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Impact of policies on wind power innovation at different income levels: Regional differences in China based on dynamic panel estimation

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ABSTRACT

Based on the expanded two-factor learning curve and adopting dynamic panel methods, we explored the driving effects of policies and policy interaction on wind power technology innovation (TIW) at different developmental levels using panel data for the period 2006–2017 in 29 provinces in China. To reveal regional heterogeneity, we classified the 29 Chinese provinces into two regions based on the 2017 per capita gross domestic product. The results indicated that public research and development policy plays the most significant role in driving TIW for all samples. We only confirmed the positive interaction effect of policies for middle-income provinces (Region 2). Additionally, the learning-by-doing effect for TIW in China was identified, though the magnitude of that effect was much smaller than that of the learning-by-searching effect. Finally, the regional differences in the impacts of different policy instruments provide new insights for future policy design to effectively promote TIW.

1. Introduction

To cope with climate change and alleviate the constraints of energy shortage, China is striving to develop renewable energy technology to achieve sustainable development. Renewable energy is also considered to be one of the most important ways to beautify the ecological environment, enrich household energy supply, and reduce the economic burden of residential commercial energy consumption [1]. According to the 2017 Innovation Report for Clean Technology, China has risen to eighteenth place. Wind power is regarded as the most cost-effective and mature technology in the renewable energy field. In the context of policy implementation, the wind power scale is growing rapidly in China, and its importance in the global power structure is increasing annually. China's cumulative wind power capacity reached 188,392 MW at the end of 2017, ranking first worldwide. China has taken the lead in terms of the scale of its wind power industry. However, there are still deficiencies in wind power technology innovation (TIW), which are reflected in the low learning rate, few international patents, limited external contribution, and so on [2–4]. Therefore, it is of great significance to study the factors affecting innovation for wind power technologies in the current context.

In wind power development, the huge upfront investment required and positive externalities easily result in market failure. Thus, the government can promote TIW by reducing market uncertainty and providing financial support. Many studies have confirmed that policy exerts very important effects on TIW [5,6]. However, because of the unbalanced regional distribution with respect to wind power in China [7]—for example, the central and eastern regions are energy load centers, but they lack energy resources, while the western regions are rich in energy resources but are relatively backward in economic development—the current policies have heterogeneous effects on TIW in different regions. However, little research has been conducted on the heterogeneous mechanism of policies on TIW in different regions of the same country. Therefore, the heterogeneity effect of policies on TIW in different regions of China needs to be fully explored as a research topic.

It is stipulated that all regions in China should be classified into four categories of resource areas for wind energy according to the status of wind energy resources, and the benchmark feed-in tariff (FIT) is formulated accordingly. However, due to the great differences in coal power prices in different regions, there is a large difference in the subsidy tariff for wind power among regions [8]. Additionally, wind power investors tend to emphasize the cost of power generation rather than the

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demand when selecting investment sites. Installed wind power capacity is mainly concentrated in the northern and western regions of China, which leads to the unbalanced regional distribution of wind power and, thus, the high wind power reduction rate in recent years [7]. In these areas, the blind expansion of wind power will instead inhibit TIW. Therefore, the FIT policy presents heterogeneity for TIW in different regions. Additionally, public research and development (R&D) policies may have different driving effects on TIW in different regions. Regions with higher income levels tend to attract more high-tech talent and enterprises due to their superior industrial chain and higher absorption of knowledge and technology. Therefore, public R&D policy should have higher innovation efficiency in regions with higher income levels.

Although many factors affect renewable energy technological innovation, including innovation investment [9], policy incentives [10,11], and multiple learning mechanisms that contribute to the creation and diffusion of new technologies, such as learning-by-searching [12,13] and learning-by-doing [14,15], this study selected per capita income (using per capita gross domestic product [GDP] as a measure) as the criterion for different regions on the basis of literary support, and this division based on different income levels has important practical significance. Many studies have shown that the economic benefits of wind power innovation are mainly reflected in the creation of employment opportunities and increased local income levels [16–18]. Further studies have shown that the main driving forces of wind power innovation in China seem to be economic growth and perceived economic benefits rather than concerns about climate change [19]. Studies have also shown that income levels significantly positively impact renewable energy innovation and that the wind power development level in high-income regions and countries is higher [20,21]. Studies on China have found that the degree of innovation and diffusion of wind power in China show obvious regional heterogeneity due to the different income levels of residents in different regions [22]. The impact of renewable energy policies also shows obvious regional heterogeneity [23]. Best and Burke [24] found that government policies may be more important for energy innovation in low- and middle-income regions in recent years.

In view of the vast territory and the quite large variance in population income, education level, and economic development level in different regions in China and considering that the demand and technological R&D for wind power is correlated with the local income level, in order to explore the regional heterogeneity of the impact of policies on TIW, this study divided all regions into two groups according to the per capita GDP, namely the high-income region and the middle-income region. This study explored the mechanism of policies and other factors related to TIW in the national sample and sub-regional samples, emphasizing the regional heterogeneity in the driving effects of policies and providing targeted policy recommendations.

This research contributes to the field as follows. First, this study considers the heterogeneity of policy innovation effects among regions with different income levels. Ignoring the regional differences in policies could lead to huge financial waste and may even inhibit industrial development. Therefore, it is of great theoretical and practical significance to examine the heterogeneous role of policies and their interaction with TIW in different regions in order to formulate targeted policies to promote innovation effectively. Second, considering the strong persistence of renewable energy technology innovation and breaking through the limitations of the negative binomial model, this study attempted to use the dynamic panel model, which is not only conducive to estimating the innovation effect of policy stability but also solves the problematic effects of deviation caused by potential endogeneity and omitted variables on the model's results.

The remainder of this paper is arranged as follows. Section 2 summarizes the findings of a literature review. Section 3 details the research design. Section 4 presents the results. Section 5 discusses the results. Finally, Section 6 draws conclusions and proposes policy suggestions.

2. Literature review

To explore the influencing factors of renewable energy technological innovation, scholars have made important contributions and proposed that the factors include policy, energy price, learning effect, and policy stability.

Among them, most studies have concluded that public R&D support belongs to technology-push policies and significantly impacts innovation for renewable energy [25,26]. First, due to the high investment risk, high upfront capital cost, and a longer payback period, private R&D investment in renewable energy is insufficient. Under such circumstances, public R&D support can reduce costs to cope with these serious market failures and compensate for the lack of private R&D to effectively drive innovation for renewable technologies [27]. Second, by providing financial support to directly stimulate patent innovation activities, public R&D support has the strongest inducing effect on renewable energy technological innovation [5]. Third, Klaassena (2005) has asserted that public R&D support can provide knowledge accumulation for innovation activities in the current period by producing a learning-by-searching effect and indirectly improving the ability to engage in and the efficiency of technological innovation, but some studies have argued that public R&D support has played a weaker role in innovation for comparatively mature technologies, such as wind power [28,29,83].

As a demand-pull policy, FIT provides fixed production support for high-cost renewable energy technology and avoids direct competition with other energy sources [30]. Some scholars believe that the impact of FIT policy on technological innovation is significantly positive [5,31] because it can promote the expansion of the renewable energy market and facilitate professional enterprises' entry into this industry [32]. Other scholars found that the FIT mechanism distinguishes the subsidy size of renewable energy power plants according to energy sources, the level of technology used, and the scale or location of power plants, or a combination of these considerations [33], and hence, the policy cost is relatively high [34]. Böhringer et al. [28] found that under the Renewable Energy Sources Act, the incentive effect of the FIT mechanism to promote innovation in renewable energy technologies in Germany has declined, thus challenging the policy's cost-effectiveness. Some studies have confirmed that the FIT policy's driving effect on TIW is insignificant [35,36], while other studies have indicated that the implementation effect of the FIT policy is heterogeneous due to the different stages and costs of different renewable energy technologies [26,37]. For example, Johnstone et al. [26] showed that the FIT policy had a significant negative impact on innovation in mature technologies with cost competitiveness (e.g., wind power) but played a significant positive role in innovation in costly energy technologies (e.g., solar energy). However, Lindman and Söderholm [6] argued that the driving impact of FIT policy on innovation in renewable energy technologies will become more significant as the technology matures. Therefore, there is no consensus on the effect of the FIT policy.

The innovation process is complex and nonlinear. Innovation can be induced not only by tacit knowledge obtained in the process of technology use, which the FIT policy encourages, but also through basic knowledge creation, which public R&D policy encourages [38]; that is, innovation is characterized by the iterations between the learning-by-using effect and the R&D process, and public R&D policy will effectively promote learning-by-using through the introduction of new technology, so as to promote future R&D activities. In contrast, the FIT policy stimulates the diffusion of new technology, and enterprises often uncover new problems and opportunities in the process of learning-by-using to improve the return rate on public R&D support [39]. Some studies have shown that the interaction of public R&D and FIT policies on renewable energy innovation is significantly positive [30,40].

Many studies have confirmed significantly positive impacts of policy stability on renewable energy technological innovation in different countries [41,42], such as Buen [43] for Denmark, Wiser et al. [44] for the United States and western Europe, and Söderholm et al. [45] for Sweden. Liang and Fiorino [46] verified that the stability and intensity of public R&D policies both positively impact patent applications in different renewable energy sectors. However, the results showed that in the long term, the effect of policy stability is often stronger than that of policy intensity.

