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Influence mechanism of technological innovation of electric power industry on carbon emission reduction in China

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Abstract

Purpose – This study aims to analyse the scientific relationship between technological innovation and carbon emissions. Taking the Chinese electric power industry as the empirical research object, this study examined the effect of power technological innovation on carbon emissions and proposed policy recommendations for the development of technological innovation in China.

Design/methodology/approach – This study first calculated the energy consumption and carbon emission level of the Chinese electric power industry from 2005 to 2018. Secondly, this study built an evaluation index system for technological innovation of electric power with six indicators: average utilisation hours of power generation equipment; power consumption rate of power plant; line loss rate; standard coal consumption for power generation; standard coal consumption for power supply; and number of patent applications granted for generation, conversion or distribution of electric power in China. Finally, from a practical point of view, the relationship between technological innovation and carbon emissions of the Chinese electric power industry from 2005 to 2018 is evaluated and analysed.

Findings – Power technology innovation has been found to have a long-term and relatively large effect on carbon emissions, and carbon emissions have a short-term and insignificant impact on power technology innovation.

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Research limitations/implications – This study puts forward relevant suggestions for developing technological innovation and technology transfer, which is essential to establishing a low-carbon or zero-carbon power system in China.

Practical implications – This study provides empirical evidence for clarifying the relationship between technological innovation and carbon emissions in the power industry and further develops research theories on technological innovation and carbon emissions.

Social implications – Relevant authorities will adopt measures to promote technological innovation and development in the power sector to reduce carbon emissions.

Originality/value – This study built an evaluation index system with six indicators for technological innovation of electric power. The evaluation method was used to measure the technological innovation level of the Chinese electric power industry. The causal link between technological innovation and carbon emissions in China was analysed.

Keywords Carbon emission reduction, Carbon emissions, Power technology, Technological innovation

Paper type Research paper

1. Introduction

With the population growth and economic development, energy consumption and carbon dioxide (CO_2) emissions have sharply increased (Obama, 2017). On the contrary, carbon emission reduction is an important aspect of achieving high-quality environmental development. Upgrading industrial structure and technological innovation are important ways to affect carbon emissions. Therefore, reducing carbon emissions and promoting a low-carbon economy are the primary targets for responding to climate change (Engström, 2016). The government participation plays an important role in reducing carbon emissions (Pan *et al.*, 2022a, 2022b).

To prevent the greenhouse effect from further aggravating and control the amount of carbon dioxide emissions fundamentally, the international community has formed a consensus on carbon emission reduction and successively put forward the development goals of carbon emission reduction. For instance, the USA has proposed to reduce carbon emissions to 50%–52% of 2005 levels by 2025, thus reaching the net-zero goal by 2050 (US Department of State, the Oval Office, 2021). The European Union will reduce its net greenhouse gas emissions by more than 55% of 1990 levels by 2030, then realising carbon neutrality across the European Union by 2050; Japan has proposed to reduce carbon emissions by 46% of 2013 levels by 2030 and achieve carbon neutrality by 2050 and build a "zero-carbon society" (The Ministry of Economy, Trade and Industry of Japan [METI], 2020). China has announced that it will peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 (State Council of China, 2021).

Technological innovation plays an increasingly prominent role in China's economic development and environmental governance, particularly in the electric power industry. It has gradually become a critical influencing factor in the rapid growth of the social economy and protecting the natural ecological environment.

1.1 Development status of electric power industry

Energy plays a vital role in economic development and is key to sustainable development (Farhani and Ben Rejeb, 2012). China is currently the largest primary energy consumer and carbon emitter globally. China's electricity production has maintained sustained and rapid growth in recent years. China's electricity production's average annual growth rate was 7.8% from 2005 to 2020. The electricity production of China was 7,626.4 billion kWh in 2020, 3.05 times that of 2005. Although electricity generation increased by 4.1% in 2020, the growth rate decreased by 0.66% compared with 2019 (NBS, 2020). Thermal and hydroelectric power are the primary power generation sources in China. Thermal power generation was 5,177 billion kWh in 2020, an increase of 2.6% over 2019, accounting for 67.88% of national power generation (4,629.6 billion kWh of coal power, a rise of 1.7% over 2019; 252.5 billion kWh of natural gas, an increase of 8.6% over 2019). Hydropower generation was 1,355.3 billion kWh in 2020, a rise of 4.1% over 2019, accounting for 17.77% of national power generation. Nuclear power generation was 366.2 billion kWh in 2020. Grid-connected wind power generation was 466.5 billion kWh in 2020. Grid-connected solar photovoltaic power generation was 261.1 billion kWh in 2020, which shows an increase of 16.6% over the previous year.

