IJCCSM
15,2

The evolution of electric technology in the context of China's low-carbon transformation: a patent analysis

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Received 14 April 2022
Revised 31 May 2022
Accepted 17 July 2022

Abstract

Purpose – Owing to increased energy demands, China has become the world's top CO2 emitter, with electricity generation accounting for the majority of emissions. Therefore, the Chinese Government aspires to achieve a low-carbon transformation of the electric industry by enhancing its green innovation capacity. However, little attention has been paid to the green development of electric technology. Thus, this paper aims to uncover the spatiotemporal evolution of electric technology in the context of China's low-carbon transformation through patent analysis.

Design/methodology/approach – Using granted green invention patent data for China's electric industry between 2000 and 2021, this paper conducted an exploratory, spatial autocorrelation and time-varying difference-in-differences (DID) analysis to reveal the landscape of electric technology.

Findings – Exploratory analysis shows that the average growth rate of electric technology is 8.1%, with spatial heterogeneity, as there is slower growth in the north and west and faster growth in the south and east. In addition, electric technology shows spatial clustering in local areas. Finally, the time-varying DID analysis provides positive evidence that low-carbon policies improve the green innovation capacity of electric technology.

Research limitations/implications – The different effects of the low-carbon pilot policy (LCPC) on R&D subjects and the LCPC's effectiveness in enhancing the value of patented technology were not revealed.

Originality/value – This paper reveals the spatiotemporal evolutionary characteristics of electric technology in mainland China. The results can help the Chinese Government clarify how to carry out innovative development in the electric industry as part of the low-carbon transformation and provide a theoretical basis and research direction for newcomers in this field.

Keywords China, Patent analysis, Electricity, Evolution, Low carbon

Paper type Research paper

This work was supported in part by the Scientific Research Foundation of Xihua University under Grant RZ2100000795, and in part by the Research Center of Scientific Finance and Entrepreneurial Finance of Ministry of Education of Sichuan Province under Grant KJJR2021-017.

Funding: Scientific Research Foundation of Xihua University (RZ2100000795). Research Center of Scientific Finance and Entrepreneurial Finance of Ministry of Education of Sichuan Province (KJJR2021-017).

International Journal of Climate Change Strategies and Management
Vol. 15 No. 2, 2023
pp. 176-194
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-04-2022-0050

1. Introduction

In recent years, because of increasing energy demands, global CO_2 emissions have increased dramatically and issues regarding carbon emissions have become a major concern for countries around the world (Martin and Saikawa, 2017; Veselov *et al.*, 2021; Behera and Dash, 2017; Mostafaeipour *et al.*, 2022). China has replaced the USA as the world's largest emitter of CO_2 (Yang and Lin, 2016; Li and Qin, 2019; Yao *et al.*, 2021), and the Chinese Government has introduced several low-carbon policies for achieving carbon reduction targets (Liu *et al.*, 2022). According to the World Resources Institute and the National Bureau of Statistics of China, the electric sector is the largest carbon emitter in China, accounting for nearly 40% of the total. The electric industry is the most important basic energy industry for China's national economic development, not only as it relates to industrial energy conservation and emission reduction but also as an important benchmark for leading other industries toward low-carbon transformation (Tang *et al.*, 2019). Therefore, the task of promoting the low-carbon transition of China's electric industry is urgent (Zhang *et al.*, 2019; Yang *et al.*, 2022).

Given the important role of electric energy in various aspects of industry, production and daily life, how to promote a low-carbon transition in the electric sector has become a key topic of research in many studies. Numerous scholars have highlighted the importance of energy technology innovation for promoting structural changes in China's electricity (Yao *et al.*, 2021). For example, Liu *et al.* (2022) used a time-varying DID model to demonstrate that although China's ability to reduce carbon emissions is constrained by energy sources such as coal, the level of innovation can change this phenomenon and effectively contribute to China's carbon reduction. Song *et al.* (2017) confirmed that continuous technology innovation is necessary to make low-carbon electricity generation a future trend. Tang *et al.* (2019) and Chen *et al.* (2018) demonstrated that the transition of the electric sector to a low-carbon structure relies on the potential for carbon reduction and low-carbon technologies. Yao *et al.* (2021) analyzed the regional electric sector in China and proposed that the low-carbon transition of the electric sector requires the vigorous development of regional thermal electricity clean technologies. In addition, in the face of a low-carbon transition and development of low-carbon technologies, some scholars have emphasized that electricity generation can be achieved using decarbonization technologies (Cunha *et al.*, 2021), such as solar smart grids (Nobre *et al.*, 2019) and power-to-gas technology (Ikäheimo *et al.*, 2022). Alternatively, the use of low-carbon energy sources to reduce CO_2 emissions has been studied. For example, in the automotive industry, firms can use plug-in hybrid electric vehicles that incorporate low-carbon electricity technologies to effectively curb increasing carbon emissions (Zhao *et al.*, 2021).

The literature contains many discussions on the low-carbon transition of electric industry, which can provide some theoretical reference for the implementation of China's carbon emission reduction strategy, but there are shortcomings. First, the extant literature mostly has focused on low-carbon electricity innovation research conducted in a certain region or field and lacks a systematic study of low-carbon electricity industry innovation over time. For example, Cheng *et al.* (2016) studied low-carbon electricity innovation in only one province in China. Additionally, some scholars have studied only specific fields, such as the automotive (Zhao *et al.*, 2021) and artificial intelligence fields (Anton *et al.*, 2021). Second, the literature on low-carbon transitions mostly starts from a macro perspective and lacks research from a micro perspective, especially for the electric industry. For example, some scholars have explored low-carbon energy and carbon emission trading mechanisms at only the macro level using provincial or different countries' panel data (Wang *et al.*, 2019; Hassan *et al.*, 2022) to develop relevant suggestions for low-carbon transitions. Third, the research subject of the literature is limited. Most studies are based on listed companies and do not cover all the subjects in the electric industry. For example, Chen *et al.* (2021) studied the electricity innovation of only A-share listed companies in Shanghai and Shenzhen, which is not fully representative of the whole electric industry in China and therefore limits the research results and impedes a perfect improvement plan.