The effect of scale on innovation level and quality is positive [47]. Some scholars chose installed renewable energy capacity as the measurement indicator for scale [48,49]. Installed capacity has been proven important in promoting innovation for renewable energy technologies [48]. This is because installed capacity has a learning effect on TIW [49], specifically the learning-by-doing effect.[1]

In the course of studying the relationship between energy consumption and technological innovation, scholars have affirmed the induced effect of energy consumption demand [51,52]. Economic growth will increase demand for energy consumption, and demand for energy consumption will stimulate energy efficiency improvement or energy structure upgrade, leading to technological innovation [51]. Increased electrical energy consumption drives the continuous improvement of the operation efficiency of electrical power production equipment to meet the consumption demand so that "hard" technological progress, such as technological inventions and technical process innovations, can bring innovation to the electrical power industry.

In sum, most of the relevant literature focuses on the following. First, in the context of different power markets or different industry policies, scholars have explored the similarities and heterogeneity of various factors' innovation effects [29,37,53]; second, focusing on different sources or stages of renewable energy technologies, scholars have examined the heterogenous impact of policies on innovation [5,37,54]. However, little research has considered the regional differences in policy innovation effects in the same power market and under identical industry policies. Different economic development levels and different institutional environments lead to different industrial structures as well as variance in the energy structure and regional governance levels in different regions, resulting in heterogeneity in the implementation contexts of policies in different regions [55]. Additionally, considering the unbalanced layouts of wind power industrial development in different regions [7], it is urgent to further explore the regional differences in the impact of policies and their interactions on TIW. Moreover, because the number of patent applications is excessively discrete, most literature uses the negative binomial model as the estimation method [25,26]. However, the negative binomial model cannot estimate the impact of policy stability or the cumulative effect on technological innovation, which has certain limitations.

3. Methods

3.1. Model

This section constructs a dynamic panel model for TIW based on learning curve theories. Argote and Epple [50] proposed the one-factor learning curve (OFLC) model for analyzing determinants of the reduction of technological investment costs:

$$TIC_{nt} = \delta_0 \cdot CC_{nt}^{-\alpha} \tag{1}$$

where TIC is total investment cost; CC represents cumulative capacity; $-\alpha$ denotes learning indicator; and δ_0 denotes the specific cost for each unit of cumulative capacity. This model implies that the unit investment cost will decrease with increased cumulative capacity.

By differentiating from Eq. (1), we get the logarithmic form as follows:

$$\ln TIC_{it} = \ln \delta_0 - \alpha \ln CC_{it} + \varepsilon_{it} \tag{2}$$

Where learning rate (LR) is defined as $1 - 2^{-\alpha}$ and is often used to express a constant percentage reduction in the investment cost when cumulative capacity doubles [36]. The OFLC regards cumulative capacity as the only variable to explain the reduction in technology costs (i.e., only considering the learning-by-doing factor) and ignores other factors, so it is often one-sided. In fact, in addition to the learning-by-doing factor, the learning-by-research factor (i.e., technology-push policies, usually measured according to public R&D policy) also plays an important role. Specifically, public R&D policy can introduce high-end talent and advanced technologies, thus contributing to the enhancement of industries' independent innovation ability. Hence, it will be very meaningful to analyze the role of public R&D support in the reduction of technology costs.

Based on this, some recent studies [40,53] have expanded the OFLC and proposed the two-factor learning curve (TFLC), holding that, in addition to cumulative capacity, public R&D policy also exerts important impacts on technology cost reduction. Compared with the OFLC, the TFLC can estimate the learning-by-searching rate, indicating the effects on technology cost reduction when public R&D support, RD_{it}, doubles (often calculated as $1 - 2^{-\beta}$). The logarithmic form of the TFLC model is as follows :

$$\ln TIC_{it} = \delta_0 - \alpha \ln CC_{it} - \beta \ln RD_{it} + \varepsilon_{it} \tag{3}$$

Considering that technological innovation (expressed above in terms of technology cost reduction) may also be significantly influenced by demand-pull policies (expressed in terms of the FIT subsidy policy) and the interaction between technology-push policies and demand-pull policies (expressed in the interaction of FIT subsidy policy and public R&D policy; [6]) and that over the long term, electricity consumption significantly positively impacts innovation [52], we expanded the TFLC model by including the FIT subsidy policy, policy interaction, and electricity consumption. The logarithmic form of the TIW model can be expressed as:

$$\begin{aligned} \ln TIW_{it} = {} & \beta_0 + \beta_1 \ln CC_{it} + \beta_2 \ln RD_{it} + \beta_3 \ln RETS_{it} + \beta_4 \ln RD_{it} \cdot \ln RETS_{it} \\ & + \beta_5 \ln EC_{it} + \alpha_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

Where I and t represent the region and time, respectively; TIW represents wind power technology innovation, measured by the number of patent applications related to wind power; CC and RD are cumulative capacity and public R&D policy, respectively; RETS represents the FIT subsidy policy, measured according to the renewable energy tariff surcharge subsidy (RETS); EC is electricity consumption; and $\ln RD_{it} \cdot \ln RETS_{it}$ denotes the interaction of the FIT subsidy policy and the public R&D policy. Here, α_i represents the time-invariant unobservable individual fixed effects (FE) and ε_{it} denotes the error term. In this study, the unobservable individual fixed effect α_i refers to province heterogeneity (time-invariant). ε_{it} refers to the error term.

Additionally, some scholars believe that the innovation process is gradual and cumulative and can bring breakthrough results through gradual accumulation [56]. Decision-making regarding promoting TIW should be a continuous process, not a short-term choice. Therefore, it is necessary to adopt dynamic methods because of the persistence of TIW.

According to the TFLC, public R&D support has time lag effects on knowledge stock. Similarly, there may be a time lag regarding when wind power enterprises' FIT subsidy can actually be transformed into power for TIW, and there exists a time lag between the installation of capacity and the availability of the power for TIW. In view of this, in the dynamic panel model, we considered the lag effect of the FIT subsidy policy, the public R&D policy, their interaction, and cumulative capacity

[1] The expansion of installed capacity brings about the expansion of industrial scale, thus stimulating industrial technological innovation; this phenomenon is called the learning-by-doing effect [50]. Cumulative capacity is regarded as the main factor for technology cost reduction in the learning curve model.

regarding innovation. Additionally, some scholars adopted lag variables to reduce potential endogeneity under lag = 1 [49]. Thus, the complete dynamic panel model for TIW can be expressed as follows:

$$\ln TIW_{it} = \beta_0 + \beta_1 \ln TIW_{i,t-1} + \beta_2 \ln CC_{i,t-1} + \beta_3 \ln RD_{i,t-1} + \beta_4 \ln RETS_{i,t-1} + \beta_5 \ln RD_{i,t-1} \cdot \ln RETS_{i,t-1} + \beta_6 \ln EC_{i,t-1} + \alpha_i + \varepsilon_{it} \quad (5)$$

Compared with Eq. (4), Eq. (5) adds the lagged dependent variable as the explanatory variable. Additionally, the lagged term RD, RETS, policy interaction and CC are used as the explanatory variables, and the definitions of other variables are the same as in Eq. (4). Moreover, all price-related variables (RD, RETS) were deflated by Consumer Price Index (2006 = 1), and each variable was standardized using the natural logarithm method. To avoid multicollinearity, the interaction term is centralized.

3.2. Variables

This section presents the measurement methods and indicators of relevant variables.

3.2.1. Explained variables

Compared with other proxies, patent application counts is sustainable, discrete, and can effectively measure innovation; it is thus regarded as a good indicator for measuring innovation [26]. The three types of patents in China are invention patents, utility model patents, and design patents. Given that invention patents are of the highest quality and can therefore better reflect the level of innovation, this study selected invention patent counts as the indicator for measuring innovation. It should be noted that the International Patent Classification codes for wind power are F03D and B63H13/00. Additionally, since only the patents that successfully complete the publication procedure are true and effective, the invention patent counts collected on the publication date was selected as the proxy for TIW in this study.

3.2.2. Explanatory variables

This research mainly studied the driving effect of demand-pull and technology-push policies as well as the policy interaction of the two on TIW. First, the primary targeted demand-pull policy for the wind power industry was the FIT policy. However, considering that FIT data for wind power in China's provinces are not available, some literature used a dummy variable to measure FIT policy [25]. This study attempts to introduce proxies from the perspective of FIT subsidies. Therefore, considering the data availability and representativeness, this study adopted RETS[2] as the proxy for demand-pull policies. The data for RETS were calculated by referring to the method He et al. [48] described.[3]

Additionally, R&D support is the key driver for renewable energy technology innovation [30]; however, data on R&D support for wind power in China's provinces are unavailable. Therefore, referring to Lin and Chen [52] and Liu et al. [57]; this study selected the provincial total R&D expenses, which is similar to the trend of R&D support in wind power. There are three main sources of R&D support: the government, enterprises, and foreign investment. Among them, governmental public R&D support better reflects provincial governments' policy support of R&D on wind power technologies [25,57]. Therefore, this study selected public R&D expenses as the indicator for measuring technology-push policies.

Considering that innovation is a complex process, public R&D support promotes innovation by contributing to the increase of basic knowledge stock, and the FIT subsidy policy will promote the use and diffusion of new technologies so as to promote innovation by contributing to increased tacit knowledge [38]. Obviously, the combination of the two policies may have an important interaction effect on TIW, a notion that Palage et al. [30] have supported. Thus, we should not only examine the individual effects of policies on TIW but also evaluate policies in combination. Hence, this study introduces the interaction term of public R&D support and renewable energy tariff subsidies to verify the policy interaction effect on TIW.