1.2 Current status of power technology innovation

Technology import and technology innovation can reduce carbon emissions, and the effective role of technological innovation in carbon emissions is more significant than the role of technology introduction to a certain extent. The number of patent applications accepted and granted for the generation, conversion or distribution of electric power increased rapidly in China from 2005 to 2020. The average annual growth rate of accepted and granted patent applications was 26.96% and 29.22%, respectively. The number of patent applications received and granted for the generation, conversion or distribution of electric power reached 136,619 and 94,818, respectively, in 2020.

The Chinese Government can guide carbon emissions trading-covered enterprises through subsidies and special funds to implement innovative activities. It will force related enterprises to reduce carbon emissions through technological innovation (Zhang *et al.*, 2020). Power generation technology continued to develop towards high parameters, large capacity, high efficiency and low emission, promoting technological innovation in the fields of supercritical coal-fired power generation technology, circulating fluidised bed combustion technology, hydropower station construction technology, third-generation nuclear power technology, wind power generation technology and equipment manufacturing industry.

1.3 Literature review

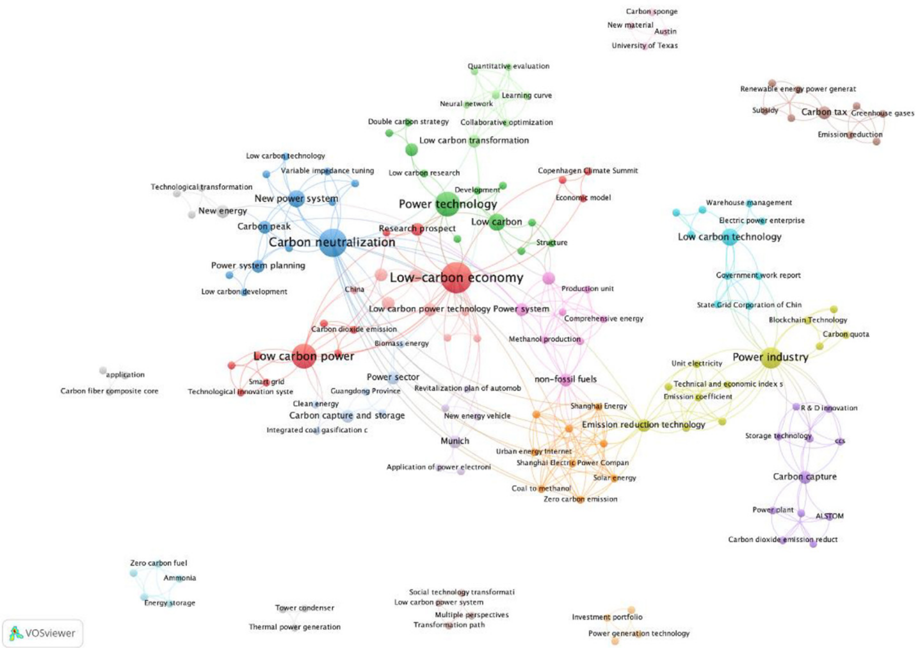
1.3.1 Effect of technological innovation on carbon emissions. Innovation recombines production factors: new products, new processes, new markets, new materials and new organisations (Schumpeter, 2017). With the current technological development, the technology in carbon emission reduction is feasible (Lu *et al.*, 2020). Technology spillover can significantly reduce embodied CO_2 emissions in trade. Electricity, transportation and cement industries have significant potential to reduce carbon emissions (Huang *et al.*, 2020). Technological progress has obvious effect on carbon emission reduction in the secondary industry (Pan *et al.*, 2022a, 2022b). It is suggested to promote the development of high-tech industries, accelerate the integration of high-tech industries, such as artificial intelligence, blockchain, Internet of things, cloud computing and big data with traditional industries, and enhance the informatisation capabilities of conventional industries (Ye *et al.*, 2022). Some studies have also proposed to turn current extensive economic development, which is too dependent on the industry, into intensive growth patterns dependent on technological progress. This change will realise the financial goal of adjusting speed without reducing momentum, increasing quantity and optimising quality, lowering CO_2 emissions and achieving the abatement commitment quicker (Jiao *et al.*, 2019).

