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Impacts of policies on innovation in wind power technologies in China

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HIGHLIGHTS

- Demand-pull policies through feed-in tariff (FIT) policy promote innovation.
- Higher feed-in tariffs induce greater patent stock of wind power technologies.
- Technology-push policies through R&D spending support patent.
- Interaction effect exits in R&D spending for industrial enterprises and FIT policy.

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ABSTRACT

The international community generally agrees that renewable energy, such as wind power, is conducive for achieving CO_2 mitigation, environmental protection, energy savings, and energy security. The innovation in wind power technologies is vital to achieving a transformation of energy structure. The study sought to investigate the effects of policies (feed-in tariffs and research and development spending), their interaction, wind power deployment and electricity prices on wind power technology innovation at the provincial level in China, based on negative binomial fixed effect regression model and provincial panel data from 2006 to 2016. The following conclusions are drawn from the findings: (1) demand-pull policies through feed-in tariff policy promote innovation in wind power technologies; (2) higher feed-in tariffs of wind power induce greater stock of patents in wind technologies; (3) technology-push policies through research and development spending support wind power technological innovation; (4) only research and development funding investment in industrial enterprises under the implementation of feed-in tariff policy can stimulate greater patent stock due to the fact that the wind power industry enterprises are gainers for feed-in tariff policy, indicating that there is an interaction effect; (5) improving the wind power deployment drives wind power technology patents; (6) increasing electricity prices will incentivize innovation of wind power manufacturers in order to reduce cost and obtain more profit.

1. Introduction

Promoting wind power is regarded as an important strategy for achieving CO_2 mitigation, environmental protection, energy savings and energy security [1]. Technological progress is the key to realizing energy conservation [2]. The innovation in wind power technologies is vital to achieving a transformation of energy structure and sustainable economy transition. The share of wind power in the total electricity generation increased from 0.1% in 2006 to 4.54% in 2017, which illustrates that though the share of wind power has increased significantly, the share is still low. It is undeniable that the booming development of wind power is conducive to the cost reduction under wind power technological innovation. However, innovation in wind power technologies relies on policy supports. In order to achieve wind power technological innovation to promote a substantial increase in wind power generation, effective policy supports need to be implemented.

The policy supports for innovation in wind power technologies include feed-in tariffs, tax incentives, tradable renewable energy certificates, investment on research and development (R&D) activities, standardization of products, domestic content protection policy and so on, which stimulate learning-by-doing and learning-by-using processes to reduce costs for wind power [3–4]. These various policies can be classified as either demand-pull policies (e.g. feed-in tariffs) or technology-push policies (e.g. R&D spending). Theoretically, the implementation of demand-pull policies and technology-push policies is conducive to promoting technological innovation which is often

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described by patent counts or patent stock [5–7].

In recent years, there have been heated discussions about the effects of policies on innovation in renewable energy technologies.

On the demand-pull policies side, Finon and Menanteau [8] and Costantini et al. [9] found that in stimulating innovation activities, price-based instruments are more effective than quantity-based instruments, such as feed-in tariffs which can produce greater incentives for innovation. Hence, many researchers began to pay attention to the innovation effect of feed-in tariffs for renewable energy technologies. Reichardt et al. [10] thought that feed-in tariffs with a sufficient level will stimulate renewable energy technology innovation. Moreover, Bergek and Berggren [11] suggested that feed-in tariffs provide predictable incentives for investors and are more conducive to innovation. In order to verify the innovation effect of feed-in tariffs, Johnstone et al. [12] used patent data on a panel of 25 countries during 1978–2003 and Nicolli and Vona [13] built a dataset for the EU countries over the period 1980 to 2007. They found that feed-in tariff levels have a significantly negative impact on innovation in wind power technologies, but have a significantly positive effect on patenting in solar power technologies. In other words, the innovation effects of feed-in tariff vary under different renewable energy technologies. In addition, Grafström and Lindman [14] showed that feed-in tariffs are not determinants of innovation using data on wind power of developed countries in Europe from 1991 to 2008. Schleich et al. [15] introduced a dummy variable to measure feed-in tariff policy and illustrate that feed-in tariff policy has a negative sign but not statistically significant. However, other researchers have different conclusions about the innovation effect of feed-in tariffs. For example, Lindman and Söderholm [16] provided empirical evidence of higher feed-in tariffs promoting innovation in wind power technologies based on data of 4 European countries between 1977 and 2009. Besides, Böhringer et al. [17] found that the innovation effect of feed-in tariffs for renewable energy technologies in Germany is positive. In fact, this result is in line with the expectation of setting feed-in tariff policy because feed-in tariffs bring more predictable price incentives for investors. The above previous studies have different conclusions on the effect of feed-in tariffs on wind power technological innovation due to the fact that they are based on different samples and the different stages of renewable energy technologies. Hence, this issue is worth to be further discussed.