3.2.3. Control variables

Given the increasing market scale of China's wind power, the country's installed wind power capacity is presently the largest in the world. According to the OFLC [50], wind power project investment costs can be reduced through the construction and application of wind power equipment, thus promoting TIW. Therefore, this study introduces installed capacity as a control variable to verify the OFLC. Additionally, some scholars believe that the increasing electricity consumption trend will make wind power more competitive, thus leading to TIW [52].

3.3. Data source and description

This study used a balanced panel dataset from 29 provinces in China, except Hong Kong, Macao, Taiwan, Tibet, Hainan, and Chongqing, for the period 2006–2017. Hainan and Chongqing were not included in the sample in view of their negligible installed capacity and patent application counts in wind power. Hong Kong, Macao, Taiwan, and Tibet were excluded due to data availability issues. We focused on the following provinces: Guizhou, Hebei, Guangdong, Guangxi, Hubei, Hunan, Heilongjiang, Jilin, Liaoning, Ningxia, Xinjiang, Zhejiang, Yunnan, Shandong, Henan, Shanxi, Inner Mongolia, Anhui, Hainan, Fujian, Shaanxi, Gansu, Qinghai, Jiangxi, Beijing, Tianjin, Shanghai, Jiangsu, and Sichuan. Finally, given that the renewable energy tariff subsidy policy has been implemented since 2006, 2006 was set as the starting point for our study.

The data were derived from the Statistical Yearbook and Annual Report series. Among them, patent application counts were derived from the State Intellectual Property Office of China's database. Data on electricity sales required for the renewable energy tariff surcharge subsidy (RETS) were obtained from the China Yearbook of Electric Power (2007–2018). The rate of RETS was obtained from the National Development and Reform Commission's policy notice. Public R&D expense data were obtained from the China Science and Technology Statistical Yearbook (2007–2018). Installed wind power capacity data were derived from the Annual Report for Electricity Regulation (2006–2017). Finally, data reflecting residents' average electricity consumption were obtained from the National Bureau of Statistics. The definitions of all variables are shown in Table 1.

Table 2 provides descriptions of the variables. This study's panel sample comprises 336 observations from 29 provinces in China within the period 2006–2017. The "average" refers to the average of the full complement of regional data from 2006 to 2017. Average TIW was 39.04 pieces; average RD was 577292.31$\times 10^4$ yuan; and average RETS was 131851.70$\times 10^4$ yuan.

[2] The National Development and Reform Commission issued a circular proposing to levy a renewable energy tariff subsidy (RETS) nationwide (excluding Tibet and rural power) as of June 30, 2006, premised on the acknowledgment of the uneven distribution of renewable energy resources and the resultant idea that the high cost of renewable energy power generation should be shared nationwide. The Interim Measures for Renewable Energy Tariffs and Cost Sharing Management clearly stipulate the mode of cost sharing as follows: "The difference between the FIT for renewable energy power and the benchmark FIT for local desulfurization thermal power shall be shared among the electricity sold at the provincial power grid and above."[25]

[3] The formula for RETS is as follows: Electricity sales of the power grid in each province = electricity consumption of the whole society by region - electricity consumption of the first industry - electricity consumption of residents: Renewable energy tariff subsidy (RETS) = electricity sales of power grid in each province * the rate of RETS.

Table 1
Definition of variables.

Variable	Definition	Unit
Wind power technology innovation (TIW)	Wind power technology-related patent application counts collected on the publication date	pieces
Technology-push policies (RD)	Governmental public R&D expenses	Ten thousand yuan
Demand-pull policies (RETS)	Renewable energy tariff surcharge subsidy	Ten thousand yuan
Cumulative capacity of wind power (CC)	Installed wind power capacity	10 MW
Electricity consumption (EC)	Electricity consumption per region	100 million kWh

Table 2
Description of variables.

Region	Variable	Obs	Mean	Std. Dev	Min	Max
All regions	TIW	348	39.04	56.55	0	359
	RD	348	577292.31	904793.72	6984.96	6074387.33
	RETS	348	131851.70	176784.64	1168.67	960790.00
	CC	348	232.26	414.65	0	2670
	EC	348	1563.568	1192.896	97.68	5958.97
Region 1	TIW	180	58.66	70.00	0	359
	RD	180	841632.76	1133004.31	10561.25	6074387.33
	RETS	180	157330.81	211511.20	1707.04	960790.00
	CC	180	237.21	447.24	0	2670
	EC	180	1894.955	1402.633	377.85	5958.97
Region 2	TIW	168	16.40	17.04	0	85
	RD	168	272284.11	334817.18	6984.96	1813752.12
	RETS	168	102452.73	119409.47	1168.67	550506.00
	CC	168	211.8119	365.1061	0	1836
	EC	168	1208.51	776.4277	97.68	3441.74

This study explored regional differences in the complex effects of policies on TIW. Specifically, referring to the World Bank's new standard[4] on per capita gross national income (GNI), issued in 2018, we confirm that China as a whole has crossed the threshold of upper-middle-income countries. Therefore, taking Hunan province as the watershed, 29 provinces were divided into two groups instead of considering three or more groups: high-income provinces (Region 1) and middle-income provinces (Region 2). According to the 2017 per capita GDP, the groupings are as follows:

- Region 1: High-income regions. GDP per capita in 2017 > 5.0 × 104 yuan. Fifteen provinces: Shanghai, Beijing, Tianjin, Guangdong, Fujian, Jiangsu, Zhejiang, Shandong, Hubei, Inner Mongolia, Shaanxi, Jilin, Liaoning, Ningxia, and Hunan. Average TIW was approximately 59 pieces; average RD was 841632.76 × 104 yuan; average RETS was 157330.81 × 104 yuan.
- Region 2: Middle-income regions. GDP per capita in 2017 = 2.4247–5.0 × 104 yuan. Thirteen provinces: Gansu, Yunnan, Guizhou, Shanxi, Guangxi, Heilongjiang, Anhui, Qinghai, Sichuan, Xinjiang, Jiangxi, Henan, and Hebei. Average TIW was approximately 16 pieces; average RD was 272284.11 × 104 yuan; average RETS was 102452.73 × 104 yuan.

As indicated in Table 3, in high-income regions, TIW, RD, and RETS are relatively high. In middle-income regions, TIW, RD, and RETS are relatively low. High-income regions mean higher public R&D expenses as well as more human capital. Moreover, in high-income regions, enterprises have stronger independent innovation awareness and vitality, and the institutional environment to foster innovation is superior. Additionally, considering the positive correlation between power consumption and economic growth and the fact that the long-term trend between the two is basically the same, electricity sales in high-income regions will significantly outpace that of middle-income regions. RETS is calculated based on each province's electricity sales, so the RETS revenue of wind power enterprises in high-income regions will also be significantly higher than that in middle-income regions. In sum, it is not difficult to see that the level of TIW in high-income regions is much higher than that in middle-income regions (as shown in Table 2, the average level of TIW in Region 1 is close to four times that in Region 2).

4. Results

The estimation was conducted in two steps to examine the heterogeneous impacts of policies on TIW in regions with different income levels. We first estimated effects over all regions, and then we estimated for the two defined regions.

In this study, pooled ordinary least squares (OLS; Model 1), FE (Model 2), system generalized method of moments (GMM-SYS; Model 3), and least squares dummy variable corrected (LSDVC; Model 4) were employed. In the case of unobservable heterogeneity, the pooled OLS or FE model for Eq. (5) will lead to biased and inconsistent estimators,

Table 3
Comparison of the characteristics of regions with different income levels.

Region	TIW	RD	RETS	CC	EC
Region 1	High	High	High	High	High
Region 2	Low	Low	Low	Low	Low
All regions	Moderate	Moderate	Moderate	Moderate	Moderate

[4] According to the standard the World Bank released in 2018, the income grouping standard is as follows: low-income countries with a per capita GNI below USD 995, lower middle-income countries with a per capita GNI between USD 996 and USD 3,895, upper middle-income countries with a per capita GNI between USD 3896 and USD 12,055, and high-income countries with a per capita GNI higher than USD 12,055. According to the average exchange rate of yuan to USD in 2018, which was USD 100 = 661.74 yuan, and the 2018 GDP per capita index, which was 106.3 (compared to 100 in the previous year), the corresponding thresholds are as follows: low income <6194 yuan, lower middle income 6194–24,247 yuan, upper middle income 24,247–77,037 yuan, and high income >77,037 yuan. Given that Gansu, the province with the lowest per capita GDP in 2017 (29,326 yuan), has crossed the upper middle-income threshold, we confirm that China as a whole has crossed the threshold of upper middle-income countries. However, considering the balanced distribution of the number of provinces in the sub-sample, this study took the province of Hunan (where the 2017 GDP per capita was 50,563) as the watershed between the sub-samples of middle- and high-income regions, and for convenience, we rounded the thresholds to the nearest 1000. Thus, our GDP per capita threshold is 50,000 yuan.

resulting in distorted economic implications. Specifically, because the lagged term of the dependent variable is related to α_i (individual fixed effect), we can prove that the pooled OLS estimation for the lagged dependent variable will be biased upward; to eliminate the individual fixed effect (α_i), FE estimation is employed as the standard method and will be biased downward even in the case of no serial correlation for the error term. These biases cannot be eliminated even if more explanatory variables are included in the equation. For the dynamic panel model, only when $T \rightarrow \infty$, can FE estimation provide consistent and effective estimators. However, the micro panel data set we used belongs to a short panel (i.e., T is generally small).

