	0.2862
Guangxi	0.4948	0.5863	0.5893	0.6239	0.9076	0.6690	0.6948	0.8501	1	0.7129
Chongqing	1	1	1	1	1	1	1	1	1	1
Sichuan	0.4856	0.4766	0.4495	0.6932	0.7031	0.6975	0.7091	0.6798	0.7755	0.6300
Guizhou	0.5881	0.5850	0.5648	0.5652	0.6321	0.6181	0.6389	0.6353	0.7137	0.6157
Yunnan	0.4660	0.5677	0.5204	0.5562	0.5487	0.6152	0.6720	0.6354	0.6291	0.5790
Shaanxi	0.3547	0.4023	0.3946	0.3647	0.4100	0.3615	0.3312	0.3459	0.3843	0.3721
Gansu	0.2112	0.2927	0.3764	0.5678	0.6534	0.6566	0.5004	0.4239	0.4739	0.4618
Qinghai	0.5734	0.4674	0.5660	0.6641	1	1	1	1	1	0.8079
Ningxia	0.2446	0.3181	0.3778	0.4702	0.7965	0.6542	0.8367	0.7430	0.7894	0.5812
Xinjiang	0.4279	0.5029	0.5077	0.4805	0.7094	1	0.8173	0.7225	0.7032	0.6524
Eastern	0.8361	0.8636	0.8597	0.8793	0.8980	0.8552	0.8222	0.8180	0.7870	0.8466
Central	0.5319	0.5742	0.5635	0.6180	0.6366	0.6527	0.6315	0.7152	0.7533	0.6308
Western	0.4638	0.4979	0.5094	0.5710	0.6996	0.6834	0.6794	0.6652	0.7115	0.6090
Whole country	0.6185	0.6523	0.6522	0.6966	0.7556	0.7382	0.7189	0.7345	0.7503	0.7019

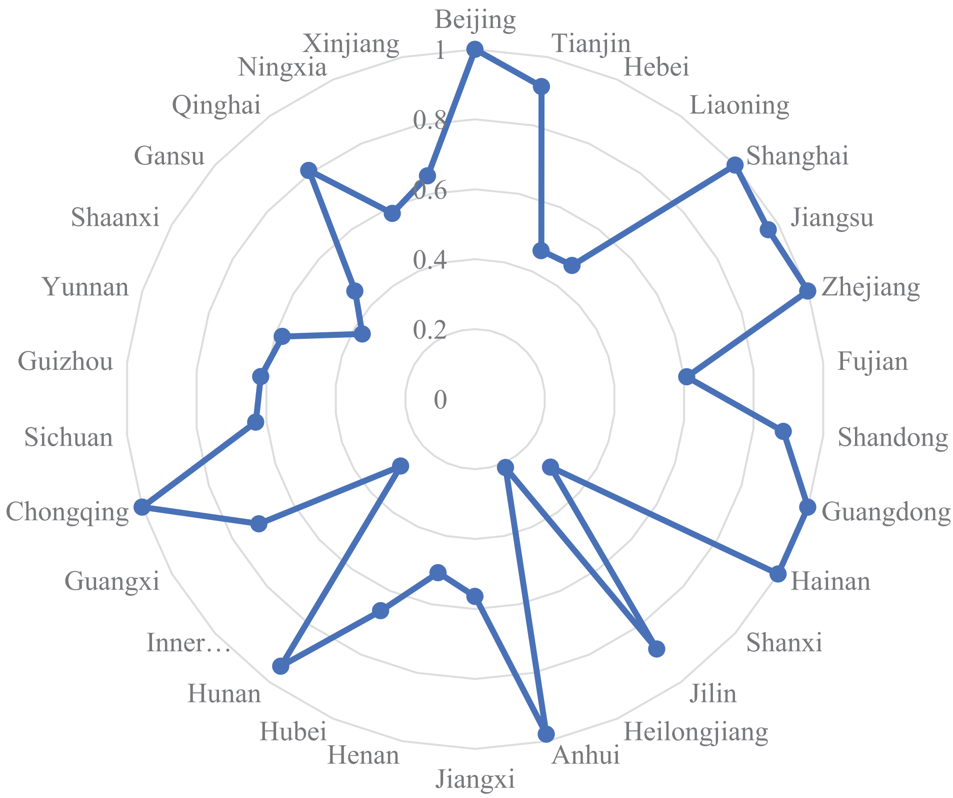

Figure 1. Average efficiency in 30 provinces.

industries, and low levels of technological innovation. These provinces rely on a large amount of resource inputs. Coal mining, steel manufacture and cement production dominate the heavy industry-oriented economic development mode, and has brought serious problems and low SIE.