Technological innovation has a significant impact on energy consumption. Tang *et al.* (2018) developed a National Energy Technology-Power (NET-Power) model to assess the effects of technological improvement and energy structure shift on the carbon emissions for each region and answer the question of carbon emissions peak in the power industry. Chen *et al.* (2020) found that China's overall domestic technological progress reduced carbon emissions over the study period. Yu *et al.* (2017) proposed a sequential meta-frontier Luenberger productivity index that incorporates undesirable outputs to measure carbon productivity growth over time. The production technology increased, and the efficiency changes fluctuated. CO_2 emissions are reduced as new energy-saving technologies are used instead of machinery and equipment with high energy consumption (Erdoğan *et al.*, 2020). Some scholars suggest that the turning point of the environmental kuznets curve by promoting technological progress in energy field, upgrading the industrial structure, promoting economic conditions and allocating higher R&D budget allocations should be given priority to achieve win-win results in controlling carbon emissions while developing economic growth (Huang *et al.*, 2021; Razzaq *et al.*, 2021). The role of renewable energy in reducing carbon emissions is investigated, suggesting the supportive role of the technology and efficiency of energy utilisation in reducing carbon emissions (Jia *et al.*, 2021; Hussain *et al.*, 2022). Using the spatial econometric model, it is examined whether energy technology innovations are beneficial for CO_2 emissions abatement in China, and the results indicate that renewable energy technology innovation facilitates CO_2 abatement, whereas fossil energy technology innovation is ineffective in reducing carbon emissions (CEs) (Wang and Zhu, 2020).

1.3.2 Knowledge mapping of power technology and carbon emissions based on co-word analysis. Carbon emission has become a vital issue widely concerned by researchers. Many studies have discussed the influencing factors of China's carbon emissions, and the analysis based on the national or provincial level is more in-depth. Many studies have also been carried out on variations in energy carbon emission, energy carbon emission distribution, strategic transformation, transformation path and carbon emissions based on spatial correlation (Yang *et al.*, 2018; Dong *et al.*, 2018; Li *et al.*, 2019). Figure 1 shows the knowledge mapping of power technology and carbon emissions based on co-word analysis. Among them, low-carbon economy, low-carbon electricity, carbon neutrality, power technology and some other keywords have more frequency, which is the leading research hotspot. The red nodes mainly focus on the low-carbon economy and low-carbon energy. The blue nodes mainly focus on carbon neutrality, carbon peak and new power system. The green nodes mainly focus on power technology and low carbon.

Researchers and institutions have extensively investigated the relationship between technological innovation and carbon emission reduction as a possible method to increase the sustainability of the economy. However, systematic research on the carbon emission reduction effect of technological innovation is lacking in the power industry at the national level. No one-size-fits-all solution can assess the carbon emission reduction effects of national power industry technological innovation. The bottlenecks in data availability, representativeness of selected indicators and accurate evaluation methods have limited the calculation.

This study has several contributions to this field. Firstly, it built an evaluation index system with six indicators for technological innovation of electric power, which provides a new evaluation method for the future research on innovation capability of electric power industry. Secondly, analysing the impact of technological innovation on carbon dioxide emissions is conducive to strengthening our scientific and systematic understanding of carbon dioxide emissions, providing strong theoretical support for the formulation of carbon emission policies, effectively alleviating environmental pollution problems faced by economic development and realising the transformation of high-quality economic development.



Source: CNKI

Figure 1. Knowledge mapping of power technology and carbon emissions based on co-word analysis

The rest of the research proceeds as follows: Section 2 states the data sources and introduces the innovation index of electric power technology. Section 3 analyses energy consumption characteristics, carbon emission trends and technological innovation factors in the power industry. Section 4 gives the calculation results and discusses the study results. Section 5 concludes the research with some policy recommendations.

2. Material and methods

2.1 Data sources

The Chinese electric power industry is taken as an empirical case in this section to analyse the causal link between technological innovation and carbon emissions in China. The original case analysis data were from 2005 to 2021, extracted from the *China Statistical Yearbook* compiled by the National Bureau of Statistics of China, the *China Electric Power Statistical Yearbook* compiled by the China Electricity Council and the *China Energy Statistical Yearbook* compiled by the Department of Energy Statistics, National Bureau of Statistics. Given that the statistical data of energy consumption in the Chinese electric power industry are combined with that of the electric power and heat industry, the statistical data of the power and heat industry was used as the research object. Given that the latest available data is up to 2018, the time interval of research is from 2005 to 2018.