For these reasons, Arellano and Bond [58] proposed adopting the first-differenced transformation of Eq. (5) to eliminate the influence of individual FE (i.e., province FE), but at this time, the main difficulty in estimating the first-differenced form of Eq. (5) lies in the correlation between the difference term of the lagged dependent variable and that of the error term, namely the endogeneity issue. Arellano and Bond [58] proposed replacing instrumental variable (IV) estimation with difference GMM estimation, and they employed all possible higher-order lagged variables (i.e., all variables with two lag periods or more) as the IV matrix. The precondition for the consistency of difference GMM estimation is that no second-order autocorrelation for the difference term of the error term can be identified.[5]

However, in the case of high persistency of the dependent variable in the difference GMM model, the use of the higher-order lagged variables as the IVs for the differenced variables will lead to the problem of weak IVs. This is because when the dependent variable is highly persistent, the differenced variables are almost zero, and the correlation between the higher-order lagged variables, and the differenced variables will become very weak. Therefore, the higher-order lagged variables used in the difference GMM become weak IVs. Additionally, for a short panel (i.e., a panel with more cross-sectional dimension than time dimension), the validity of difference GMM estimation will be further weakened. Therefore, in the above two cases, GMM-SYS outperforms difference GMM [59]. Moreover, Blundell et al. [60] also indicated that difference GMM estimation has largely limited sample deviation and very low accuracy. In these cases, the difference GMM estimation for the lagged dependent variable has a strong downward bias, and its deviation direction is the same as that of the FE estimator [61].

As we will see in this study, the high persistence hypothesis is applicable to TIW. Therefore, the GMM-SYS method was chosen. GMM-SYS is equivalent to the simultaneous combination of the first-differenced equation and the original level equation, using the higher-order lagged variables (variables with two lag periods and above)[6] as the IVs for the first-differenced equation and the lag term for the differenced variable as the IV for the original level equation [59].

There are three test statistics in the GMM-SYS model. One is the Hansen test, which can be employed to test whether there are over-identifying restrictions, that is, to test the validity of IVs. The other two test statistics are for serial correlation (SC), that is, SC_1 and SC_2, which can be employed to test whether there is a first-order or second-order serial correlation in the error term, respectively. It is generally considered that under the hypothesis of zero serial correlation, the GMM-SYS estimators gradually follow the standard normal distribution. We will report test statistics for the Hansen test and for SC_1 and SC_2 when presenting the preliminary regression results to test the validity of the IVs and the serial correlation of the first- and second-order in the error term.

In the case of high persistence of the dependent variable, the LSDVC method can also be employed. This method begins with dynamic estimation and is completed with recursive correction of the bias of the FE estimation [62]. Based on the Monte Carlo simulation, Bruno [63] proved that LSDVC estimation outperforms GMM estimation when the number of individuals is small and when the panel is seriously unbalanced. Although GMM estimation is more suitable for our all-region sample, which belongs to a typical short panel (the timespan is obviously less than the number of cross sections), we still chose LSDVC estimation as the mode of comparison, considering that the short panel characteristics of the Region 1 sample and the Region 2 sample are not obvious (the timespan is relatively similar to the number of cross sections).

To test the multicollinearity, this study applied the variance inflation factor (VIF) test and found that the mean VIF value is 3.25, and the highest value is 5.53; given that these are less than six, there is no serious multicollinearity in these variables. All variables passed the stationarity test. Tables 4 and 5 show the estimated values for all regions, as well as for Regions 1 and 2, according to the above estimation methods. As discussed, we mainly focused on the test results of GMM-SYS (Model 3) and employed the other three methods as a reference to test whether the estimated results are robust.

Table 4 shows the estimations for all regions using the above four methods. According to the above, the real parameter for the lagged dependent variable should be greater than the result of FE estimation and less than that of pooled OLS estimation. Obviously, the result of the GMM-SYS meets the requirements and is consistent with the LSDVC estimation, which indicates its relative robustness.

The coefficient of $\ln TIW_{t\text{-}1}$ is 0.362 and is significant at the 5% level. On the one hand, it shows the persistency of TIW due to the inertia of the innovation environment and behavior; on the other hand, it can be seen that through the accumulation of knowledge or experience, technological innovation in previous periods will promote innovation output in the current period.

The coefficient of $LnCC_{t\text{-}1}$ is 0.144, which is significant at the 10% level, confirming the learning-by-doing effect on TIW. According to the learning rate formula, the learning-by-doing rate (LDR) is 10.30%, which indicates that the unit investment cost of wind power decreases by 10.30% for each doubling in cumulative capacity.

The coefficient of $LnRD_{t\text{-}1}$ is 0.231, which is significant at the 1% level. The large coefficient of public R&D support indicates that for all regions in China, public R&D policies have a very important impact on supporting TIW, a finding that many scholars support [30,37].

The coefficient of $LnRETS_{t\text{-}1}$ is −0.236, which is insignificant, showing that the effects of the FIT subsidy policy on TIW are insignificant, which is consistent with Johnstone et al. [26] and Emodi et al. [35]. The coefficient of $LnRD_{t\text{-}1}\_lnRETS_{t\text{-}1}$ is 0.028, which is insignificant, showing that the interaction effect of the FIT subsidy policy and the public R&D policy is not obvious. Moreover, our finding is consistent with the implementation status of FIT policy in China, where most of the subsidies granted under the current domestic FIT policy are used to maintain wind power production and operation [64],[7] and technology R&D investment in wind power is limited, especially with the expansion of installed capacity; there is a great gap in RETS, which cannot form an effective innovation incentive mechanism. Therefore, for the all-regions sample, the driving role of the FIT subsidy policy is unsatisfactory.

The coefficient of $\ln EC_{t\text{-}1}$ is 0.204 and is significant at the 1% level, indicating that TIW is significantly enhanced with EC. Our results are consistent with Li and Chen [52].

Table 5 shows the regression results of the model with two lags. In particular, the impact coefficients f for $LnTIW_{t\text{-}2}$ and $LnRD_{t\text{-}2}$ are 0.598

[5] Arellano and Bond [58] proposed the test method for the second-order autocorrelation of the differenced error term in their model.

[6] Similar to the difference GMM estimation method.

[7] According to the Trial Measures for the Administration of the Feed-in Tariff and Cost Sharing for Renewable Energy [82], renewable energy tariff surcharge subsidy funds are used to subsidize the gap between the FIT for renewable energy and the benchmark FIT for local desulfurization thermal power, the grid connection cost, and the operation cost subsidy for an independent renewable energy power system.

Table 4
Estimation results: TIW model for all regions.

Variables	Pooled OLS (M_1)	Pooled OLS (M_1)	FE (M_2)	FE (M_2)	GMM-sys (M_3)	GMM-sys (M_3)	LSDVC (M_4)	LSDVC (M_4)
$LnTIW_{t-1}$	0.567***	0.546***	0.238***	0.174***	0.366**	0.362**	0.318***	0.289***
	(0.04)	(0.05)	(0.05)	(0.05)	(0.08)	(0.07)	(0.05)	(0.05)
$LnCC_{t-1}$	0.02	0.023	−0.003	−0.013	0.120*	0.144*	0.007*	0.008*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.07)	(0.07)	(0.03)	(0.03)
$LnRD_{t-1}$	0.295***	0.318***	0.217*	0.320**	0.215***	0.231***	0.290**	0.111*
	(0.04)	(0.04)	(0.14)	(0.14)	(0.06)	(0.06)	(0.12)	(0.06)
$LnRETS_{t-1}$	−0.05	−0.048	0.140**	0.110*	−0.212*	−0.236	0.103*	0.373
	(0.03)	(0.03)	(0.06)	(0.06)	(0.08)	(0.09)	(0.06)	(0.14)
$LnEC_{t-1}$	0.302***	0.017***	0.353***	0.633***	0.208***	0.204***	0.188	0.063*
	(0.06)	(0.01)	(0.49)	(0.22)	(0.06)	(0.06)	(0.08)	(0.09)
$LnRD_{t-1}\_lnRETS_{t-1}$		0.317**		0.044**		0.028		0.024
		(0.06)		(0.01)		(0.01)		(0.01)
Constant	−3.939***	−4.314***	−4.347***	−7.129***				
	(1.48)	(0.55)	(1.44)	(1.63)				
Arellano-Bond test for AR (1)					z = −4.25***	z = −4.29***		
Arellano-Bond test for AR (2)					z = 2.95*	z = 1.90*		
Hansen test					24.96	25.10		
Observations	319	319	319	319	319	319	319	319

Notes: Standard errors are shown in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 5
Estimation results: TIW model for all regions (Two-period lag).

Variables	GMM-sys (M_3)	GMM-sys (M_3)	LSDVC (M_4)	LSDVC (M_4)
$LnTIW_{t-2}$	0.604***	0.598***	0.307***	0.275***
	(0.09)	(0.08)	(0.06)	(0.07)
$LnCC_{t-2}$	0.019	0.021	−0.005	−0.005
	(0.06)	(0.06)	(0.04)	(0.03)
$LnRD_{t-2}$	0.206***	0.210***	0.255	0.345**
	(0.13)	(0.05)	(0.16)	(0.17)
$LnRETS_{t-2}$	−0.147**	−0.146*	0.124*	0.137**
	(0.13)	(0.07)	(0.07)	(0.07)
$LnEC_{t-2}$	0.270***	0.268***	0.125	0.061
	(0.07)	(0.06)	(0.12)	(0.12)
$LnRD_{t-2}\_lnRETS_{t-2}$		−0.045***		0.028
		(0.11)		(0.02)
Arellano-Bond test for AR (1)	z = −3.75***	z = −3.56***		
Arellano-Bond test for AR (2)	z = 1.57	z = 1.31		
Hansen test	20.29	22.39		
Observations	290	290	290	290

Notes: Standard errors are shown in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

and 0.210, respectively, and are significant at the 1% level. This is consistent with the above findings, but the Arellano-Bond test for AR (2) is not significant, and the significance of the coefficients of the interaction term is not consistent with the regression significance of the LSDVC model, demonstrating that there is no higher-order autocorrelation in the GMM model at this point and that the results are not robust to some extent. Although the above findings are confirmed to some extent, we still use the lagged one-period model as the main study model.