Therefore, this paper aims to conduct a comprehensive study on the electric industry in the context of the low-carbon transition to better comprehend the development trend of low-carbon transition in the industry and provide a solid factual foundation for its green development. Because of the uneven regional economic development and disparate implementation time of low carbon pilot policies in mainland China, this paper depicts the full picture of electric technology from both time and space dimensions, i.e. a spatiotemporal evolutionary analysis. Specifically, all granted green invention patent data from 2000 to 2021 in the electric industry are used to conduct an exploratory and spatial autocorrelation analysis. Meanwhile, a time-varying DID analysis is employed to empirically analyze the effectiveness and marginal effects of low-carbon pilot policies. The following are the research questions to be answered in this paper.

RQ1: What are the temporal variations and regional differences in China's electric industry?

RQ2: Is there any spatial correlation in the industry? What are the evolutionary trends?

RQ3: What is the influence of the low-carbon pilot policy? Does the policy effect vary by region and time?

The contribution of this paper lies in the following aspects. First, to the best of our knowledge, this paper is the first exploratory and empirical analysis of the electric industry in the context of a low-carbon China from a micro perspective, i.e. from a patent perspective, which can provide concrete and effective insights for the development of this industry. Second, this paper investigates the effect of low-carbon pilot policies in different periods, which enriches the research results and supports the Chinese Government in clarifying how to carry out innovations in the electric industry in the context of low-carbon transition and also provides a theoretical basis and research direction for newcomers to this field.

The rest of the paper is structured as follows. Section 2 describes the data and methods to be used; subsequently, a descriptive and empirical analysis is conducted in Section 3; finally, Section 4 summarizes the findings and presents limitations.

2. Data and methods

This section describes the data sources, the main methods and the corresponding variable settings used in the article.

2.1 Data sources

Green patents are a reliable indicator of the green innovation capability (Du *et al.*, 2019); hence, this paper uses granted green invention patent data to explore the spatiotemporal evolutionary characteristics of electric technology in the context of low-carbon transformation. The data on granted patents for green inventions in the electric industry were obtained from the China National Intellectual Property Administration (CNIPA, http://www.cnipa.gov.cn). The reasons for focusing on granted invention patents are as follows. First, the technical content of invention patents is higher than that of utility model patents and design patents (Gu, 2020). Second, the quality, novelty and utility of granted invention patents will be more strictly examined by CNIPA examiners (Dang and Motohashi, 2015; Motohashi and Yun, 2007).

The original data search was based on the main international patent classification (IPC) classification of green patents in the electric industry. The specific search formula refers to Cambini *et al.* (2016) and the IPC classification of green patents in world intellectual property organization [1] (Table 1), and a total of 11,951 patents were obtained.

Before data analysis, a series of cleaning work was conducted on the original data. First, 649 relevant patents in Hong Kong, Macao and Taiwan were deleted because these data could not reflect the patent innovation capacity of mainland China. Second, because the data volume of granted green patents in the vast majority of regions before 2000 was 0, the 23 patents occurring before then were removed. Finally, after removing the missing and duplicate data (two records), an analysis dataset of 11,277 green patents in China's electric industry, spanning the period of 2000–2021, was obtained (as shown in Figure 1).

Regional information appearing subsequently is shown in Table 2, with reference to the Regulations on Administrative Divisions of the State Council of China [2].

B60K6/28	F21L4/02	H01M4/98	H01M14/00	H02J7/35
B60L8/00	F21S9/03	H01M8/00	H01M12/00	H02J9/00
B60L53/51	G01R11/02	H01M8/24	H01M12/08	H02J13/00
B60L53/52	H01G9/20	H01M10/44	H01M14/00	H02J15/00
B60L53/64	H01G11/00	H01M10/45	H02J3/28	H02K7/18
F21L4/00	H01M4/86	H01M10/46	H02J7/00	H02S10/00

Table 1. IPC Classification of electric industry

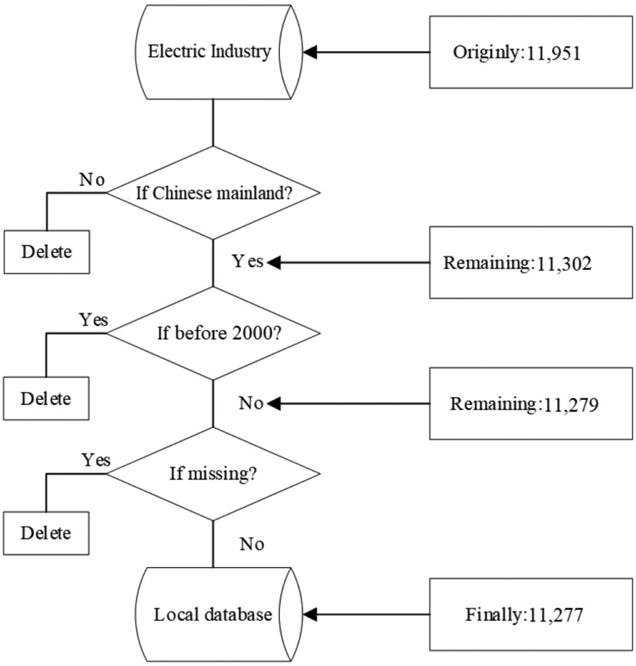

Figure 1. Data cleaning process

Table 2.
Geographical division contained in this paper

Regions	Provincial units
Eastern China	Shandong(SD), Jiangsu(JS), Anhui(AH), Zhejiang(ZJ), Fujian(FJ), Jiangxi(JX), Shanghai(SH)
South China	Guangdong(GD), Guangxi(GX), Hainan(HI)
Central China	Hubei(HB), Hunan(HN), Henan(HA)
North China	Beijing(BJ), Tianjin(TJ), Hebei(HE), Shanxi(SX), Inner Mongolia(IM)
Northwest China	Ningxia(NX), Xinjiang(XJ), Qinghai(QH), Shaanxi(SN), Gansu(GS)
Southwest China	Sichuan(SC), Yunnan(YN), Guizhou(GZ), Xizang(XZ), Chongqing(CQ)
Northeast China	Liaoning(LN), Jilin(JL), Heilongjiang(HL)