The carbon emissions of the Chinese electric power industry were calculated from the energy consumption data of the electric power and heat industry. The carbon emission intensity was calculated by dividing the total carbon emissions by the electricity production of the power industry. The remainder of the data was obtained directly from the statistical yearbooks.

2.2 Data detection

The Augmented Dickey-Fuller unit root test should be conducted before proving the causal link between power technology innovation and carbon emissions. The standard augmented dickey-fuller (ADF) test for any index X_t can be expressed as follows:

$$\Delta X_{i,t} = u_i + \beta_{i,t} X_{i,t-1} + \sum_{j=1}^{k} c_{i,j} \Delta X_{i,t-j} + e_{i,t}$$

$$\Delta X_{i,t} = u_i + \alpha_i t + \beta_{i,t} X_{i,t-1} + \sum_{j=1}^{k} c_{i,j} \Delta X_{i,t-j} + e_{i,t}$$

where $\Delta X_{i,\ t}$ represents the first difference of the index i at time t; $e_{i,\ t}$ is the white noise interference term; and k is the lag length determined according to T – sig method.

The ADF test for model variables considering structural breakpoints is as follows:

$$\Delta X_t = u + \lambda t + \beta_t X_{t-1} + \sum_{j=1}^{n} \theta_j DU_{j,t} + \sum_{j=1}^{n} \gamma_j DT_{j,t} + \sum_{i=1}^{k} c_i \Delta X_{t-i} + e_t$$

where $DT_{j,t}$ represents the virtual variable of structural disconnection corresponding to the change of trend equation in time. In the sample interval regression, t_α will be chosen as a structural breakpoint when the test statistic of coefficient β_t is the most significant.

2.3 Carbon emissions accounting methods

Given that the relevant statistical yearbooks of China do not directly publish the carbon emission data, the carbon emissions of China's power industry should be estimated first. Its estimation method refers to the research of Xu and Luan (2016). Specifically, we used the following estimation formula:

$$C = \sum_i E_i \times n_i \tag{1}$$

In Formula (1), C represents the total amount of carbon emissions; E_i represents the energy consumption of category i; n_i represents the carbon emission coefficient of category i energy. i = 1, . . ., 9 and i, respectively, means coal, coke, petroleum, gasoline, kerosene, diesel oil, fuel oil, natural gas and electricity. n_i values vary with different energy sources in Table 1.

Type	Coefficient	Type	Coefficient	Type	Coefficient
Coal	0.7559	Gasoline	0.5538	Fuel oil	0.6185
Coke	0.8550	Kerosene	0.5714	Natural gas	0.4483
Petroleum	0.5857	Diesel oil	0.5921	Electricity	0

Table 1. Carbon emission coefficient of various energy sources (unit:104 t/104 t)

2.4 Innovation index of electric power technology

According to the principles of system comprehensiveness, operability and effectiveness, after selecting five indicators based on the main electric power technology innovation index from *China Energy Statistical Yearbook*, this study added the patent indicator based on the findings of Mo (2021). We selected the publicly available data of several power technology indicators issued from 2005 to 2018 for factor analysis. We calculated the technological innovation factor value as the independent variable to represent the technological innovation index of the power industry. The specific power technology indicator names are listed in Table 2.

3. Empirical analysis

3.1 Energy consumption characteristics of power industry

The composition of energy consumption adopted coal equivalent calculation, as shown in Table 3. The total energy consumption showed steady growth from 2005 to 2018, but the structural changes were significant. The consumption of coal and coke showed a slight fluctuating growth, in which coal consumption accounted for an annual increase of 94.98%. Petroleum, gasoline, kerosene, diesel and fuel oil consumption were relatively small and decreased significantly. Natural gas and electricity consumption grew relatively fast, accounting for 0.24% and 5.36% of total energy consumption in 2018, respectively, which are higher than 0.016% and 4.09%, respectively, in 2005.

3.2 Development trend of carbon emissions in power industry

Table 4 presents the computed carbon emissions results, the growth rate of carbon emissions, electricity production of the power industry, carbon emission intensity and reduction rate of carbon emission intensity. The total carbon emissions and electricity generation of the power industry increased yearly from 2005 to 2018.

The growth rate of carbon emissions and carbon emission intensity in the power industry reached 4.99% and 2.08, respectively, which were at a relatively low growth level in 2018. The reduction rate of carbon emission intensity was 3.15%, as shown in Table 4.