Table 6 shows the estimated results for the two defined regions. For Region 1, except for $LnTIW_{t-1}$, the coefficient of $LnRD_{t-1}$ is the greatest (0.138) and is significant at the 1% level, and the coefficient of $LnTIW_{t-1}$ is 0.432 and is significant at the 1% level. Therefore, for Region 1, public R&D support is the important driver for TIW, which can confirm the learning-by-searching effect. Furthermore, the coefficient of $LnRETS_{t-1}$ is −0.113 and is not statistically significant; the coefficient of $LnRD_{t-1}\_lnRETS_{t-1}$ is 0.020 and is not statistically significant. Therefore, for Region 1, the sole use of the FIT subsidy policy has played a weak role in inhibiting TIW, and even if combined with public R&D policy, the driving role of policy interaction is not obvious. The coefficient of $LnCC_{t-1}$ is 0.006 but is not statistically significant and thus cannot confirm the learning-by-doing effect. Similar to the results for all regions, the coefficient of $LnEC_{t-1}$ is 0.118 and is significant at the 5% level, showing that electricity consumption still has a significant positive effect on TIW.

The results for Region 2 are similar to those for Region 1. Generally, public R&D support has important incentive effects on TIW (the coefficient is 0.181), confirming a significant learning-by-searching effect. The persistence of TIW is confirmed at the 1% level. The coefficient of $LnCC_{t-1}$ is only 0.151 and is not statistically significant and thus cannot confirm the learning-by-doing effect. The coefficient of $LnEC_{t-1}$ is 0.440 and is significant at the 5% level, which shows that residential electricity consumption is significantly positively correlated with TIW. The difference between Regions 1 and 2 mainly lies in the specific effect of the FIT subsidy policy on TIW: The coefficient of the policy interaction term ($LnRD_{t-1}\_lnRETS_{t-1}$) is 0.026 and is significant at the 10% level. Therefore, for Region 2, the sole application of the FIT subsidy policy plays an insignificant role in TIW, and when combined with public R&D policy, it will play a significant role in driving TIW.

Therefore, across all regions, as well as for Regions 1 and 2, respectively, we have confirmed that public R&D policy is an important driver for TIW, while the individual effect of FIT subsidy policy is not significant; as for the interaction effect of the two policies, we cannot confirm the existence of a positive policy interaction effect for all regions and Region 1, but for Region 2, we can confirm the existence of a positive policy interaction effect. Additionally, for all regions and subregions, we have confirmed the high persistence of TIW and the significant driving effect of electricity consumption on TIW.

In the regions with different income levels defined above, the impact of the FIT subsidy policy alone and its interaction with public R&D policy on TIW show heterogeneity, which is not completely consistent with the income category. Other factors, such as the market structure of the wind power industry and human capital, may be the key reasons for these heterogeneities, which will be the direction of future research.

5. Discussion

There are several interesting findings based on the results.

First, for all regions, this study confirms that public R&D support is the important factor driving TIW (at a 1% significance level). Besides public R&D support, cumulative capacity has significant positive effects on TIW at the 10% level, indicating that increased installed capacity also promotes TIW to a certain extent. This shows that both public R&D support and cumulative capacity can promote TIW while simultaneously highlighting the learning-by-searching and learning-by-doing effects for all regions.

However, for Regions 1 and 2, this study has failed to verify the OFLC and can only verify the driving impact of public R&D support on

Table 6
Estimation results: TIW model for Region 1 and Region 2.

Variables	Region 1				Region 2			
	Pooled OLS (M_1)	FE (M_2)	GMM-sys (M_3)	LSDVC (M_4)	Pooled OLS (M_1)	FE (M_2)	GMM-sys (M_3)	LSDVC (M_4)
$LnTIW_{t-1}$	0.556***	0.206***	0.432***	0.291***	0.441***	0.050	0.382***	0.166**
	(0.06)	(0.07)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)
$LnCC_{t-1}$	0.004	0.100*	0.006	0.099*	0.043*	−0.121*	0.151	−0.113*
	(0.03)	(0.05)	(0.03)	(0.06)	(0.02)	(0.04)	(0.04)	(0.05)
$LnRD_{t-1}$	0.311***	0.397*	0.138***	0.364	0.276***	0.448**	0.181***	0.179**
	(0.05)	(0.22)	(0.03)	(0.25)	(0.06)	(0.27)	(0.05)	(0.08)
$LnRETS_{t-1}$	−0.046	−0.06	−0.113	−0.085	−0.018	0.194**	−0.152	0.497**
	(0.05)	(0.12)	(0.05)	(0.14)	(0.05)	(0.08)	(0.07)	(0.20)
$LnRD_{t-1}\_lnRETS_{t-1}$	0.001	0.022	0.020	0.022	0.032	0.105***	0.026*	0.059**
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
$LnEC_{t-1}$	0.368***	0.863	0.118**	0.810	0.348***	0.846***	0.440**	0.484**
	(0.07)	(0.54)	(0.05)	(0.61)	(0.10)	(0.28)	(0.15)	(0.23)
Constant	−4.51***	−8.28**			−4.23***	−10.58***		
	(0.82)	(4.14)			(0.73)	(2.06)		
Arellano-Bond test for AR (1)			Z = −2.49***				Z = −3.10***	
Arellano-Bond test for AR (2)			Z = 1.54				Z = 1.51	
Hansen test			13.81				11.33	
Observations	151	151	151	151	139	139	139	139

Notes: Standard errors are shown in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

innovation in the TFLC model. Whether for Region 1 or 2, public R&D policy is the important and significant factor driving TIW. In contrast, cumulative capacity has no significant driving effect on TIW. It can be seen that China is still in the early large-scale development stage with regard to renewable energy; at this stage, public R&D policy will have significant driving effects on renewable energy technological innovation. Many studies support this [30,37,49]. Specifically, in the early stage of TIW, if there is high uncertainty regarding the results of R&D activities, wind power manufacturers are likely to under-invest in technologies [65]. Technology-push policies, such as public R&D support, can effectively reduce this uncertainty, stimulate manufacturers' innovation power, and promote TIW [66].

Across all regions and sub-regions (Regions 1 and 2), the driving effect of cumulative capacity on TIW is relatively weak (the coefficients of cumulative capacity for all regions and for Regions 1 and 2 are 0.144, 0.006, and 0.151, respectively), and for Regions 1 and 2 in particular, the driving effects are not statistically significant. This shows that the learning-by-doing effect is obviously weaker than the learning-by-searching effect for China. Specifically, increased installed wind power capacity through the accumulation of experience and knowledge among wind power manufacturers does not significantly contribute to innovation incentives for China's wind farms. On the contrary, innovation activities are mostly driven by public R&D support. Hayashi et al. [67] have confirmed this. Some recent studies have indicated that the learning-by-searching ratio (LSR) for wind power is typically higher than the LDR in the TFLC [68,69]. In particular, Söderholm and Klaassen [40] implied an LDR of 3.1% and an LSR of 13.2%. This means that the driving impact of public R&D policy on TIW is obviously higher than cumulative capacity, which coincides with this study's results.

Second, the coefficient of $LnRETS_{t-1}$ is negative and insignificant for all regions; for Regions 1 and 2, the coefficient of $LnRETS_{t-1}$ is also negative and insignificant. This implies that the individual effects of the FIT subsidy policy on TIW are not significant.

The results for Regions 1 and 2 are consistent with Johnstone et al. [26] and Emodi et al. [35]; who argued that FIT subsidies have no significant effect on driving more mature technology innovation, such as TIW. Presently, the insignificant impact of the FIT subsidy policy on TIW is due to the following.

First, wind power FIT does not consider the factors of price decline and wind turbine technological progress (the investment cost of wind power has presented a declining tendency, falling from 6500 yuan/kWh in 2008 to about 3500 yuan/kWh in 2012), so it will bring excessive compensation and protection to wind power operators, which is not conducive to TIW [70]. Second, with the expansion in the installed capacity scale for wind power, the burden of FIT subsidy for wind power is too heavy to issue the tariff subsidy on schedule, which affects the operation of the entire wind power industry chain,[8] causing the whole wind power industry to fall into a vicious circle of low-level production [8]. Third, the form of wind power FIT leads to the heterogeneity of the implementation effect of FIT subsidy policy in different regions. The FIT of wind power adopts the form of benchmark FIT for local coal-fired units plus subsidy tariff. However, the price of coal power varies greatly by region. For instance, the price of coal power is significantly lower in Xinjiang, Yunnan, Gansu, and Inner Mongolia, while that in Guangdong, Shanghai, Zhejiang, and other eastern regions is significantly higher, which means that the subsidy tariff of wind power in different regions is quite different. For regions with a high coal power price (these regions basically belong to Region 1), the incentive of wind power FIT subsidy is weak and may even play a weak inhibitory role, while for regions with a low coal power price (these regions basically belong to Region 2), the incentive of FIT subsidy policy is somewhat strong [7]. Fourth, under the high monopoly level, the role of the FIT subsidy policy in promoting TIW will be inhibited [71]. Given the increasing concentration of the wind power industry in China, Qin [72] has argued that the wind power industry market in China has evolved into an oligopoly market (by 2017, China's top five wind turbine manufacturers accounted for 67.1% of the market share of new installed capacity),[9] and in the case of an oligopoly market, the innovation effect of wind power FIT subsidy policy is not significant. Additionally, our conclusion is consistent with recent research [73] arguing that in areas with better wind power resource endowment, the FIT policy incentivizes low-productivity plants' entry into the industry, while the growth rate of plants with a higher production technology level decreases; that is, the FIT policy intensifies the distortion of resource misallocation in the wind power industry, which is not conducive to TIW.