Note: The abbreviations shown in parentheses will be used in the following figures and tables

2.2 Methods

First, this paper analyzes the growth trend of electric technology using the calculation method of Hicks *et al.* (2001)and Wang *et al.* (2018), as in equation (1).

$$lnpatnum = a + bt \tag{1}$$

where *patnum* represents the number of granted green invention patents per year and t represents the number of years from 1 to 22. This is a semilogarithmic model, which is a better way to calculate the growth rate than the linear model (Fletcher *et al.*, 2004). The coefficients b in the equation are considered growth rates.

Second, this paper uses spatial autocorrelation method to explain the spatial evolution of electric technology. Consistent with the methods of Shao (2018) and Wang *et al.* (2020), this paper uses the global autocorrelation method to determine whether there is spatial correlation among all research objects based on whether the result of Global Moran's I index is greater than 0, less than 0 or equal to 0 to determine whether the study objects show aggregation, dispersion or random distribution. The calculation formula of the global Moran's I index is shown as follows.

$$Ig = \frac{N\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}\right)\sum_{i=1}^{N}(x_i - \bar{x})^2} (i \neq j) \tag{2}$$

where W_{ij} is the spatial weight matrix, which indicates the topological relationship between spatial units. The matrix is generated by the method of inverse distance matrix of powers of two, and the distance threshold is set to 1,106 km, which is the distance to find at least one proximity element in the division of China's provincial administrative regions (He *et al.*, 2020); x_i and x_j are the observations at spatial locations i and j; N is the total number of elements. $\boldsymbol{I_g}$ takes values ranging from −1 to 1; a significant positive (negative) value indicates that there is a positive (negative) correlation in the spatial distribution, while 0 indicates that there is no spatial autocorrelation.

Then, local Moran's I index can identify spatial clusters and spatial anomalies with statistical significance (Deng *et al.*, 2022). A significant positive value indicates that the element has similar high values (high–high cluster) or low values (low–low cluster) with neighboring spatial elements, while a negative value indicates that the element does not have similar attribute values (high–low outlier or low–high outlier) with neighboring spatial elements. The formula is shown below.

$$I = \frac{(N-1)x_i - \bar{x}}{\sum_{j=1,j\neq i}^{N} (x_j - \bar{x})^2 - (N-1)_x^{-2}} \sum_{j=1,j\neq i}^{N} W_{i,j(x_j - \bar{x})} \quad (3)$$

Finally, this paper explores whether the low carbon pilot policy (LCPC) has a significant effect on the green innovation capacity of electric technology using the time-varying DID model. The marginal effect approach is used to analyze whether this policy effect produces differential results depending on the spatial and temporal differences.

To avoid the impact of artificial time division on the policy evaluation of the time-varying DID analysis, the study period in this paper is broken up into four parts (shown in Table 3) according to the date of the circular of the National Development and Reform Commission of China to each region.

It is noted that the first batch of LCPC in 2010 and the second batch of LCPC in 2012 are oriented to the provincial level, and the availability of relevant data is high; however, the third batch of LCPC in 2017 is implemented mainly at the city level. Therefore, this paper uses the first and second batches of LCPC as quasi-natural experiments and excludes the experimental groups that are not provinces, municipalities directly under the Central Government and autonomous regions. The following econometric model is developed in this paper.

$$grepatent_{it} = \alpha_0 + \alpha_1 D_{it} + X'_{it}\beta + T_t + P_i + \varepsilon_{it}; t = 2010, 2012 \quad (4)$$

where $grepatent_{it}$ represents the number of granted green invention patents in province i in year t; D represents the interaction term, which is "1" if the location is treated by LCPC, and vice versa for "0"; thus, the coefficient α_1 indicates the impact of the LCPC on the green technological innovation. T is a time fixed effect and is used to measure the time trend; P is a regional fixed effect and is used to control for unnoticed characteristics that may affect regional innovation; X' is a set of control variables; and ε_{it} is an error term.

2.3 Variable declaration

In the empirical analysis, the variables were set as described in Table 4, and the data, except for patent data, were obtained from the China Statistical Yearbook.

Periods	Exact date	Implement regions
Period 1	01.01.2000–07.18.2010	None
Period 2	07.19.2010–11.25.2012	GD、LN、HB、SN、YN、TJ、CQ
Period 3	11.26.2012–01.06.2017	BJ、SH、HI
Period 4	01.07.2017–12.31.2021	None

Table 3. Time division and geographical description

"ei" stands for environmental pollution control investment. Because low-carbon technology innovation requires a large amount of capital and has the characteristics of large initial investment and high risk. When the intensity of environmental investment is low, insufficient funds cannot effectively promote low-carbon technology innovation. With the increase in environmental investment, firms and universities will be encouraged to carry out low-carbon technology innovation. Therefore, consistent with the approach of Liu and Sun (2021), environmental investment is selected as a control variable.

"ii" represents the regional innovation capacity, which is influenced by the innovation base, such as R&D personnel participation equivalents, R&D funding and aggregated patent stocks and entrepreneurship in each city (Wiesenthal *et al.*, 2012). The Peking University Open Research Data platform offers scores on regional innovation capacity, which are used as a control variable in the study (Lee *et al.*, 2013).