On the technology-push policies side, Popp et al. [18] and Johanstone et al. [19] have proved that the quality and level of technologies determined by R&D investment are very crucial for innovation at the micro and macro levels. Based on the country-level dataset, many researchers found that specific R&D expenditures can induce additional innovation in wind power technologies [12–13,15–16,20]. However, other studies [14,17] indicated that public R&D spending is not a significant determinant of wind power technology invention, especially in the mature stage. At the early and large-scale development phase for renewable energy, perhaps the investment in R&D activities plays a positive role in innovation. The above previous studies also have different conclusions on the effect of the investment in R&D activities on wind power technological innovation. Based on firm-level dataset, Rong et al. [21] investigated Chinese listed firms during the period 2002 to 2011 and showed that R&D stocks and patent counts have a significant positive relationship. At the national and firm levels, Hu et al. [22] compared the wind energy in China, Denmark, Germany, and the USA and found that China's R&D spending is ranked top but patent counts lagged behind other countries. The results suggest that the government should pay attention to efficiently utilize R&D expenditure to drive wind power technological innovation activities. In other words, investment in R&D activities plays an important role in promoting technological innovation.

Additionally, the innovation process is complex and R&D support will impact on patenting through different processes, including the basic knowledge generated by R&D expenditures and the tacit knowledge induced by feed-in tariff policy [4,23]. Lindman and Söderholm [16] pointed out that the marginal effect of R&D funding on innovation in wind power technologies will depend on the implementation of feed-in tariff policy for wind power. Therefore, the interaction effect between feed-in tariff policy and R&D spending will be discussed in this paper.

This paper attempts to fill the gaps in the previous literature.

First, it is noted that few studies have considered the effects of feed-in tariff policy, R&D spending, their interaction term, deployment of wind power and incentive from electricity prices on innovation in wind power technologies together. In addition, the existing literature only pays attention to one of the perspectives of feed-in tariff policy or feed-in tariffs of wind power. This paper would consider both of them. Though feed-in tariffs and R&D expenditure have positive effects on innovation on wind power technology innovation, which is consistent with the expectation of feed-in tariff policy and R&D expenditure, based on different samples and different stages of renewable energy technologies, the impacts of feed-in tariffs and R&D expenditure on wind power technological innovation are different. There is a controversy about the impacts of feed-in tariffs and R&D spending on wind power technology innovation. Hence, this is of great significance to call for further discussion to enhance better understanding.

Second, in terms of methodology, due to the abnormal distribution of the count data model, the previous literature in empirical analysis mostly used the Poisson regression model and negative binomial fixed effect regression model. This paper follows previous literature to investigate the effects of policies (feed-in tariffs and R&D spending) and their interaction on wind power technological innovation. In addition, most literature used patent counts to proxy innovation. However, the latest literature also indicated patent stock contains the information of current patent counts and past patent counts under the knowledge depreciates and reflects the sector-specific effect, knowledge stock, and knowledge infrastructure level. Hence, the patent stock is a more suitable proxy for innovation.

Finally, most literature considers the impacts of policies on wind power technological innovation focusing on the cross-country level or firm level, rather than at the provincial level in an individual country, especially neglecting sample of China. China has the largest cumulative installed capacity of wind power globally. This paper would provide a more different and important perspective.

Following the aforementioned background and literature review, this paper will investigate the effects of policies (feed-in tariffs and R&D spending), their interaction term, deployment of wind power and incentive from electricity prices on wind power technological innovation at the provincial level in China. The introduction to the support policies and innovation in wind power technologies in China is provided in Section 2. Section 3 describes the variables, data, and negative binomial fixed effect regression model. Section 4 discusses the results of economic analysis and robustness checks. Section 5 draws the conclusions and offers some targeted policy suggestions.