Departing from the general view that FIT policy has an innovation incentive effect on wind power technology, Guo and Yin [74] have argued that with industry maturity and the widened subsidy gap, the gradual reduction of wind power FIT subsidy can effectively force technological progress and cost reduction in enterprises; we also believe

[8] Given that the subsidy cannot be recovered, wind power operation enterprises default on payment with respect to wind power whole-machine enterprises, which, in turn, default on payment with respect to components enterprises, forming a debt triangle.

[9] The data are from Qianzhan Industry Research Institute.

that the lowering of the wind power FIT subsidy level may be conducive to TIW. This explains why the coefficient of $LnRETS_{t-1}$ is negative for all regions.

Third, regarding the interaction of RETS and public R&D support, for the national sample and Region 1, the interaction of the two policies has no significant driving effect on TIW; the interaction is significantly positive (at the 10% level) for Region 2 only. This shows that in Region 2 only, where a middle-income level is prevalent, the interaction effect of FIT subsidy policy and public R&D policy plays a significant role in driving TIW, and the interaction effect of the two policies has obvious regional heterogeneity. This result is consistent with the reality of the wind power industry in China; that is, the varied dependence of different wind power resource zones[10] on the FIT policy results in different policy interaction effects in different regions. Generally, the regions with richer wind power resources tend to have higher policy dependence [74], while those with rich wind power resources mostly coincide with regions with a middle-income level. Therefore, compared with Region 1, Region 2 has a greater dependence on the FIT policy, and this greater policy dependence means a greater interaction effect of policies, which leads to regional heterogeneity in the interaction effect of wind power FIT policy and public R&D policy on TIW.

Relevant research also confirms the conclusion [75] that in those middle-income provinces that rely excessively on renewable energy FIT subsidy policy, increasing local renewable energy public R&D support is the most powerful factor in enhancing the renewable energy promotion effect. Hence, regarding the FIT subsidy policy on renewable energy technology innovation in middle-income provinces rich in wind power resources, more attention should be paid to improving the level of public R&D support. This conclusion also confirms that in provinces rich in renewable energy resources, government policies, including public R&D support policies, play a very important role in renewable energy technological innovation [76].

Fourth, across all regions, as well as Regions 1 and 2, respectively, the coefficient of electricity consumption is significantly positive, which indicates that TIW will increase as energy consumption needs increase. This is consistent with Lin and Chen [52]; who hold that energy consumption has an important positive impact on inducing renewable energy innovation.

Our finding is also supported by Brookes and Grubb [51]; who have argued that the demand for electrical energy consumption will stimulate the upgrading of industrial structure and trigger technological innovation in industries related to the production of electrical energy while improving the efficiency of electrical energy consumption. Given the increased demand for power consumption, the power industry continues to climb the value chain, abandoning low-value-added production equipment and processing. Through the introduction of technical equipment, improvements to power energy efficiency can continue.

Fifth, the coefficients of $LnTIW_{t-1}$ are 0.362, 0.432, and 0.382 for all regions and Regions 1 and 2, respectively, with a 5% significance level for all regions and a 1% significance level for Regions 1 and 2, indicating the persistence of TIW. Generally, both the intensity and stability of government financial support policies have positive effects on renewable energy technological innovation. However, in the long run, the driving effect of policy stability is more significant than policy magnitude [46]. Conversely, the uncertainty of financial support policies will increase the capital cost, thus delaying investment decisions, which is not conducive to renewable energy technological innovation [77]; hence, reducing policy instability is an important criterion for effective renewable energy policy [42]. In terms of wind power technology, sustainable policies supporting a sizable and stable wind power market are most likely to improve the competitiveness of the wind power industry, effectively driving TIW [78].

6. Conclusions

6.1. Conclusions and policy suggestions

We employed a dynamic method to explore the policies influencing TIW in 29 provinces of China from 2006 to 2017. To examine the regional endogeneity in the complex effects of policies and other factors on TIW, we classified the 29 provinces into two regions based on the 2017 per capita GDP. To study the interaction effect of public R&D policy and FIT subsidy policy, we introduced the interaction term of the two policies into the TFLC model. We also included electricity consumption to explore the impact of energy consumption. Therefore, we expanded the TFLC to explain the complex relationship among cumulative capacity, public R&D support, FIT subsidy, policy interaction, electricity consumption, and TIW so as to reveal the regional endogeneity in the driving effects of policies and other factors on TIW, further explore the deep-seated reasons for the differences, and provide governments in regions with different income levels with targeted policy suggestions on more effectively promoting TIW. Furthermore, four estimation methods (pooled OLS, FE, GMM-SYS, and LSDVC) were employed to obtain more precise estimates for all regions and two sub-regions.

First, across all regions, as well as for Regions 1 and 2, it can be confirmed that public R&D support is a significant and important factor driving TIW, which indicates that China is still in the primary large-scale development stage with respect to wind power. Given the improvement in public R&D expenses, the level of TIW will be significantly improved. This conforms to the technology-push theory [79], which assumes that technological innovation is mainly driven by a supply-side linear process from R&D to innovation. Second, for Region 2, the coefficient of FIT subsidy is −0.152, but it is not significant; for all regions and Region 1, the coefficient is weakly negative and not significant. Thus, it can be concluded that the effect of the FIT subsidy on TIW is not significant. This is supported by Emodi et al. [35] and Söderholm and Klaassen [40]. Third, we verified the learning-by-dong effect for TIW in China (the coefficient of $LnCC_{t-1}$ is 0.144, 0.006, and 0.151, respectively, for all regions and for Regions 1 and 2). We also confirmed that the driving effect on TIW of learning-by-doing is much weaker than that of learning-by-searching, which Jamasb [80] supports. Mainly, electricity consumption has significantly positive effects on TIW (the coefficients of $LnEC_{t-1}$ are 0.204, 0.118, and 0.440, respectively, for all regions and for Regions 1 and 2).

Moreover, referring to Table 7[11] and Jamasb's [80] proposal, we can confirm that for all regions and sub-regions (Regions 1 and 2), TIW is currently in the period of transition from the evolving stage of

Table 7
Technology development indicators in various innovation stages.

Development stage of technology	Learning by doing	Learning by searching	Market opportunities
Mature	Low	Low	High
Reviving	Low	High	High
Evolving	High	High	Low
Emerging	Low	Low	Low

Source: Jamasb [80].

[10] The government classifies China into four categories of wind power resource zones according to the status of wind power resources and project construction conditions and establishes the wind power benchmark FIT mechanism accordingly.

[11] Table 3 indicates, in another way, that emerging technologies present totally different effects of R&D (learning-by-research), FIT subsidy (market opportunities), and installed capacity expansion (learning-by-doing) across various innovation stages.

technological development to the reviving stage, and at this stage, public R&D support is still the most important driver for TIW, while the driving role of FIT subsidy (representing market opportunities) is not significant. Although in this transitional stage, the learning-by-doing effect (namely, the driving force of cumulative capacity) still has a positive impact on TIW, its magnitude is significantly smaller than that of the learning-by-searching effect (namely, the driving force of public R&D support).

The following policy suggestions are proposed based on the results of this study.

First, effective measures should be taken to strengthen public R&D support for wind power technologies. According to our findings, public R&D policy has important incentive effects on TIW for all regions and sub-regions. Moreover, the existence of policy interaction in Region 2 has confirmed that the combination of FIT subsidy policy and public R&D policy has superior performance in terms of stimulating TIW. To improve the utilization efficiency of R&D funds, on the one hand, the government should strive to reduce the uncertainty of R&D return caused by information asymmetry, while on the other hand, the government should design a public R&D plan in combination with its practical application.

Second, the decline mechanism of wind power FIT should be formulated based on technological innovation and market supply and demand. Presently, the wind power FIT subsidy policy in China belongs to the fixed FIT mechanism[12] and has limited incentive impacts on TIW. With wind power technological development, the high degree of protection of the wind power industry may hinder technological progress in the long run, and excessive subsidies to wind power enterprises will negatively impact technological innovation [40]. Therefore, it is suggested that the government formulate a wind power FIT mechanism that can promote technological innovation. Specifically, we should determine the FIT through competition, have the FIT gradually decline, and strive to realize on-grid wind power parity so as to promote continuous cost reduction in the industry and more effectively promote TIW.