"is" represents the industrial structure, and this paper uses the ratio of the secondary sector to the current nominal gross domestic product (GDP) to calculate the industrial structure of a region, which is used to illustrate the contribution of the electric sector to the economic development of the region (Tian *et al.*, 2019).

"lngdp" represents the economic growth of the region, which is the logarithm of the GDP; it is important to note that the GDP value are calculated based on the 1989 price index (Zhang *et al.*, 2020).

"fdi" represents the degree of regional openness and is reflected by the actual amount of foreign capital used in the secondary industry (Wang *et al.*, 2022)."pop" refers to the population density of the area, measured by the population size (Kennedy *et al.*, 2014; Creutzig, 2016).

"ci" denotes carbon emission intensity, which refers to carbon emissions generated per unit of GDP growth and is used to quantify the relationship between regional economic growth and carbon emissions (He *et al.*, 2020). This paper uses the method of Lin *et al.* (2018) to calculate the carbon emissions intensity by using the electricity consumption, carbon emission coefficient of each regional electricity grid, annual electricity consumption and regional nominal GDP data.

It should be noted that ei, pop and fdi are logarithmically included in the model during the analysis.

3. Results and discussions

3.1 Overview of electric technology

Figure 2 shows the growth trend of in the electric technology from 2000 to 2021. Generally, despite a downward trend beginning in 2017, electric technology has witnessed amazing growth. The annual number of patents for electric technology has

Variable	Meaning	Mean	Std. Dev.	Min	Max
grepatent	granted green invention patents	16.54	41.42	0.00	426.00
ei	environmental investments	11.59	1.37	4.81	14.16
ii	innovation index	62.00	23.73	1.73	99.97
is	industrial structure	0.42	0.08	0.16	0.62
lngdp	logarithmic value of GDP	8.93	1.28	4.66	11.62
fdi	openness level	1,047.78	1,927.53	0.07	12,027.63
pop	logarithmic value of the total population	8.08	0.86	5.54	9.44
ci	carbon intensity	0.01	0.01	0.00	0.04

Table 4.
Description analysis of variables

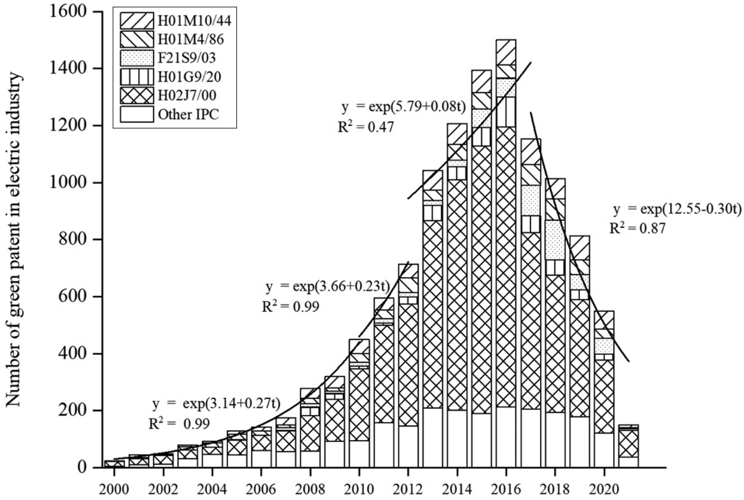

Figure 2.
Growth trend of electric technology from 2000 to 2021

increased from 23 to a maximum of 1,500, representing a 65-fold rise and an average annual growth rate of 8.1%. Specifically, we discover that there are significant differences between stages. From 2000 to 2012, the electric technology exhibits a favorable growth scenario, with an annual growth rate of approximately 25%. Although the growth rate slowed considerably between 2012 and 2017, the patent scale continued to rise. We believe this might be because of the fact that the R&D of science and technology has reached a bottleneck era and enterprises need to make significant advances in critical technologies before they can resume the growth pattern observed prior to 2012. However, from 2017 to 2021, the number of patents began to decline at an annual rate of 30%, and by 2021, the scale of patents had regressed back to 2006 levels. This could be attributed to China's increasingly stringent patent examination system, with an average patent examination period of 19 months. As a result, a portion of the patents in this period are still in the examination phase and are therefore excluded from the granted patent data in this paper, resulting in the fourth period's lowest growth rate.

Additionally, it could also be found from Figure 2 that the top five IPC categories in the electric industry are H02J7/00, H01M10/44, H01M4/86, F21S9/03 and H01G9/20, involving fields like Energy Conservation, Alternative Energy Production and Transportation, with the number of patents accounting for 57.46%, 7.67%, 5.46%, 5.16% and 4.40% of the total, respectively.

The spatial distribution of granted green invention patents in the electric industry is shown in Figure 3. In general, the patent distribution has obvious spatial heterogeneity, with smaller numbers in the north and west and larger numbers in the south and east, denoting that green patents in China's electric industry are mainly distributed in areas with higher economic levels, such as GD, BJ and ZJ. Specifically, patent numbers in the southern region and the eastern coastal region are generally higher than those in the northern and western regions. The distribution of patents in the northern region is mostly concentrated in BJ, TJ, LN, JL, etc. Green patents in the southern region are mostly concentrated in GD, while the green patents in eastern and central China are relatively balanced.