2. Innovation and policies: China's case of wind power technologies

As a renewable energy technology, the development of wind power in China began in 1985. The development of the wind power industry has experienced three stages: the first and second stages are a pilot phase (1985–1993) and an industrialization phase (1993–2003), respectively, and the third stage is a large-scale commercialization stage (2003-Nowadays) [24]. As wind energy development has greater economic value, social value and environmental value, wind energy in China has become the largest share in the renewable energy source. The share of wind power in the total electricity generation was 4.54% in 2017, while the share of renewable energy in the total electricity generation was 6.07% in 2017. Driven by national policies and development of the global wind power market, China's wind power has also shown strong development momentum in a recent decade. Especially in

2010, China's cumulative installed capacity of wind power exceeded that of the United States of America and became the leader globally [25]. The cumulative installed capacity of wind power reached 188.23 GW in 2017, accounting for over one-third of the global cumulative installed capacity of wind power, while the new installed capacity of wind power was 19.5 GW, accounting for 37% of global new installed capacity of wind power.

However, China's wind power industry shows the characteristics of innovation behind deployment [26]. In general, many studies considered patent counts which are applied to measure the outcome of the technological development process as an important indicator to proxy innovation. Before 1996, the wind farm was mainly used for scientific research or as a demonstration project. In other words, wind power development during that period has not entered the phase of large-scale commercialization and lacked the core technologies. Therefore, patent counts of wind power were less before the wind power industry under the phase of large-scale commercialization. Until 1996, the Chinese government published the "Riding the Wind Program" to encourage innovation in wind power technologies [27]. The National Development and Reform Committee (NDRC) provided guidance and plan for the development of renewable energy in 2005, and Ministry of Science and Technology included wind power project technology into the "863 Plan", to a certain extent, which stimulated wind power technological innovation.

In general, the International Patent Classification (IPC) code of patents for wind power technologies is F03D in some literature [15,18,28]. Therefore, based on this definition, patents under the F03D are used in this paper to measure innovation in wind power technologies. Patents in China's wind power technologies are presented in Fig. 1. As shown in Fig. 1, the number of patents for wind power technologies in China has increased over the period 2006–2012, in line with the continuous expansion of wind power development. Nevertheless, due to the impact of the economic environment, the development of wind power market has slowed down after 2012, which led to a decrease in research and development (R&D) spending and decline in patent counts for wind power technologies. However, the annual patent counts have increased after 2014, because of high enthusiasm in investment in wind power under increasing support policies [29].

In fact, in China, enterprises are the main bodies of the R&D activities and innovation. As shown in Fig. 2(a) and (b), though the share of innovation contribution from universities in 2017 has increased compared with that in 2006, the share of innovation contribution from enterprises is still taking the dominant position.

Fig. 3 shows the patent quantity of wind power technologies in various provinces in China. China's wind power resources are mainly distributed in the northern and northeastern areas [30] and coastal areas. However, areas with rich wind energy resource are also far from power grids and lack huge power consumption capacity. Hence, the government encourages investment in wind power in the southeastern

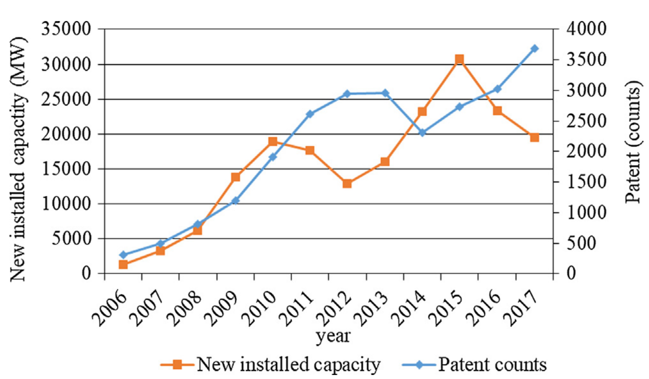

Fig. 1. Patent counts in wind power technologies and new installed capacity of wind power in China from 2006 to 2017.