Sustainable innovation efficiency in economically developed eastern is relatively high, while the underdeveloped central and western regions is much lower. Central and western regions have similar efficiencies, showing a slow growth trend, with values 0.6308 and 0.6090. Innovation efficiency in the eastern region is much higher than the national level. Innovation efficiency values in central and western regions are much lower. It is clearly that eastern region plays the key role in advancing China's s technological innovation.

4. Causal relationship analysis

4.1. Methods and models

Granger causality test is most used in testing causality of two series (Ozturk 2010). Cointegration test is usually needed before the Granger causality test, while stationarity test is the premise of cointegration test.

(1) Stationarity test

Before regression, panel data models need to test the stationarity. Non-stationary data series may also exhibit trends, although these series may not be directly related and the regression analysis results are meaningless. If the data series is not stationary, false causality will appear and it will lead to spurious regressions. This phenomenon is called 'pseudo-regression' (He and Maekawa 2001). Then, the standard T test and F test are invalid and cannot accurately reflect the internal logical relationship between variables. Panel unit root test is the most used method in stationarity test. Panel unit root tests could be divided into two categories for different assumptions of autoregressive coefficients. The first category assumes that all autoregressive coefficients are the same, that is, with a 'common root'. The representative methods include Levin-Lin-Chu (LLC) test (Levin, Lin, and Chu 2002), Breitung test (Breitung 2001) and Hadri test (Hadri 2000). The other category allows different autoregressive coefficients for each panel unit. The representative methods include Augmented Dickey-Fuller (ADF) Fisher test (Choi 2001; Maddala and Wu 1999), Im-Pesaran-Shin (IPS) test (Im, Pesaran, and Shin 2003) and Phillips-Perron (PP) Fisher test (Maddala and Wu 1999). Among all the above test methods, panel unit root test usually only uses LLC for the common root test and the ADF-Fisher for different root test. Data series are stationary only if both results reject null hypothesis.

The generation process of panel unit root data is shown in Equation (2):

$$y_{it} = \rho_i y_{i,t-1} + X_{it}\delta_i + \varepsilon_{it} \tag{2}$$

$i = 1, \dots, n$ represents cross-sectional units. $t = 1, \dots, T$ represents observation periods. ρ_i is the autoregressive coefficient. X_{it} is an exogenous variable. ε_{it} is a stationary disturbance term. The null hypothesis is '$H_0{:}\rho_i = 1, \forall_i$'. Alternative hypothesis is '$H_1{:}\rho_i < 1$'.

(2) Cointegration test

Cointegration test is used for testing the long-term equilibrium relationship among variables. If non-stationary variables can be linearly combined to make the series stationary, there is a cointegration relationship between these variable series. The premise of the cointegration relationship is that it must be single-integration of the same order (MacDonald and Kearney 1987). Panel cointegration tests are grouped into two categories. The first category bases on panel data regression residuals, including Kao test (Kao and Chiang 2000), Pedroni test (Pedroni 1999, 2001) and Westerlund test (Westerlund 2007). Another type is based on regression coefficients, including the Johansen-Fisher panel cointegration test and the Larsson test (Larsson, Lyhagen, and Löthgren 2001). The cointegration relationship exists only if the results reject the null hypothesis.

The regression model of the Pedroni test is shown in Equation (3).

$$y_{it} = \alpha_i + \delta_i t + \gamma_{1i}x_{1it} + \gamma_{2i}x_{2it} + \cdots + \gamma_{ki}x_{kit} + \cdots + \gamma_{Kit}x_{Kit} + \varepsilon_{it} \tag{3}$$

In the equation, $t = 1,2,3, \dots, T$. $i = 1,2,3 \dots, N$. $k = 1,2,3, \dots, K$. T represents the total number of periods. N is cross-sections number. k is exogenous variables. α_i is the individual effect. δ_i represents the trend effect. ε_{it} represents the residual term.