Table 5 provides the distributional features of patent owner types. It can be seen that 72.38% of granted patents for green inventions in China's electric industry originate from

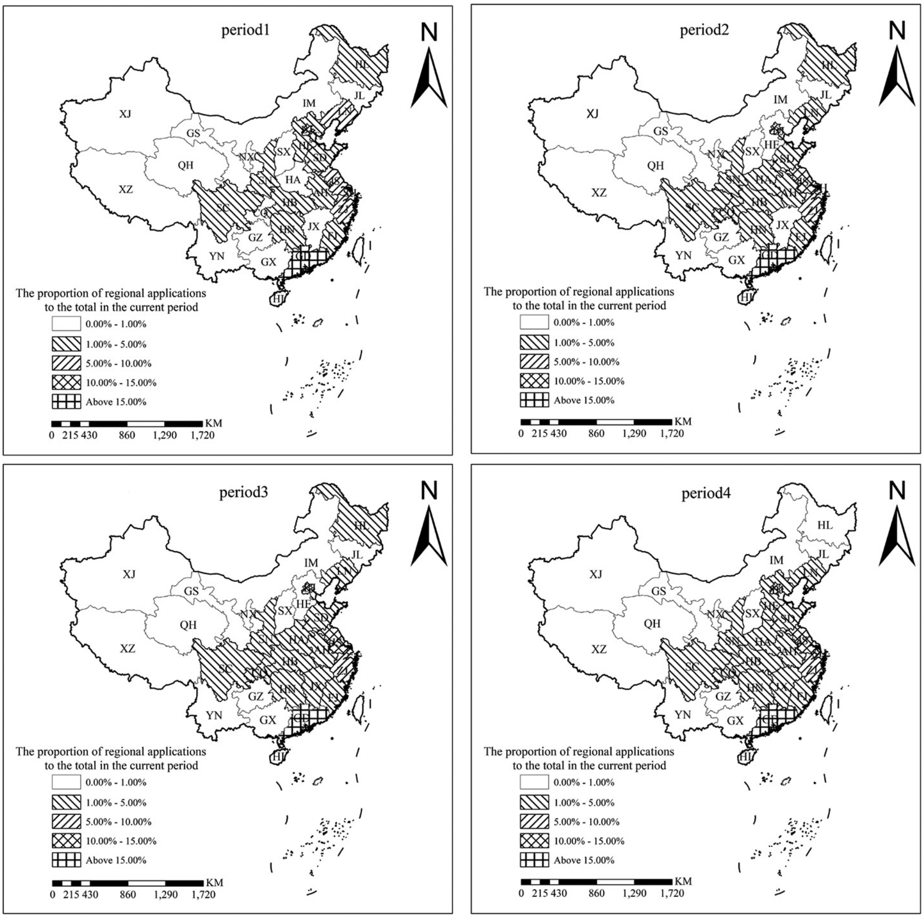

Figure 3.
Spatial evolution of electric technology

Table 5.
Distribution of patent owner types

Categories of applicants	Period 1	Period 2	Period 3	Period 4
Individuals	177 (1.57%)	111 (0.98%)	300 (2.66%)	106 (0.94%)
Firms	777 (6.89%)	944 (8.37%)	3,731 (33.09%)	2,710 (24.03%)
Universities and research institutes	290 (2.57%)	260 (2.31%)	1,086 (9.63%)	785 (6.96%)

firms. The number of patents from universities and research institutions (URI) occupies second place, followed by the individuals. Specifically, the difference in the first and second periods is small. In the third period, however, the number of patents from firms increases by nearly 3.95 times, and the number of patents from URI increases by nearly 4.18 times, indicating that the incentives for China's low-carbon transition policy for URI and firms are quite obvious in this period. In contrast, the fourth period shows a slight decline, which might be attributed to the delay in data inclusion.

Using the same method as Burke and Reitzig (2007) and Fernández *et al.* (2022), this paper evaluates the quality of green patents by *t* patent citations, non-patent citations, the number of patent cooperation treaty (PCT) applications and patent transfers and shows the results in Table 6.

From Table 6, it can be concluded that patent citations and non-patent citations related to Period 3 increased the most compared with the previous two periods, though the trend of the fourth period decreased. The decline trend is seen in the fourth period might be that patent grants require a certain examination time . Therefore, it is believed that, by and large, the general trend of patent quality is growing over time. However, from PCT column, the degree of recognition and discourse of China's patents internationally is relatively weak, which indicates that the whole electric industry needs to further enhance its international competitiveness. The number of patent transfers is relatively low, which may be because of the low number of technology transactions in the electric industry between different firms and between firms and universities. This may be a protective measure generated by firms to ensure industry barriers for the sake of competitive monopolies. However, this can also reflect the low level of technology exchange and the relatively slow progress of industry-academia-research integration.

3.2 Spatial autocorrelation analysis of green electric technology

The spatial distribution of electric technology shows obvious heterogeneity. Therefore, further exploration is needed to determine whether a certain spatial correlation exists for electric industry. Hence, this paper uses a spatial autocorrelation analysis in this section.

The global Moran's I is first used to analyze the global autocorrelation of the distribution of green patents in each province and the specific results are shown in Table 7. When $I > 0$, there is an overall positive spatial correlation; the distribution tends to cluster among regions with similar conditions. When $I < 0$, there is an overall negative spatial correlation; the distribution tends to disperse. In this paper, the significance test of the Moran's I for the four periods shows that the index does not pass the 95% significance test except the last period. The value of index is relatively low, indicating that there is no significant clustering or dispersion of green patents on the whole; that is, the development of electric technology in China as a whole is not significantly influenced by geography.

	Patent citations			Nonpatent citations			PCT		Nr. of patent transferred		
Period	0 (%)	1 (%)	>1 (%)	0 (%)	1 (%)	>1 (%)	Yes (%)	No (%)	0 (%)	1 (%)	>1 (%)
Period 1	1.07	1.36	8.60	8.83	1.29	0.91	0.47	10.56	8.18	2.16	0.69
Period 2	1.33	1.40	8.93	8.18	2.14	1.35	0.71	10.95	8.59	2.39	0.68
Period 3	9.19	8.10	28.09	36.04	5.71	3.63	2.64	42.73	34.92	7.90	2.55
Period 4	16.28	7.18	8.47	24.66	3.65	3.62	1.79	30.14	25.61	5.34	0.98

Table 6. Patent quality analysis

Period	Period 1	Period 2	Period 3	Period 4
Global Moran's I	0.005	0.002	0.014	0.049
Pseudo *p*-value	0.169	0.197	0.132	0.047
Z-value	0.723	0.537	0.796	1.538

Table 7. Results of global autocorrelation analysis

In this paper, after the verification of the global Moran's I, although the results illustrate that there is no clustering of electric technology overall, it cannot be determined whether clustering or dispersion is generated within the local area. Therefore, this paper uses GeoDa software to measure the local Moran's I and draws the local indicators of spatial association (LISA) clustering diagrams, as shown in Figure 4.