3.3 Factor analysis of power technology innovation

Factor analysis was used to study the multiple indicators that constitute the technological innovation index expressed as *TI*. However, the comprehensiveness between various variables is little because of the differences in the indicators' order of magnitude and measurement units. Therefore, standardising the values of each variable first is necessary.

Indicator name	Unit
Average utilisation hours of power generation equipment (AUH)	Hours
Power consumption rate of power plant (PCR)	%
Line loss rate (LLR)	%
Standard coal consumption for power generation (SCG)	g/kWh
Standard coal consumption for power supply (SCS)	g/kWh
Number of patent applications granted for power generation, conversion or distribution (NPAG)*	Items

Sources: Department of Energy Statistics, National Bureau of Statistics. *China Energy Statistical Yearbook*. China Statistics Press, 2020. * Department of Social, Science and Technology and Cultural Statistics National Bureau of Statistics; Department of Strategy and Planning Ministry of Science and Technology. *China Statistical Yearbook on Science and Technology*. China Statistics Press, 2020

Table 2. Evaluation index system for technological innovation of electric power

Year	Coal	Coke	Petroleum	Gasoline	Kerosene	Diesel oil	Fuel oil	Natural gas	Electricity
2005	105,016.00	6.00	28.60	20.31	0.32	121.78	1195.01	17.49	4,543.04
2006	121,059.67	6.70	11.40	21.77	0.24	345.37	961.43	29.49	5,116.87
2007	133,651.89	7.45	8.42	19.06	0.25	275.74	597.96	70.74	5,654.34
2008	136,725.09	7.13	9.93	21.99	0.23	284.23	382.83	73.92	5,902.41
2009	143,904.00	8.00	4.09	26.53	0.12	121.66	216.65	127.91	6,240.35
2010	149,726.00	4.00	3.64	24.64	0.03	83.08	119.43	180.81	6,986.65
2011	170,949.00	8.00	2.11	25.23	0.02	84.89	43.40	215.58	7,999.62
2012	181,090.00	0.49	2.46	27.76	0.03	74.17	22.51	225.02	8,066.56
2013	189,848.00	7.00	2.25	27.28	0.06	73.54	26.04	244.47	8,824.36
2014	177,098.00	49.00	0.33	26.01	0.05	65.16	11.58	262.60	9,196.78
2015	165,422.00	39.00	0.27	25.97	0.08	60.74	8.38	343.66	9,132.81
2016	169,441.00	35.00	0.26	23.88	0.07	55.00	6.38	407.83	9,799.62
2017	183,107.00	39.00	0.20	21.88	0.04	58.91	4.61	446.10	10,186.24
2018	192,239.00	39.00	0.21	19.07	1.29	48.68	3.93	487.32	10,916.91

Sources: Department of Energy Statistics, National Bureau of Statistics. *China Energy Statistical Yearbook*. China Statistics Press, 2020

Table 3. Energy consumption and carbon emissions of the power and heat industry

Year	Carbon emissions (10^4 tons of carbon)	Growth rate of carbon emissions (%)	Electricity production in the power industry (100 million kWh)	Carbon emission intensity (ton carbon/10,000 kWh)	Reduction rate of carbon emission intensity (%)
2005	80,233.97	9.88	24,975	3.21	3.46
2006	92,345.96	15.10	28,499	3.24	−0.86
2007	101,614.28	10.04	32,644	3.11	3.94
2008	103,812.93	2.16	34,510	3.01	3.36
2009	109,064.40	5.06	36,812	2.96	1.51
2010	11,3401.21	3.98	42,278	2.68	9.47
2011	129,416.16	14.12	47,306	2.74	−1.99
2012	137,061.90	5.91	49,865	2.75	−0.47
2013	143,697.79	4.84	53,721	2.67	2.68
2014	134,088.37	−6.69	56,801	2.36	11.75
2015	125,285.63	−6.56	57,400	2.18	7.54
2016	128,343.14	2.44	60,228	2.13	2.37
2017	138,693.90	8.06	64,529	2.15	−0.86
2018	145,607.95	4.99	69,947	2.08	3.15

Sources: Department of Energy Statistics, National Bureau of Statistics. *China Energy Statistical Yearbook*. China Statistics Press, 2020

Table 4. Carbon emissions, electricity production and carbon emission intensity from 2005 to 2018

According to factor analysis, Kaiser-Meyer-Olkin measure of sampling adequacy value is 0.746, which is generally considered suitable if it is more significant than 0.6. The significance of Bartlett's test is 0.000, which indicates rejection. The results of these two tests show that the time series of this study is suitable for factor analysis.