The Kao cointegration test model (Equation 4) is similar to the Pedroni test model, but the individual effects of different cross-sections are different while the trend effects are the same.

$$\begin{aligned} y_{it} &= \alpha_i + \beta x_{it} + \varepsilon_{it} \\ y_{it} &= y_{i,t-1} + \mu_{it} \\ x_{it} &= x_{i,t-1} + \nu_{it} \end{aligned} \tag{4}$$

Its auxiliary regression model form is shown in Equation (5).

$$\varepsilon_{it} = \varphi \varepsilon_{i,t-1} + \gamma_{it} \tag{5}$$

(3) Granger causality test

Granger causality test is proposed by Granger (1969) to analyse the causal relationship between variables. Later, Granger causality test has become a widely accepted and used measurement method by economists (Sims 1972, 1980). If the change of X leads to the change of Y, then X should precede the change of Y. X helps to change the prediction accuracy of Y. There is a Granger causality between X and Y. The model for the Granger causality test is shown in Equation (6). The random error terms μ_t and v_t are assumed to be uncorrelated.

$$Y_t = \sum_{i=1}^{m} \alpha_i X_{t-i} + \sum_{j=1}^{m} \beta_j Y_{t-i} + \mu_t$$
$$X_t = \sum_{i=1}^{m} \lambda_i X_{t-i} + \sum_{j=1}^{m} \delta_j Y_{t-i} + v_t \tag{6}$$

Since the results are affected by the length of the lag period, it is necessary to select an appropriate length of the lag period before conducting the test (Kang 1989).

The panel vector autoregressive model (PVAR) is commonly used in the Granger causality test. PVAR model is a dynamic panel model with fixed effects that analyzes endogenous variables without having to distinguish between endogenous and exogenous variables. PVAR model can reduce the requirements of the vector autoregressive model on the length of the time series, and can analyse the influence of individual differences of samples on the model parameters (Holtz-Eakin, Newey, and Rosen 1988).

The PVAR model constructed in this paper is shown in Equation (7).

$$y_{it} = \alpha_i + \sum_{j=1}^{m} \beta_j y_{i,t-n} + \delta_{it} + \varepsilon_{it} \tag{7}$$

The column vector y_{it} contains two variables. i is region. t represents time. n represents lag order of the model. α_0 is the intercept vector, reflecting the individual effect. $\beta_j y_{i,t-n}$ is the n-order lag term of $\beta_j y_{i,t}$. δ_{it} is the column vector, and ε is the 'white noise' disturbance term that obeys the normal distribution.

When the condition of $T \geq m + 3$ is satisfied, the parameters of the equation can be estimated. If the condition of $T \geq 2m + 2$ is further satisfied, the hysteresis parameter in steady state can be obtained. m is lag order. T is time series length.

4.2. Indicators and data

Compared with GDP, per capita GDP can better reflect the economic development level. We use per capita gross regional product (PGDP) of each province to indicate regional economic growth. Considering the changes in prices and consumption indices, this paper uses the real GDP per capita in each province, which is obtained by contracting nominal GDP to avoid the influence of inflationary factors on the variable. The nominal GDP data comes from the China Statistical Yearbook. SIE values are calculated in Section 3.

4.3. Empirical analysis

(1) Stationarity test

Since the Data used in this paper are balanced panel data, this paper conducts a unit root test on per capita GDP and SIE. To avoid possible bias of unit root test, three test methods are used in this paper, including LLC test, Breitung test and ADF-Fisher test. Table 3 shows the results. Panel unit root test reject the null hypothesis of the existence of the unit root at the 1% significance level, indicating that these two variables have no unit root and can be regarded as stationary variables.

Table 3. Panel unit root test results.