Figure 4 shows that the number of regions with weaker green patent innovation capacity in China is much larger than the number of regions with stronger patent innovation capacity at the 5% significance level, which is also consistent with the spatial distribution depicted in Figure 3. Specifically, most provinces in the northwest region (GS, QH and XJ) and the SC region in the southwest region show a significant low–low cluster, and the clustering area gradually expands over time, indicating that the level of green patents in these regions is generally low, which shows a positive correlation in space. Only the ZJ region in East China shows a significant high–high cluster in all four periods, and the neighboring AH region

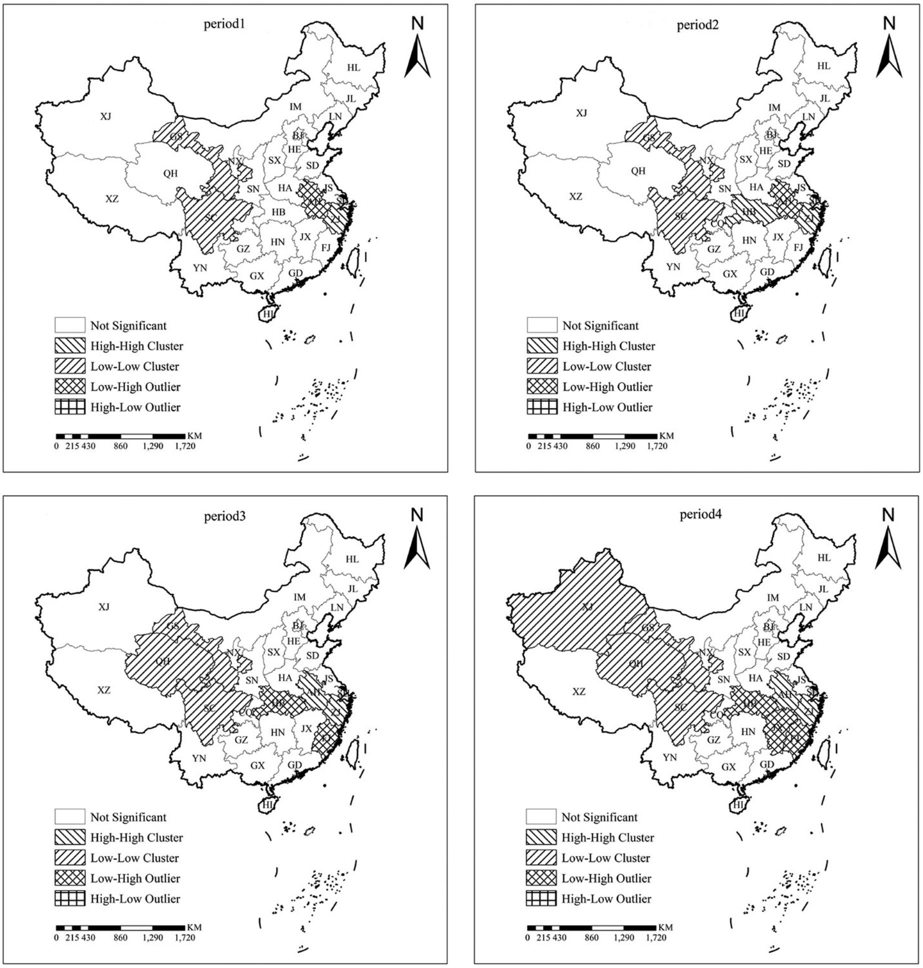

Figure 4.
LISA cluster diagram of green electric technology

changes from low–high outlier in Periods 1 and 2 to high–high cluster in Periods 3 and 4, which indicates that the ZJ region has a higher green patent innovation capability and drives the development of green patent innovation in the neighboring provinces, with a radiation effect.

However, there is also a province with relatively low innovation capacity in East China (for example, the FJ region) that has been showing a low–high outlier from the third period, and the neighboring JX region has also shown a significant low–high outlier in the fourth period. The changes in these regions largely indicate the mutual exclusivity and negative correlation of green patent development among regions, and the stronger coastal innovation provinces have little traction on them. This paper speculates that there is a certain "siphon effect" on the innovation resources of green patents between regions in China. Talents and investments are often concentrated in some developed coastal provinces and cities, and it is difficult to support the development of the rest of the regions. Therefore, this paper argues that the spatial differences in China's green patent innovation capacity are obvious, the linkages between regions are weak, and the green innovation level of most Chinese regions in the electric industry still needs to be enhanced.

3.3 Low-carbon pilot policy analysis

The results of the previous analysis show that there is a relatively significant difference in time and space dimension. Therefore, is the difference caused by the low-carbon pilot policies or because of the random natural formation? To explore the issue, this paper presents the following empirical evidence on the effectiveness of low-carbon pilot policies using the time-varying DID analysis.

3.3.1 Parallel trend test. An important prerequisite assumption of the DID method is that there are no systematic differences between the treatment and control groups prior to policy implementation (Marcus and Sant'Anna, 2021). In this paper, parallel trend tests were conducted from the six periods before the policy implementation and the five periods after the policy implementation (to avoid the impact caused by the third batch of low-carbon pilot cities policy in 2017). The specific results are shown in Figure 5.