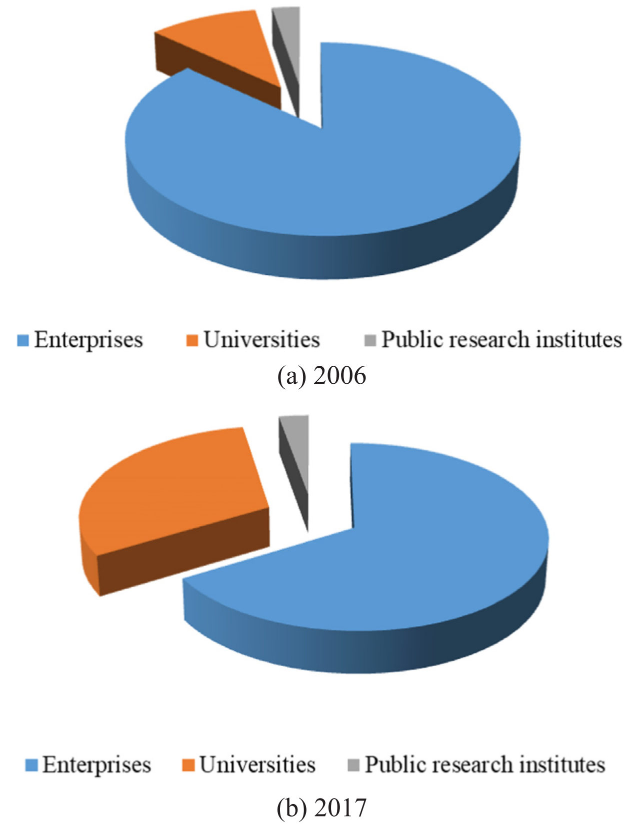

Fig. 2. Innovation contribution of wind power technologies from different bodies in 2006 and 2017.

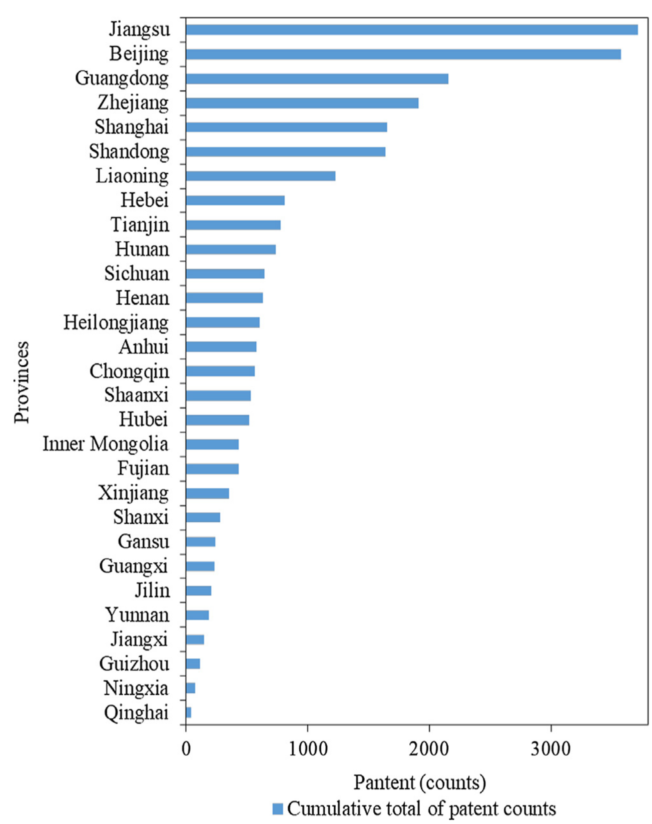

Fig. 3. Cumulative total patent counts of wind power technologies across 29 provinces in China during 2006–2017 (excluding Hainan, Tibet, Hong Kong, Macao and Taiwan).

areas closed to power load centers. In addition, southeastern areas have more universities, large-scale enterprises, and R&D person, which can provide the knowledge and talent resource foundation. As illustrated in Fig. 3, the patent counts in many southeastern areas have exceeded those in the northern and northeastern areas. Hence, the patent counts of Jiangsu, Beijing, Guangdong, Zhejiang, and Shanghai are relatively high.