Viable	*LLC* test with trending items t^*	*LLC* test without trending items t^*	Breitung test Λ	*ADF-Fisher* test P	Z	L^*	Pm
PGDP	−7.70*** (0.00)	−8.78*** (0.00)	−4.86*** (0.00)	121.72*** (0.00)	−4.17*** (0.00)	−4.23*** (0.00)	5.63*** (0.00)
SIE	−9.53 *** (0.00)	−6.46*** (0.00)	−2.56*** (0.00)	143.08*** (0.00)	−6.49*** (0.00)	−6.40*** (0.00)	7.58*** (0.00)

Note: The accompanying probability of the statistic is in brackets. *** represents rejection of the null hypothesis with a unit root at the 1% significance level.

(2) Panel cointegration test

Our data have passed the unit root test and meet the panel cointegration test conditions, and can be tested for cointegration. In this study, Kao test, Pedroni test and Westerlund test were used to conduct cointegration test on variables. The results obtained are shown in Table 4. The cointegration test results indicate that each statistic rejects null hypothesis of 'no cointegration relationship', and there exists a cointegration relationship between the variables. There exists long-run equilibrium relationship between the variables.

(3) Optimal lag length

In this paper, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan-Quinn Criterion (HQIC) are used to select the time lag order. The results are shown in Table 5. The optimal lag length selected by the three criteria are the same, which are all first-order lags. Therefore, this study chooses a PVAR model with a lag of first order, which also meets the requirements of the above inequality conditions.

(4) Granger causality test

Although some researches have studied innovation efficiency and economic growth, only a few studies have been done through PVAR model. In order to further study the causal relationship between SIE and economic growth, this paper conducts Granger causality test on SIE and economic growth. There is the presence of long-run equilibrium relationship between these variables. Is this relationship the result of economic growth caused by sustainable innovation efficiency, or the result of economic growth caused by sustainable innovation efficiency growth? Further examination is needed to test the causal relationship between the variables. Panel data vector autoregressive model is used to test the Granger causality, and it is estimated by the systematic generalised method of moments (GMM). Results are shown in Table 6.

Seen from estimation results, the p-value of H1 is 0.752, that is, the null hypothesis is still not rejected at 10% significance level, H1 is accepted, indicating that sustainable innovation is not the Granger cause of economic growth. The p-value of H2 is 0.000, that is, the null hypothesis is rejected

Table 4. Panel cointegration test results.

Testing method	Kao test	Pedroni test			Westerlund test
Statistic name	Augmented Dickey-Fuller	Modified Phillips-Perron	Phillips-Perron	Augmented Dickey-Fuller	Variance ratio
Statistic value	2.2770** (0.0114)	4.0314*** (0.0000)	−2.6632*** (0.0039)	−2.9458*** (0.0016)	3.3472*** (0.0004)

Note: The value in brackets is the accompanying probability of the statistic. ** and *** represent rejection of the null hypothesis that there is no cointegration relationship at the 5% and 1% significance levels, respectively.

Table 5. Lag length calculation results.

Time lag	AIC	BIC	HQIC
1	−5.70872*	−4.68865*	−5.29634*
2	−4.19214	−2.98591	−3.70307
3	−4.34807	−2.90297	−3.76097

Note: * means significant at the 10% level.

Table 6. Granger causality test results.

Null hypothesis	*p*-value	Judge	Conclusion
H1. Sustainable innovation is not the Granger cause of economic growth.	0.752	Accept	Sustainable innovation is not the Granger cause of economic growth.
H2. Economic growth is not the Granger cause of sustainable innovation.	0.000	Reject	Economic growth is the Granger cause of sustainable innovation.

at 1% significance level, which means that economic growth is the Granger cause of sustainable innovation. In summary, economic growth is the one-way Granger cause of regional sustainable innovation at 1% significance level. This indicates that faster economic growth leads to increased innovation efficiency, rather than increased innovation efficiency leading to faster economic growth. With the rapid economic growth, regional technological innovation capabilities have been enhanced, bringing about an increase in sustainable innovation efficiency. This reveals that China's technological innovation has not yet been able to effectively support economic growth. So far, good circular mechanism has not been established between technological innovation and economic growth in China.