From Figure 5, the coefficients of the six periods before the policy implementation are all approximately 0 and contain 0 at the 5% significance level, so it can be concluded that the

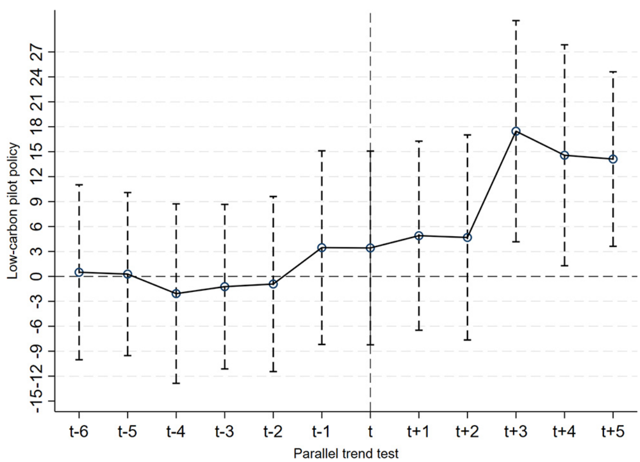

Figure 5.
Parallel trend test

treatment and control groups passed the parallel trend test before the policy implementation and the model premise of the DID method holds. Figure 5 shows that the coefficients in the third period after the t-period (i.e. the policy implementation period) is higher than 0 at the 5% significance level, so the preliminary judgment of this paper is that the LCPC may have a two-period lag effect, which may be because of the fact that it takes time for the government to introduce policies to the concrete implementation, that it takes time for the policies' effectiveness to be transmitted to innovation subjects such as firms and universities and that it takes even more time for these innovation subjects to be encouraged to invent the relevant patents.

3.3.2 Main empirical results. Table 8 shows the results of the baseline regressions, where Model 1 includes only time fixed effects (year), Model 2 includes only regional fixed effects, Model 3 includes both regional and time fixed effects and Model 4 does not include fixed effects. By controlling for regional fixed effects, we can obtain the region-to-region differences that do not vary over time; by controlling for time fixed effects, we can obtain the changes in the explanatory variables caused when the explanatory variables change by time (Xu, 2017; Davies *et al.*, 2008). By invoking the above fixed effects, this paper seeks to derive proof of the effectiveness of the low-carbon pilot policy and to explore whether differences in region or differences in time are responsible for the changes in LCPC effectiveness.

As seen in Table 8, all regression results show that the coefficients of D are positive and significant at the 1% level, which indicates that the LCPC positively promotes the innovation capability for electricity in the pilot regions. The Porter hypothesis suggests that environmental policies enhance green innovation in firms, and it also affirms the role of government in coordinating economic growth with environmental policies (Ciabuschi *et al.*, 2012; Porter and Van der Linde, 1995). Therefore, this paper provides an academic basis for proof of Porter's hypothesis in China. From the coefficients of Models 1 and 4, we find that the inclusion of the time effect decreases the effectiveness of the policy by 2.1 units. From the coefficients of Models 2 and 4, we find that the inclusion of regional fixed effects increases policy effectiveness by 4.76 units. That is, the spatial factor affects the positive increase in LCPC effectiveness, while the temporal factor has a smaller and possibly negative effect on effectiveness (Hu and Jefferson, 2009).

3.3.3 Marginal effect analysis. This paper finds that the effectiveness of the LCPC produces different results based on regional and temporal differences. Therefore, a DID marginal analysis is conducted to explore the differences in the effectiveness of LCPC for

Table 8. Impact of the LCPC on green innovation capability

	Model (1)	Model (2)	Model (3)	Model (4)
D	15.89*** (3.63)	22.75*** (5.48)	20.86*** (5.39)	17.99*** (3.93)
ie	−4.405** (1.92)	1.742 (1.64)	−1.960 (1.50)	−2.412 (1.50)
ii	0.623** (0.27)	0.0292 (0.14)	−0.0856 (0.15)	−0.0212 (0.20)
is	126.4*** (41.68)	−115.6*** (20.24)	−104.6*** (23.78)	−3.743 (18.14)
lngdp	−42.88*** (12.50)	0.781 (3.66)	−0.737 (4.21)	−3.741 (4.82)
fdi	0.0199*** (0.00)	0.0162*** (0.00)	0.0166*** (0.00)	0.0197*** (0.00)
pop	125.1*** (24.57)	3.374 (2.69)	8.016** (4.06)	124.4*** (25.14)
ci	−600.5*** (163.10)	132.6 (110.16)	140.4 (115.27)	−763.5*** (166.60)
constant	−624.0*** (198.83)	0.0443 (9.73)	−2.226 (10.08)	−953.6*** (194.47)
Region	No	Yes	Yes	No
Year	Yes	No	Yes	No
adj. R-sq	0.81	0.67	0.68	0.79

Notes: Standard errors in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

specific regions and specific time points, taking an approach consistent with Wheeler *et al.* (2018). As mentioned above, the number of patents in GD has the highest share among the four periods, so GD is used as the benchmark in the regional difference analysis in this paper. The year 2010 is the first year of policy implementation, so this paper selects it as the benchmark for the year difference analysis.

According to the results on the left side of Figure 6, it could be seen that the coefficients are different under different regions, which indicates that there is significant spatial heterogeneity in the effectiveness of the LCPC in the experimental regions. Specifically, first, GD receives the lowest effect of the LCPC, although it is the region with the most granted green invention patents in electricity, while HI, as a low-level region, receives the best effect of policy incentives. Second, we find that the northern region (TJ, BJ) is slightly better stimulated by the LCPC than the southern and central regions (GD, HB) and the difference between the eastern region (SH) and the western region (CQ, YN) is not significant.

According to the results on the right side of Figure 6, it could be found that there is a significant difference between the coefficients before and after the two LCPC implementation years in 2010 and 2012, which indicates that although both LCPCs have a positive impact on the innovation capability in electricity, the magnitude of the impact is different. Combining with the results of parallel trend test that the LCPC may have a two-period lag effect, the reason may be that the research and development of green patents in the electric industry was just starting and needed certain research results as a foundation. Moreover, the LCPC is a relatively new low carbon strategy, and time is needed for the government and firms to adapt (Zhou *et al.*, 2022).