Third, it is advisable to formulate targeted wind power FIT policies and policy combinations to adapt to the heterogeneity of different regions. According to the results, in Region 2, policy interaction has a significant positive impact on TIW, while for all regions and Region 1, the impact of policy interaction is not significant, which shows that the policy interaction effect presents significant regional endogeneities. To some extent, the differences in the impact of wind power policies are attributed to the obvious regional heterogeneity of provinces with different income levels in aspects of industrial structure, industrial monopoly, energy market liberalization, regional governance level, and environmental awareness [29,37]. Therefore, it is necessary to formulate targeted wind power FIT policies and policy combinations based on the heterogeneity across individual regions. The current wind power FIT subsidy policy in China is formulated by dividing all regions into four categories of resource areas according to the local wind energy resources and project construction conditions, a classification system that has some defects. Therefore, it is suggested that based on regional heterogeneity and focusing on technological innovation, local governments emphasize guiding wind power investors' decision-making from the demand side [7] and formulate a wind power FIT policy that stimulates innovation to promote balanced regional development. Moreover, in view of multiple policy failures, regarding systems and institutions, it is necessary to conduct multi-faceted policy intervention in renewable energy development using a combination of policy tools as opposed to a single policy tool because the interaction effect of policy tools can provide more clear and systematic solutions to the multiple failures that have been experienced. According to our results, the interaction of the FIT subsidy policy and public R&D policy can effectively drive TIW in Region 2.

Fourth, electricity consumption can maintain the same frequency with technological innovation in the wind power industry. Electrical energy consumption, in a sense, represents economic growth; that is, economic growth can pull the electrical energy demand and thus drive technological innovation in the wind power industry. This enlightens the provinces with low power and energy consumption and slow economic growth to actively engage in technical exchanges and cooperation with provinces with high power and energy consumption and fast economic growth.

Fifth, it would be beneficial to establish a long-term policy mechanism while actively exploring various incentivizing means. The importance of policy stability to technological innovation cannot be ignored. Presently, the wind power industry in China is in the process of transforming from the protection of infant industries to long-term incentives, and the policy mechanism and means need to be further improved [74]. Therefore, it is suggested that the government strive to reduce policy fluctuations and establish a long-term policy mechanism.

6.2. *Research gaps and outlook*

Since the National Bureau of Statistics of China has not specifically released the R&D expenditure for the wind power industry, the measurement for public R&D support policy used in this study is drawn from Lin and Chen [52]; and total investment in R&D activities was used as an indirect measurement for it, creating certain limitations. Additionally, independent variables such as environmental policy stringency, population density, and education level have not been included in this study but do represent future research directions.

Author statement

Zhengxia He: Conceptualization, Data curation, Writing- Original draft preparation. **Changshuai Cao:** Methodology, Software, Supervision. **Leyi Kuai:** Visualization, Investigation. **Yanqing Zhou:** Software, Validation. **Jianming Wang:** Writing- Reviewing and Editing.

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[12] Presently, the FIT for wind power in China = the benchmark FIT for local coal-fired units + subsidy tariff, which is essentially a fixed FIT mechanism. In comparison, although Germany has also implemented a fixed FIT mechanism for wind power, the FIT for wind power = initial fixed FIT + the annual decrease in the tariff, which takes the factors of technological progress into account; Spain implements a premium mechanism for wind power, where the price higher than a certain level of the electricity market price is regarded as the actual FIT for wind power; Denmark implements a tariff subsidy policy, where the FIT for wind power = market electricity price + tariff subsidy. Generally, a fixed FIT policy may be problematic in terms of risk sharing and benefit distribution because it is separated from the market signal, while a premium mechanism for wind power FIT can alleviate this problem because it is connected with the market price signal. The tariff subsidy policy is most closely connected with the market signal, which is equivalent to providing additional revenue for wind power without changing the market competition rules. Hence, the fixed FIT mechanism for wind power in China has limited incentive effects on stimulating TIW because it is difficult for this fixed mechanism to reflect the technological progress of wind power since it is separated from the market signal. However, it is conducive to TIW for the wind power FIT policies implemented in Germany, Spain, and Denmark because these policies reflect technological progress or introduce the market bidding mechanism [81].

Declaration of competing interest

None.

Data availability

Data will be made available on request.

References

[1] B. Zhu, W. Zhang, J. Du, W. Zhou, T. Qiu, Q. Li, Adoption of renewable energy technologies (RETs): a survey on rural construction in China, Technol. Soc. 33 (3–4) (2011) 223–230.

[2] J. Gosens, Y. Lu, From lagging to leading? Technological innovation systems in emerging economies and the case of Chinese wind power, Energy Pol. 60 (2013) 234–250.

[3] L.T. Lam, L. Branstetter, M.L. Azevedo Inês, China's wind industry: leading in deployment, lagging in innovation, Energy Pol. 106 (2017) 588–599.

[4] C. Li, Y. Liu, G. Li, J. Li, D. Zhu, W. Jia, et al., Evaluation of wind energy resource and wind turbine characteristics at two locations in China, Technol. Soc. 47 (2016) 121–128.

[5] E. Hille, W. Althammer, H. Diederich, Environmental regulation and innovation in renewable energy technologies: does the policy instrument matter? Technol. Forecast. Soc. Change 153 (2020), 119921.

[6] Å. Lindman, P. Söderholm, Wind energy and green economy in Europe: measuring policy-induced innovation using patent data, Appl. Energy 179 (2016) 1351–1359.

[7] F. Xia, F. Song, The uneven development of wind power in China: determinants and the role of supporting policies, Energy Econ. 67 (2017) 278–286.

[8] Y.Y. Yu, Comparison of incentive policies for wind power industry and discussion on its application in China, Inq. Econ. Issues 2 (2015) 120–125 (in Chinese).

[9] K. Kim, Y. Kim, Role of policy in innovation and international trade of renewable energy technology: empirical study of solar PV and wind power technology, Renew. Sustain. Energy Rev. 44 (2015) 717–727.

[10] D. Campisi, D. Morea, E. Farinelli, Economic sustainability of ground mounted photovoltaic systems: an Italian case study, Int. J. Energy Sect. Manag. 9 (2) (2015) 156–175, https://doi.org/10.1108/IJESM-04-2014-0007.

[11] L. Liu, T. Zhang, A.P. Avrin, X. Wang, Is China's industrial policy effective? An empirical study of the new energy vehicles industry, Technol. Soc. 63 (2020), 101356.

[12] Y. Qiu, L. Diaz Anadon, The price of wind power in China during its expansion: technology adoption, learning-by-doing, economies of scale, and manufacturing localization, Energy Econ. 34 (2012) 825–835, https://doi.org/10.1016/j.eneco.2011.06.008.

[13] T. Tang, Explaining technological change in the US wind industry: energy policies, technological learning, and collaboration, Energy Pol. 120 (2018) 197–212.

[14] J. Grafstrom, A. Lindman, Invention, innovation and diffusion in the European wind power sector, Technol. Forecast. Soc. Change 114 (2017) 179–191, https://doi.org/10.1016/j.techfore.2016.08.008.

[15] G.F. Nemet, Subsidies for new technologies and knowledge spillovers from learning by doing, J. Pol. Anal. Manag. 14 (4) (2012) 469–494, https://doi.org/10.1002/pam.21643.

[16] T. Ejdemo, P. Söderholm, Wind power, regional development and benefit-sharing: the case of Northern Sweden, Renew. Sustain. Energy Rev. 47 (2015) 476–485.

[17] E. Lantz, S. Tegen, Variables affecting economic development of wind energy, in: Conference Paper Presented at Windpower 2008, NREL/CP-500-43506, National Renewable Energy Laboratory, Houston, TX, 2008. June 1-4, 2008.

[18] M.C. Slattery, E. Lantz, B.L. Johnson, State and local economic impacts from wind energy projects: Texas case study, Energy Pol. 39 (2011) 7930–7940.

[19] Y. Guo, P. Ru, J. Su, L.D. Anadon, Not in my backyard, but not far away from me: local acceptance of wind power in China, Energy 82 (2015) 722–733.

[20] R. Best, P.J. Burke, Adoption of solar and wind energy: the roles of carbon pricing and aggregate policy support, Energy Pol. 118 (2018) 404–417.

[21] P.J. Burke, Income, resources, and electricity mix, Energy Econ. 32 (2010) 616–626.

[22] X.L. Yuan, J. Zuo, D. Huisingh, Social acceptance of wind power: a case study of Shandong Province, China, J. Clean. Prod. 92 (2015) 168–178.

[23] E. Baldwin, S. Carley, J.N. Brass, L.M. MacLean, Global renewable electricity policy: a comparative policy analysis of countries by income status, J. Comp. Pol. Anal. (2016) 1–22.

[24] R. Best, P.J. Burke, The importance of government effectiveness for transitions toward greater electrification in developing countries, Energies 10 (9) (2017) 1247.

[25] B. Lin, Y. Chen, Impacts of policies on innovation in wind power technologies in China, Appl. Energy 247 (2019) 682–691.

[26] N. Johnstone, I. Haščič, D. Popp, Renewable energy policies and technological innovation: evidence based on patent counts, Environ. Resour. Econ. 45 (1) (2010) 133–155.

[27] David Popp, Innovation and climate policy, Annu. Rev. Resour. Econ. 2 (2010) 275–298.

[28] C. Böhringer, A. Cuntz, D. Harhoff, E. Asane-Otoo, The impact of the German feed-in tariff scheme on innovation: evidence based on patent filings in renewable energy technologies, Energy Econ. 67 (2017) 545–553.

[29] L. Nesta, F. Vona, F. Nicolli, Environmental policies, competition and innovation in renewable energy, J. Environ. Econ. Manag. 67 (3) (2014) 396–411.

[30] K. Palage, R. Lundmark, P. Söderholm, The innovation effects of renewable energy policies and their interaction: the case of solar photovoltaics, Environ. Econ. Pol. Stud. 21 (2019) 217–254.