In China, the demand-pull policies (e.g. feed-in tariffs) and technology-push policies (e.g. R&D spending) are implemented. On the feed-in tariff policy side, the National Development and Reform Committee (NDRC) issued the Notice on Improving Wind Power Pricing (Price [2009] NO.1906) in 2009 and benchmark prices of four categories was 0.49 CNY/kwh, 0.52 CNY/kwh, 0.56 CNY/kwh and 0.61 CNY/kwh, respectively. Whereafter, the NDRC released notices to reduce the benchmark prices of four categories for wind power in 2014, 2015 and 2016, respectively [31]. On the R&D spending side, there are 38 national energy R&D centers approved by the National Energy Administration (NEA) of China [27]. Six of the national R&D centers concentrate on all aspects of wind power technologies involving blades, wind turbines and so on [32]. Additionally, many manufacturing firms of wind power have their own R&D centers. For instance, Goldwind with rapidly increasing R&D expenditure is heading towards being a top R&D spender [22].

3. Data and methods

3.1. Variables

In this paper, the effects of policies (feed-in tariffs and R&D spending) on innovation in wind power technologies are investigated.

Explained variable: Some empirical literature takes patent counts and patent stock to proxy innovation [14–17,22,26,33–37]. Though not all invention is patented, there are three strengths over patents and patent stock compared to other indicators that represent wind power technology innovations. One is that most of the related invention is counted into the patent counts and patent stock, and second is that classification and standard of patent gain much consensus, which is beneficial to make comparative analysis [38]. The third is that the data on the patent counts are publicly available for a long time series, and the indicator of patent stock is easily obtained from the patent count, which can provide specific and detailed technical information [16,36]. In addition, the classification code of wind power technologies is F03D, including motors, masts and rotors, and related technology of wind turbine generator, but do not cover other auxiliary technologies. There are application date and public date shown in the Chinese Patent Online Databases. Unless a patent is published, it cannot be called a true patent [39]. Therefore, this paper collected the data on patent counts based on public date. In addition, due to the strict review process, a patent based on public date is a more appropriate indicator. In China, a patent application will be submitted to China's State Intellectual Property Office (SIPO). At that time, it will obtain an application date. Subsequently, the patent application will undergo a strict review process. The examination procedures of different types need to take different time. There are three types of patents in China: invention patents, utility model patents, and design patents [29]. In general, the review process of the invention patents is approximately 18 months, while the corresponding time for utility model patents and design patents takes about 6–8 months [40]. Hence, the average of examination procedures is nearly 12 months. A patent would be published after passing the review, and the public date would be also obtained. For utility model patents and design patents, authorization can be obtained after passing the preliminary examination. However, invention patents require both preliminary review and substantive review before they can be authorized, so more review time is required. In recent years, the Chinese government has continuously improved the quality and efficiency of examination procedures for patents. Therefore, the time required for the examination process has been continuously shortened. In order to avoid the problem of biased empirical results caused by the long period of the review process, this paper will consider time lag for explanatory variables and control variables. Schleich et al. [15] indicated that compared with patent counts, the patent stock may have a more fully reflection for sector-specific effect. For instance, technology suppliers' learning-by-inventing can be shown in patent stock. Moreover, the patent stock not only contains the information of current patent counts but also includes the information of past patent counts under the knowledge depreciates, which reflects the knowledge stock and knowledge infrastructure level. Hence, the patent stock covers a broader range of innovation information. This paper makes use of patent stock (PS) as the explained variable and also applies the number of patent counts (PC) as a proxy for innovation in the section of robustness checks. According to the calculation method of Kim et al. [37], the patent stock of wind power technologies can be represented as follows:

$$PS_t = PC_t + (1 - \delta)PS_{t-1} \tag{1}$$

In China, the patent data (F03D) are published from 1985. Hence, PS_0 is the initial value of patent counts in 1985. PC_t is the patent counts in time t. The depreciation rate (δ) is 15%, which is in line with Grafström and Lindman [14], Park and Park [36] and Kim et al. [37]. PS_{t-1} is the patent stock in time t-1. PS_t is the patent stock in time t.

Explanatory variable: The demand-pull policies (e.g., feed-in tariffs), technology-push policies (e.g., R&D spending) and their interaction term can stimulate innovation in wind power technologies [16]. First, the notice for setting benchmark feed-in tariffs of wind power was published by the NDRC in 2009, which is the first policy about feed-in tariffs of wind power in China. The feed-in tariff policy provides a greater driving force for innovation in wind power technologies than other demand-pull policies [17]. Hence, the dummy variable (FIT) is introduced as an explanatory variable representing the indicator of demand-pull policies. FIT would be defined as follows:

$FIT = 1$ for the period of 2009 to 2016, and 0 otherwise.