Factor expressions of each variable were obtained based on the component matrix as follows:

$$AUH = 0.869TI_1 + \xi_1, \ldots, NPAG = 0.939TI_6 + \xi_6 \quad (2)$$

According to the component score coefficient matrix, the linear expression of *technological innovation (TI)* is established as follows:

$$TI = 0.162AUH + 0.181PCR + 0.176LLR + 0.181SCG + 0.181SCS - 0.175NPAG \quad (3)$$

The standardised power technology innovation index data were substituted into the linear expression of *TI*. The technological innovation index sequence has been obtained in Table 5.

4. Results and discussion

As shown in Table 5, the total factor value represents the technological innovation index, and the standardised carbon emission value represents the carbon emission index of the power industry. The vector auto-regressive (VAR) model was constructed to analyse the correlation between TI_t and CE_t.

TI_t represents the technological innovation index in t year; CE_t represents carbon emissions in t year; ΔTI_t is the first difference of technological innovation index; ΔCE_t is the first difference of carbon emissions; $\Delta^2 TI_t$ is the second difference of technological innovation index; and $\Delta^2 CE_t$ is the second difference of carbon emissions. Judgment criteria: P-value should be less than 0.05.

Automatic-based on akaike information criterion (AIC), the ADF statistic of $\Delta^2 CE_t$ is −3.921976, which is less than the critical value of −3.259808 given a 5% significance level in the distribution table. The p-value is 0.0198, which is less than 0.05. Thus, the null hypothesis of unit root is rejected at the significance level of 5% and 1%. Therefore, $\Delta^2 CE_t$ is a stationary time series. Accordingly, CE_t is a second-order single integer series.

Automatic-based on AIC, the ADF statistic of $\Delta^2 TI_t$ is −8.674250, which is less than the critical value of −4.200056 given the 1% significance level in the distribution table. The p-value is 0.0000, which is less than 0.05. Therefore, the null hypothesis of unit root is rejected at less than a 1% significance level. Therefore, $\Delta^2 TI_t$ is a stationary time series. Accordingly, TI_t is a single integer series. Consequently, the cointegration estimation of CE_t and TI_t sequences can be carried out.

Under the condition of an unconstrained VAR model, the lag period was tested according to the minimum value of *likelihood ratio*, *final prediction error*, *AIC* and *schwarz information criterion* in Table 6, and the lag order was selected as order 1. The VAR model was constructed using equations (4) and (5), and the model test results indicated that no root lies outside the unit circle. That is, VAR satisfies the stability condition.

Table 5. Standardised data of technological innovation index and carbon emissions from 2005 to 2018

Year	Carbon emissions	Technological innovation	Year	Carbon emissions	Technological innovation
2005	−0.67470584	0.98754859	2012	0.98577284	−0.32937757
2006	−0.32080046	0.85589646	2013	1.17966982	−0.44911418
2007	−0.04998565	0.60542733	2014	0.89888804	−0.62849263
2008	0.01425756	0.31030841	2015	0.64167729	−0.75742250
2009	0.16770262	0.16057326	2016	0.73101578	−1.01810027
2010	0.29442163	−0.10519765	2017	1.03345908	−1.07462482
2011	0.76236891	−0.16830043	2018	1.23548338	−1.29977435

$$\Delta^2 CE_t = 0.177788204905^*\Delta^2 CE_{t-1} - 0.886941626236^*\Delta^2 TI_{t-1} + 0.00063569261857 \quad (4)$$

$$\Delta^2 TI_t = 0.10824630335^*\Delta^2 CE_{t-1} - 0.929216291273^*\Delta^2 TI_{t-1} + 0.00915454101661 \quad (5)$$

By establishing the VAR model, the conclusion of the impulse response analysis further confirms the influence mechanism between technological innovation and carbon emissions, which is shown as follows:

The dynamic relationship between power technology innovation and carbon emissions is shown in Figure 2. As can be seen from the response of carbon emissions to power technology innovation shocks, a positive shock of power technology innovation by the size of one-unit standard deviation has a positive impact on carbon emissions in the first period and a negative response in the second period. Then, the impact effect begins to fluctuate and converge for a relatively long time and gradually returns to the original level after more than ten periods.