5. Discussion

5.1. Contribution to theory

China faces increasingly serious energy and environmental problems in the process of sustainable economic and social development. While vigorously promoting technological innovation, more attention is needed to the improvement of sustainable efficiency. Through empirical research on sustainable efficiency, this paper enriches the relevant theoretical research on innovation efficiency. Also, it provides theoretical support for sustainable innovation development. By examining the casual relationship between SIE and economic growth, this paper provides a useful exploration for regional economic growth theory.

5.2. Contribution to practice

Sustainable innovation activities involve many aspects, involving a large amount of capital, manpower and material resources investment, as well as energy consumption and environmental pollution, which need to be evaluated effectively and accurately. This paper evaluates the efficiency of regional sustainable innovation, which provides new ideas for empirical research on China's sustainable innovation. It also provides useful supports for improving the innovation capabilities of backward regions and narrowing the gaps in innovation performance between regions. In addition, by analysing the relationship between SIE and regional economic development, it provides valuable thinking for narrowing the economic gaps between regions. What's more, this study provides policy makers with policy inspirations, which have certain practical significance for solving current problems and improving the governance system of technological innovation.

5.3. Limitations

This research also has several limitations. Firstly, the selection of indicators in the efficiency evaluation model needs to be improved. Although there are many indicators used for evaluating innovation efficiency, researchers have not yet formed a unified understanding, which to a certain extent affects the selection of evaluation indicators in this study. In addition, due to the limitations of DEA method, only six indicators are selected in the evaluation model, which fails to fully cover all aspects of regional sustainable innovation performance.

Secondly, research methods and data samples need to be improved. DEA method has shortcomings in dealing with random errors. The data in our study are mainly from statistical yearbooks. Due to the limitations of objective factors such as missing data, changes in statistical calibre, and lag in statistical data, it is difficult to collect indicator data in some years. In addition, considering the time lag period of input and output, this paper only studies SIE in China from 2008 to 2016, but cannot conduct a longer research period.

Thirdly, there are deficiencies in our empirical research. The research on the relationship between SIE and economic growth in this paper is not comprehensive enough. The relationships include many aspects. This paper only studies the Granger causality between the two, but fails to address the threshold effect and spatial correlation between the two.

5.4. Further research

Future research could explore the other aspects of sustainable innovation. It is necessary to explore the social and economic connotations of sustainable innovation, select other undesirable output indicators and appropriate methods, and conduct qualitative or quantitative research. Future research could study the relationship between SIE and economic growth. It may be meaningful to study the relationship between SIE and economic growth from multiple perspectives, such as using spatial econometric methods to study the spatial correlation, and using threshold effect models to study the relationship between different levels of SIE and economic growth.

6. Conclusions and implications

This paper evaluates the SIE in China based on the perspective of energy and environmental constraints, and empirically tests its relationship with economic growth. The results demonstrate that there are obvious efficiency differences between regions. The national efficiency value shows a slow upward trend, indicating that the continuous efforts in innovation investment and environmental protection have paid off. Meanwhile, the efficiency values vary greatly among regions. Through Granger causality test, this paper found that economic growth is the one-way Granger causality of SIE. Economic growth drives the improvement of innovation efficiency, not the improvement of innovation efficiency drives faster economic growth. This indicates that a good circular mechanism has not been established between technological innovation and economic growth in China, and sustainable innovation has not yet achieved coordinated development with the economy.

More importance should be attached to enhance sustainable innovation governance, and promote sustainable economic and environmental development. To achieve sustainable regional development, it is necessary to reduce the generation of environmental undesirable outputs in the process of innovation. The upgrading of the energy structure should be accelerated, new energy should be vigorously developed. Since sustainable governance requires good policies and practices, it is appropriate to establish and improve the supervision mechanism. The relationship between SIE and economic growth should be properly viewed. Economic growth is an important factor affecting the improvement of SIE. At present, a good circular mechanism has not been established between China's technological innovation and economic growth, and sustainable innovation has not yet been able to achieve coordinated development with the economy. While striving to achieve economic growth and improving the efficiency of sustainable innovation, the coordinated development of economy and innovation should be encouraged, not just economic development.

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