Additionally, it is difficult to get data on R&D funding of wind power at the provincial level in China [27]. The R&D spending is a relatively representative driving force for stimulating technological innovation [41–42]. The universities and public research institutes make a limited contribution to innovation in wind power technologies [27], but the patent counts from wind power industry enterprise account for a large share of innovation in wind power technologies. The wind power industry enterprises not only are the main bodies for research and development but also are the gainers for feed-in tariff policy. The data on the R&D funding investment of industrial enterprises above designated size are available, as a whole, which also has the same trend with the data on R&D investment in wind power. Moreover, the R&D efforts from industry and government should be not neglected [43], while the R&D funding investment of industrial enterprises above designated size contains the enterprises' R&D expenditure and government's R&D spending. To a certain extent, the R&D funding investment of industrial enterprises above designated size (RD) can proxy for technology-push policies (e.g., R&D spending). It has been deflated by CPI (2006 = 1).

Because the innovation process is complex and R&D support will impact on patenting through different processes, Lindman and Söderholm [16] point out that the marginal effect of R&D funding on the innovation of wind power technologies will depend on the implementation of the FIT policy of wind power. In order to investigate the interaction effect between R&D expenditure and FIT policy of wind power, the R&D funding (RD) multiplies by FIT policy (FIT) to obtain a new variable.

Control variables: Since 2006, the market size of China's wind power has gradually increased, and the cumulative installed capacity ranked first in the world in 2010. Wind power is built and operated, which drives innovation in order to realize cost reduction [44]. The boom of wind power will promote patenting activities [17,45]. Hence, China's cumulative installed capacity of wind power (CIC) is introduced as a control variable. Additionally, increasing electricity prices will not only make wind power more competitive but also signal a higher profit in the future, which will stimulate renewable energy technological innovation activities [46–47]. Thus, electricity prices for households (EP) would be adopted as a proxy for electricity prices, following some studies [12–13,15].

3.2. Data sources and description

Provinces such as Hainan and Tibet are excluded from the sample in this paper due to the fact that their shares of installed capacity and patent counts of wind power are extremely small which can be ignored. Moreover, data on the installed capacity of wind power for Hong Kong, Macao, and Taiwan are not reported. The data on electricity prices for households are only available during the period from 2006 to 2016. Therefore, our provincial data was obtained from 29 provinces (excluding Hainan, Tibet, Hong Kong, Macao, and Taiwan) over the period 2006 to 2016.

The patent counts were sourced from the Chinese Patent Online Databases published by China's SIPO. The data on R&D spending are obtained from data of Xu and Lin [42] and WIND. The data on electricity prices for households are available in WIND. The data on cumulative installed capacity of wind power for the period 2006 to 2016 were also obtained from the Report on China's Wind Power Capacity Statistics published by the Chinese Wind Energy Association (CWEA). The detailed introduction of the variables is shown in Table 1.

This paper has a panel sample of 319 observations from 29 provinces in China from 2006 to 2016. Table 2 summarizes the statistics of the variables. The standard deviation of PS is larger than the mean of PS, which indicates that the count data model may have the problem of over-dispersion.

3.3. Model specifications

Due to the abnormal distribution of the count data model, the Poisson regression model and negative binomial fixed effect regression model are generally used for estimation [48]. Because negative binomial fixed effect regression model can deal with the problem of over-dispersion in the count data model and has been illustrated to be more efficient [16,49–50], this paper uses negative binomial fixed effect regression model [15,51]. The correlations between policies and innovation in wind power technologies with the negative binomial fixed effect regression model are estimated as follows:

$$E[PS_{i,t}] = exp[C + \beta_1 FIT_{i,t-1} + \beta_2 RD_{i,t-1} + \beta_3 CIC_{i,t-1} + \beta_4 EP_{i,t-1} + \alpha_i + \varepsilon_{i,t}]$$

$$E[PS_{i,t}] = exp[C + \beta_1 FIT_{i,t-1} + \beta_2 RD_{i,t-1} + \beta_5 RD_{i,t-1} * FIT_{i,t-1} + \beta_3 CIC_{i,t-1} + \beta_4 EP_{i,t-1} + \alpha_i + \varepsilon_{i,t}] \tag{2}$$