[31] K. Reichardt, S.O. Negro, K.S. Rogge, M.P. Hekkert, Analyzing interdependencies between policy mixes and technological innovation systems: the case of offshore wind in Germany. Technological Forecast, Soc. Change 106 (2016) 11–21.

[32] J. Noailly, R. Smeets, Directing technical change from fossil-fuel to renewable energy innovation: an application using firm-level patent data, J. Environ. Econ. Manag. 72 (2015) 15–37.

[33] L. Kitzing, C. Mitchell, P.E. Morthorst, Renewable energy policies in Europe: converging or diverging? Energy Pol. 51 (2012) 192–201.

[34] C. Jägemann, M. Fürsch, S. Hagspiel, S. Nagl, Decarbonizing Europe's power sector by 2050 - analyzing the economic implications of alternative decarbonization pathways, Energy Econ. 40 (2013) 622–636.

[35] N.V. Emodi, G. Shagdarsuren, A.Y. Tiky, Influencing factors promoting technological innovation in renewable energy, Int. J. Energy Econ. Pol. 5 (3) (2015) 889–900.

[36] J. Grafström, Å. Lindman, Invention, innovation and diffusion in the European wind power sector, Technol. Forecast. Soc. Change 114 (2017) 179–191.

[37] F. Nicolli, F. Vona, Heterogeneous policies, heterogeneous technologies: the case of renewable energy, Energy Econ. 56 (2016) 190–204.

[38] X. Yao, Y. Liu, S. Qu, When will wind energy achieve grid parity in China? Connecting technological learning and climate finance, Appl. Energy 160 (2015) 697–704.

[39] N. Rosenberg, Inside the Black Box: Technology and Economics, Cambridge University Press, Cambridge, 1982.

[40] P. Söderholm, G. Klaassen, Wind power in Europe: a simultaneous innovation-diffusion model, Environ. Resour. Econ. 36 (2) (2007) 163–190.

[41] Paolo Agnolucci, Use of economic instruments in the German renewable electricity policy, Energy Pol. 34 (2006) 3538–3548.

[42] M.J. Barradale, Impact of public policy uncertainty on renewable energy investment: wind power and the production tax credit, Energy Pol. 38 (2010) 7698–7709.

[43] J. Buen, Danish and Norwegian wind industry: the relationship between policy instruments, innovation and diffusion, Energy Pol. 34 (18) (2006) 3887–3897.

[44] Ryan H. Wiser, Pickle Steven, Goldman Charles, Renewable energy and restructuring: policy solutions for the financing dilemma, Electr. J. 10 (10) (1997) 65–75.

[45] Patrik Söderholm, Ek Kristina, Pettersson Maria, Wind power development in Sweden: global policies and local obstacles, Renew. Sustain. Energy Rev. 11 (2007) 365–400.

[46] J. Liang, D.J. Fiorino, The implications of policy stability for renewable energy innovation in the United States, 1974-2009, Pol. Stud. J. 41 (1) (2013) 97–118.

[47] T. Nicholas, Scale and Innovation during two U.S. Breakthrough Eras, Working Paper. 15-038 October 14, 2015.

[48] Z.X. He, S.C. Xu, Q.B. Li, B. Zhao, Factors that influence renewable energy technological innovation in China: a dynamic panel approach, Sustainability 10 (2018) 124, https://doi.org/10.3390/su10010124.

[49] J. Schleicha, R. Walza, M. Ragwitza, Effects of policies on patenting in wind-power technologies, Energy Pol. 108 (2017) 684–695.

[50] L. Argote, D. Epple, Learning curves in manufacturing, Science 247 (4945) (1990) 920–924.

[51] L.G. Brookes, M. Grubb, Energy efficiency and economic fallacies: a reply, Energy Pol. 20 (5) (1992) 390–392.

[52] B. Lin, Y. Chen, Does electricity price matter for innovation in renewable energy technologies in China? Energy Econ. 78 (2019) 259–266.

[53] G. Klaassen, A. Miketa, K. Larsen, T. Sundqvist, The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom, Ecol. Econ. 54 (2–3) (2005) 227–240.

[54] V. Costantini, F. Crespi, C. Martini, L. Pennacchio, Demand-pull and technology-push public support for eco-innovation: the case of the biofuels sector, Res. Pol. 44 (3) (2015) 577–595.

[55] P. Spodniak, S. Viljainen, Institutional analysis of wind power in Finland, in: International Conference on the European Energy Market, IEEE, 2012.

[56] K. Neuhoff, Large-scale deployment of renewables for electricity generation, Oxf. Rev. Econ. Pol. 21 (1) (2005) 88–110.

[57] M. Liu, L. Liu, S. Xu, M. Du, X. Liu, Y. Zhang, The influences of government subsidies on performance of new energy firms: a firm heterogeneity perspective, Sustainability 11 (17) (2019) 4518.

[58] M. Arellano, S. Bond, Some tests of specification for panel data: Monte Carlo evidence and application to employment equations, Rev. Econ. Stud. 58 (1991) 277–297.

[59] M. Blundell, S. Bond, Initial conditions and moment restrictions in dynamic panel data models, J. Econom. 87 (1998) 115–143.

[60] R. Blundell, S. Bond, F. Windmeijer, Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator, Adv. Econom. 15 (2002) 53–91.

[61] S. Bond, Dynamic panel data models: a guide to micro data methods and practice, Portuguese Econ. J. 1 (2002) 141–162.

[62] M.J.G. Bun, J.F. Kiviet, On the diminishing returns of higher order terms in asymptotic expansions of bias, Econ. Lett. 79 (2003) 145–152.

[63] G.S.F. Bruno, Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models, Econ. Lett. 87 (2005) 361–366.

[64] J.L. Shi, An analysis of the efficiency of renewable energy tariff surcharge subsidy, Wind Energy 12 (2013) 50–52 [in Chinese].
[65] J. Ye, Q. Wan, R. Li, Z. Yao, D. Huang, How do R&D agglomeration and economic policy uncertainty affect the innovative performance of Chinese high-tech industry? Technol. Soc. 69 (2022), 101957.
[66] A. Midttun, K. Gautesen, Feed in or certificates, competition or complementarity? Combining a static efficiency and a dynamic innovation perspective on the greening of the energy industry, Energy Pol. 35 (2007) 1419–1422.
[67] D. Hayashi, J. Huenteler, J.I. Lewis, Gone with the wind: a learning curve analysis of China's wind power industry, Energy Pol. 120 (2018) 38–51.
[68] P.H. Kobos, J.D. Erickson, T.E. Drennen, Technological learning and renewable energy costs: implications for US renewable energy policy, Energy Pol. 34 (2006) 1645–1658.
[69] E.S. Rubin, I.M.L. Azevedo, P. Jaramillo, S. Yehb, A review of learning rates for electricity supply technologies, Energy Pol. 86 (2015) 198–218.
[70] Jiahai Yuan, Chunning Na, Yan Xu, Feed-in tariff for onshore wind power in China, Emerg. Mark. Finance Trade 52 (6) (2016) 1427–1437 (in Chinese).
[71] Y.L. Chen, The Comparison of Renewable Portfolio Standards and Feed-In Tariff from Economics Perspective. Doctoral Dissertation, Fudan University, 2014 [in Chinese].
[72] B.C. Qin, The Research for the Development of Chinese Wind Power Industry Based on SCP Model (Master's Dissertation), North China Electric Power University, 2012 (in Chinese).
[73] C.H. Yu, X.Q. Wu, W.C. Lee, J.S. Zhao, Resource misallocation in the Chinese wind power industry: the role of feed-in tariff policy, Energy Econ. 98 (2021), 105236, 2021.
[74] X.D. Guo, J.Y. Yin, Research on the relationship between wind power benchmark price and the development of wind power industry in China, Price Theor. Pract. 4 (2017) 56–59 (in Chinese).
[75] G. Zhao, P. Zhou, W. Wen, Feed-in tariffs, knowledge stocks and renewable energy technology innovation: the role of local government intervention, Energy Pol. 156 (2021), 112453.
[76] Y. Wang, D.Y. Zhang, Q. Ji, X.P. Shi, Regional renewable energy development in China: a multidimensional assessment, Renew. Sustain. Energy Rev. 124 (2020), 109797.
[77] N. Gatzert, N. Vogl, Evaluating investments in renewable energy under policy risks, Energy Pol. 95 (2016) 238–252, https://doi.org/10.1016/j.enpol.2016.04.027.
[78] J.I. Lewis, R.H. Wier, Fostering a renewable energy technology industry: an international comparison of wind industry policy support mechanisms, Energy Pol. 35 (2007) 3067–3077.
[79] V. Bush, Science and Endless Frontier: a Report to the President by Vannevar Bush, Director of the Office of Scientific Research and Development Report United States Government Printing Office, 1945.
[80] T. Jamasb, Technical change theory and learning curves: patterns of progress in electricity generation technologies, Energy J. 28 (3) (2007) 51–72.
[81] Z.Q. Wu, J. Li, G.N. Tian, Study on the classification of world wind power policy and its specific measures, J. North China Electr. Power Univ. (Soc. Sci. Ed.) 6 (2017) 1–8 (in Chinese).
[82] Gov. cn, Interim Measures on Renewable Energy Electricity Prices and Cost Sharing Management, 2006 (NDRC Price[2006]7), http://www.gov.cn/ztzl/2006-01/20/content_165910.htm.
[83] G. Klaassen, A. Miketa, K. Larsen, T Sundqvist, The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom, Ecol. Econ. 54 (2–3) (2005) 227–240.