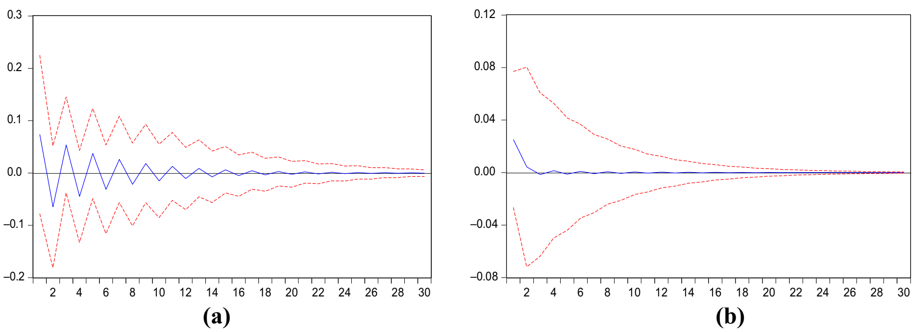
Figure 2 also shows the response of power technology innovation to carbon emissions shocks. A positive shock of carbon emissions by the size of one-unit standard deviation positively impacts power technology innovation in the first period. Still, the impact effect weakened rapidly and recovered to the original level in the third period.

The results show that power technology innovation has a long-term effect on carbon emissions, and carbon emissions have a short-term impact on power technology innovation.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	6.047188	NA	0.001397	−0.899375	−0.855547	−0.993955
1	15.63399	12.78240*	0.000425*	−2.140887*	−2.009404*	−2.424627
2	17.14526	1.343355	0.000930	−1.587837	−1.368698	−2.060737
3	23.50352	2.825889	0.001183	−2.111892	−1.805099	−2.773952*

Notes: *Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); HQ: Hannan-quinn information criterion

Table 6. VAR lag order selection criteria



Notes: (a) Response of $\Delta^2 CE_t$ to $\Delta^2 TI_t$ innovation using Cholesky (d.f. adjusted) factors; (b) response of $\Delta^2 TI_t$ to $\Delta^2 CE_t$ innovation using Cholesky (d.f. adjusted) factors

Figure 2. Response of power technology innovation and carbon emission reduction to one standard deviation innovation

Variance decomposition: The variance decomposition method evaluates the importance of different structural shocks by analysing the contribution of each structural shock to the change of endogenous variables. The variance decomposition can give new information about the relative importance of each random disturbance affecting the variables in the VAR model. The variance decomposition of CE and TI is shown in Tables 7 and 8.

In the variance decomposition of CE, the change of carbon emission is mainly caused by the information shock itself, which reaches the maximum of 100% in the first stage and gradually decreases in the following stages, basically remaining at approximately 80%. The contribution rate of technological innovation efficiency of the energy industry to the fluctuation of carbon emissions was 0 in the first phase. It continued to grow steadily from the second phase and reached a maximum of 19.41% in the 30th phase. The impact of carbon emissions is greater than the impact of technological innovation efficiency in the energy industry, and the impact of technological innovation efficiency in the energy industry on carbon emissions has a certain lag. The contribution rate of carbon emissions

Period	SE.	CE	TI	Period	SE.	CE	TI
1	0.256553	100.0000	0.000000	16	0.286868	80.64489	19.35511
2	0.268148	92.28999	7.710007	17	0.286903	80.62525	19.37475
3	0.273923	88.43986	11.56014	18	0.286927	80.61158	19.38842
4	0.277962	85.89073	14.10927	19	0.286944	80.60207	19.39793
5	0.280733	84.20479	15.79521	20	0.286956	80.59545	19.40455
6	0.282647	83.06945	16.93055	21	0.286964	80.59084	19.40916
7	0.283971	82.29701	17.70299	22	0.286970	80.58764	19.41236
8	0.284890	81.76770	18.23230	23	0.286974	80.58540	19.41460
9	0.285527	81.40323	18.59677	24	0.286977	80.58385	19.41615
10	0.285970	81.15141	18.84859	25	0.286979	80.58277	19.41723
11	0.286279	80.97702	19.02298	26	0.286980	80.58201	19.41799
12	0.286493	80.85607	19.14393	27	0.286981	80.58149	19.41851
13	0.286642	80.77207	19.22793	28	0.286982	80.58113	19.41887
14	0.286746	80.71370	19.28630	28	0.286982	80.58087	19.41913
15	0.286818	80.67312	19.32688	30	0.286982	80.58069	19.41931