In Eq. (2), PS denotes patent stock of wind power technologies. The FIT is a dummy variable for demand-pull policy, and RD represents R&D funding investment of industrial enterprises above designated size as a proxy for technology-push policy. The interaction term between FIT and RD is *RD*FIT*. CIC and EP are control variables, i.e. the cumulative installed capacity of wind power and electricity prices for households, respectively. In Eq. (2), $i = 1,\ldots\ldots,29$ indexes the 29 provinces in China, and $t = 2006, \ldots\ldots,2016$ indexes time. The unobserved province-fixed effect (α_i) is introduced in the model. The error term ($\varepsilon_{i,t}$) are clustered. In our estimations, in order to make the data stable, all the variables except for dummy variable (FIT) and patent stock are in natural logarithm. Hence, the coefficients for log-transformed variables may be regarded as elasticities, while the coefficient for the dummy variable may be semi-elasticity. In order to avoid the issue of multicollinearity, our study processes the data on their interaction through centering. Moreover, because the process of patent application and authorization takes some time, there may be a lag effect of policies (feed-in tariffs and R&D spending), their interaction, wind power deployment, and electricity price on innovation. In addition, lagging variables is a common choice in many studies, such as Costantini et al. [9], Schleich et al. [15] and so on, which can reduce potential endogeneity problems. Therefore, this paper considers all explanatory variables under the lag = 1.

Table 2
Summary statistics of the variables used in the estimations.

Variable	Observation	Mean	Std.Dev.	Min	Max
PS	319	220.9687	332.2689	2	1958
FIT	319	0.7273	0.4461	0	1
RD	319	183.0152	241.3139	2.2214	1289.397
CIC	319	2347.3240	4121.755	0	28,064
EP	319	501.5256	60.7983	336.8	648.17

4. Empirical results and discussion

4.1. Results of economic analysis

Table 4 reports the innovation impacts of feed-in tariff policy of wind power and R&D spending in Eq. (2) using negative binomial fixed effect regression model. Table 3 shows that all coefficients among variables in Eq. (2) are lower than 0.6. Hence, according to the results of Pearson's correlation coefficient, the models would include all the variables. Additionally, this paper also investigates the interaction effect between R&D expenditure and FIT policy of wind power on innovation in wind power technologies. The coefficient between FIT dummy variable and the interaction effect between R&D funding and FIT policy of wind power is almost lower than 0.6 (see from Table 3). According to the Variance Inflation Factor (VIF) test, the values of VIF for all variables are far lower than 10 and mean value of VIF is 1.72, which indicate that the problem of multicollinearity does not really exist. Therefore, the interaction term would be added into Table 4 Model 2, which can reflect the marginal impact of R&D spending on innovation depending on the feed -in tariff policy of wind power.

As shown in Table 4, the coefficients of FIT, lnRD, lnRD*FIT, $\ln CIC_{(t-1)}$ and lnEP are all statistically significant. The values of alpha are both significant indicating that there is the problem of over-dispersion.

Table 1
Introduction of variables.

Category	Variable (Unite)	Content	Data sources
Innovation	PS (count)	Patent stock of wind power technologies	Chinese Patent Online Databases
Demand-pull policy	FIT (dummy)	Feed-in tariff policy	According to the *Notice on Improving Wind Power Pricing (Price [2009] NO.1906)* published by NDRC
Technology-push policy	RD (100 million)	R&D funding investment of industrial enterprises above designated size	Data of Xu and Lin [42] and WIND
Wind power capacity	CIC (MW)	Cumulative installed capacity of wind power	Report on China's Wind Power Capacity Statistics
Electricity prices	EP (CNY/kkWh)	Electricity prices for households	WIND

Table 3
Correlation of the variables used in the regression.

	FIT	lnRD	lnRD*FIT	lnCIC	lnEP
FIT	1				
lnRD	0.1450	1			
lnRD*FIT	−0.6502	0.0062	1		
lnCIC	0.3906	0.0737	−0.1084	1	
lnEP	0.3219	0.5537	−0.0965	0.0785	1

Table 4
Results of innovation impacts of demand-pull policy and technology-push policy.