Then, to comprehensively explore the spatiotemporal evolution of LCPC effectiveness, this paper multiplies the interaction terms of regional differences and year differences to conduct marginal analysis. Because the direct use of year data would cause multicollinearity, this paper draws on the four periods previously divided as time effects and introduces the interaction term with the regional location effects into the marginal analysis to obtain the results in Figure 7.

It could be seen from the results in Figure 7 that, limiting the same region, there is a certain difference in the positive impact of the LCPC on innovation capability between the two times and the magnitude of this difference varies according to the change in the area. When limiting the same period, the LCPC presents significantly different results on the enhancement of different regions and this differential result will change according to the change of the period. Specifically, the coefficients of GD, TJ and BJ represent that LCPC effectiveness do not overlap under the four periods, while the coefficients of other regions overlap. In summary, this paper concludes that there are significant spatiotemporal

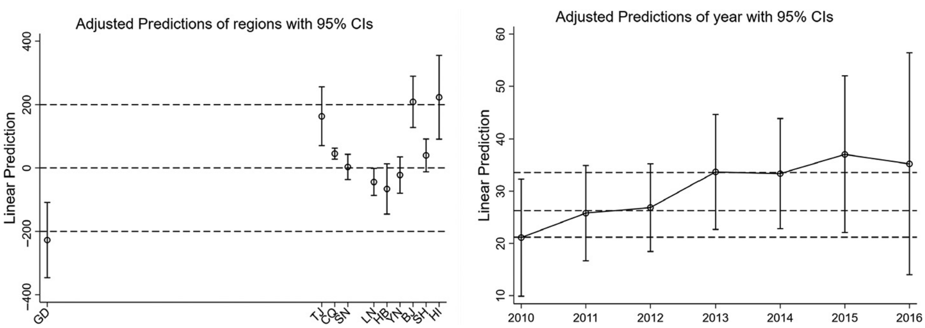

Figure 6.
DID marginal analysis for regions and years

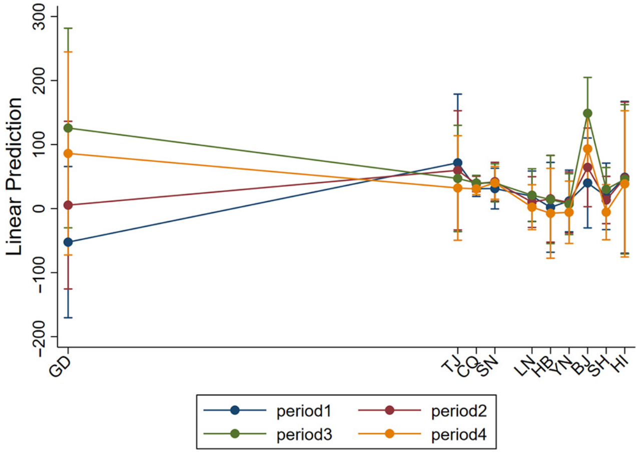

Figure 7.
DID marginal analysis for the interaction of regions and years

differences in the positive impact of the LCPC on innovation capability, i.e. the LCPC differentiated results for different periods and regions. The Chinese Government needs to continuously adjust and improve the LCPC in practice to better achieve the goal of low-carbon development.

4. Conclusions

This paper uses the 2000–2021 granted green invention patents in the electric industry in mainland China to analyze the spatiotemporal evolutionary characteristics of electric technology in the context of low-carbon transformation. Specifically, the research analyzes the growth rate of patents, patent IPC categories, patent owner types, patent values, patent spatial distribution and clustering and the influence of LCPC on green innovation capacity. The study yielded the following results. First, the development of the electric industry under the low-carbon background is remarkable, and the average annual growth rate is 8.1%, but the growth rates in different periods have significant differences, with the highest being 27.1% and the lowest being −30.1%; the spatial distribution of patents has obvious heterogeneity, indicating slower growth in the north and west and faster growth in the south and east; the quality of patents has been significantly improved, but international recognition is still weak.

Second, there is no obvious spatial correlation of electric technology on the whole, but there is a clustering and siphoning phenomenon in the local region, exhibited mostly by low–low clustering in the west and high–high clustering in the southeast.

Third, low-carbon policy (LCPC) has a significant positive impact on green innovation capacity, but there are variances in the time-space evolution process of policy efficacy, and the policy has a two-period lag effect.

This article derives the following policy implications from these findings. First, green patents in the electric industry are spatially heterogeneous, with weak links between regions and the green innovation capability in most regions still needs to be developed. To achieve balanced development, the Chinese Government should take steps to help developing regions and boost technological exchange between developed and developing regions.

Second, the government should create a favorable R&D environment for firms, universities and research institutions through institutional design to increase the enthusiasm of innovation subjects, enhance the quality of green technology innovation in the electric industry and provide technical support and assurance for the achievement of low-carbon development.

Third, low-carbon policies must be continuously adjusted and improved in practice, including the gradual exploration of programs suitable for different development stages and regions and the implementation of differentiated low-caron policies for different time periods and regions to better achieve environmental and economic goals.

Finally, there are some shortcomings in this paper. For example, this paper mainly studies the evolution of the number of granted green invention patents in China's electric industry for low carbon based on time and space, and only simple statistics and descriptions are provided for the R&D subjects and patent quality. Therefore, it fails to reveal the different roles of LCPC for R&D subjects and the effectiveness of enhancing the quality of patents, which will be taken as the future research direction in this paper.

Notes

1. www.gov.cn/zhengce/2020-12/27/content_5574237.htm
2. www.gov.cn/zhengce/2020-12/27/content_5574237.htm

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