Table 7.
Variance decomposition of CE

Period	SE.	CE	TI	Period	SE.	CE	TI
1	0.087655	8.280490	91.71951	16	0.165493	2.424009	97.57599
2	0.117418	4.750829	95.24917	17	0.165572	2.421765	97.57824
3	0.133939	3.663810	96.33619	18	0.165627	2.420205	97.57979
4	0.144351	3.164249	96.83575	19	0.165665	2.419121	97.58088
5	0.151174	2.891163	97.10884	20	0.165692	2.418366	97.58163
6	0.155748	2.727865	97.27214	21	0.165711	2.417841	97.58216
7	0.158855	2.624910	97.37509	22	0.165723	2.417476	97.58252
8	0.160982	2.557822	97.44218	23	0.165732	2.417222	97.58278
9	0.162446	2.513161	97.48684	24	0.165739	2.417045	97.58296
10	0.163458	2.483004	97.51700	25	0.165743	2.416922	97.58308
11	0.164159	2.462446	97.53755	26	0.165746	2.416836	97.58316
12	0.164645	2.448340	97.55166	27	0.165748	2.416776	97.58322
13	0.164982	2.438618	97.56138	28	0.165750	2.416735	97.58327
14	0.165217	2.431897	97.56810	28	0.165751	2.416706	97.58329
15	0.165380	2.427240	97.57276	30	0.165751	2.416686	97.58331

Table 8.
Variance decomposition of TI

was 8.3% at the initial stage but was in a declining stage from the 2nd phase to the 11th phase and stabilised at approximately 2.4% after the 12th phase. The result of variance decomposition of carbon emission is the proof and supplement of the impulse response diagram.

In general, technological innovation in the electric power industry will have a considerable long-term impact on carbon emissions. Carbon emissions will decrease with the improvement of technological innovation capacity in the electric power industry. In contrast, the impact of carbon emissions on technological innovation in the electric power industry is short-term and relatively insignificant.

5. Conclusion and policy implications

This study built an evaluation index system for technological innovation of electric power with six indicators to represent the technological innovation index of the power industry. The VAR model is established to analyse the influence of technological innovation in the electric power industry on carbon emission reduction. We found that technological innovation in the electric power industry will have a considerable long-term impact on carbon emissions, whereas the impact of carbon emissions on technological innovation in the electric power industry is short-term and relatively insignificant.

This research result has important theoretical and practical significance. On the one hand, it provides empirical evidence for the theory that technological innovation affects carbon emissions and gives theoretical support for the electric power industry to improve technological innovation. In particular, the VAR model was established by analysing pulse graphs and variance decomposition. Thus, a new method is provided for studying the relationship between technological innovation and carbon emissions by comparing to the past, only focusing on the unilateral discussion on the impact of technological innovation on carbon emissions. On the other hand, relevant departments will take corresponding measures to improve the level of scientific and technological innovation in the power industry, thereby reducing carbon emissions and promoting the development of a low-carbon economy.

With the rapid development of science and technology, the technology innovation system is increasingly well understood at an aggregate level and developing continuously and rapidly. Accordingly, China should strengthen the primary research, establish the principal status of enterprises in the technology innovation system and strengthen the application and implementation regime of government subsidies. To improve the construction of the technology innovation system, the interaction among the elements of the technological innovation system, such as business, government, research institutions, technology intermediaries and financial institutions, is also required to change to technology innovation. Furthermore, China should establish low-carbon industries and enterprises and centred and market-oriented technology innovation systems to improve capacity utilisation and ecological benefits. In this process, the government should pay more attention to regional differences and steadily advance step by step. The management of policy signals is also essential to guide enterprises to engage in low-carbon innovative activities.

The electrification of energy consumption and cleaning electricity production are key factors influencing carbon neutrality. Consequently, establishing a low-carbon or zero-carbon power system based on technological innovation is essential. China should encourage technology transfer activities, increase technology transfer performance requirements, integrate the essential constituent elements of technology transfer and optimise the technology transfer process to improve the technology innovation system construction, promote technology transfer and development of high-tech industries and enhance the contribution of technology in action. Furthermore, on the basis of the nature and profitability of low-carbon or zero-carbon technology transfer, China should further optimise the technology transfer environment, establish a new technology transfer consortium and strengthen government guidance and institution guarantee.

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