	Model 1	Model 2
$FIT_{(t-1)}$	0.5777^{***}	0.8031^{***}
	(0.0825)	(0.1141)
$lnRD_{(t-1)}$	0.5410^{***}	0.5378^{***}
	(0.0936)	(0.0960)
$lnRD*FIT_{(t-1)}$		0.4403^{**}
		(0.1901)
$lnCIC_{(t-1)}$	0.1269^{***}	0.0999^{***}
	(0.0354)	(0.0377)
$lnEP_{(t-1)}$	1.4367^{***}	1.3050^{***}
	(0.4668)	(0.4903)
Constant	-7.8964^{***}	-7.0822^{***}
	(3.0249)	(3.1854)
Log likelihood	−1216.4614	−1210.1013
alpha	0.0375^{***}	0.0353^{***}
Sample size	250	250

Note: ***, ** and * indicate the significance at the 1% level, 5% level and 10% level, respectively. The standard error is reported in the parentheses.

Hence, the negative binomial fixed effect regression model used in this paper is more appropriate.

Focusing first on the demand-pull policy, the coefficient of FIT is positive and significant at 1% level in Model 1, which is in contrast to the results of Johnston et al. [12] and Schmidt et al. [52]. But our result is consistent with those of Lindman and Söderholm [16] and Böhringer et al. [17]. Feed-in tariff policy leads to higher level of innovation due to the fact that they provide more predictable price incentives for investors and have a stronger driving force on demand. From Model 1 and Model 2, the existence of a feed-in tariff policy of wind power raises the mean patent stock by about 58%-80%.

Regarding the technology-push policy, there is a significantly positive relationship between R&D expenditure and innovation in wind power technologies in the two models above. Our finding is similar to Costantini et al. [9], Nicolli and Vona [13] and Schleich et al. [15]. On the technology-push policies side, R&D spending inspires wind power technological innovation. From Model 1, a 1% increase in R&D expenditure raises the mean patent stock by about 2.57%. The contribution of Enterprises to the R&D activities is the main body [53]. Hence, using market stimulus and encouraging enterprises' R&D support will be good approaches to promote innovation.

With respect to the interaction effect between R&D funding and feed-in tariff policy of wind power, the interaction term exerts a significantly positive impact on the patent stock of wind power technologies. This result supports our hypothesis that there is the interaction effect between R&D funding and feed-in tariff policy of wind power, in line with Lindman and Söderholm [16]. Hence, a marginal increase in R &D spending encourages more patenting in wind power technologies if the feed-in tariff policy is implemented. From Model 2, a 1% increase in R&D spending under the implementation of feed-in tariff policy will induce a roughly 2.6% (2.55% + 0.05%) increase in the mean patent stock of wind power technologies. This result suggests that R&D funding to wind power technologies can play a more important role in innovation under the feed-in tariff policy. The innovation in power technologies is spurred by both demand-pull policies and technology-push policies.

Furthermore, the coefficient for a cumulative installed capacity of wind power is positive and statistically significant. Recent studies by Böhringer et al. [17] and Schleich et al. [15] concluded that there is a significant positive effect of the market size, measured by installed capacity, on innovation. Innovation takes time to respond to signals from the deployment of wind power. Thus, this result is consistent with the characteristics of leading in deployment and lagging in innovation for the wind power industry. From Model 1 and Model 2, a 1% increase in deployment of wind power is generally associated with a 0.64%-0.82% increase in mean innovation capacity of wind power technologies.

Finally, the coefficient of electricity prices for households is positive and significant at 1% level. As Johnston et al. [12] expected, the increasing electricity prices make wind power more competitive and signal a higher profit in the future. A reasonable increase in electricity prices can incentivize innovation of wind power manufacturers in order to reduce cost and obtain more profit. Unlike wind power in developed countries, China's wind power is a relatively higher cost technology which needs incentives from electricity price. From Model 1 and Model 2, a 1% increase in electricity price suggests an 8.12%-8.94% increase in mean innovation capacity of wind power technologies.

4.2. Robustness checks

The robustness checks of the results in Table 4 through a series of different model specifications and an alternative classification of variables are presented in this section.

First, the Poisson fixed effect regression model with cluster-robust standard errors [17] is used to estimate the variables in Table 4. The results are similar to those of the negative binomial fixed effect regression model. The relationship between all variables except for cumulative installed capacity and patent stock of wind power technologies are positive and significant. However, the standard errors and p-values are too low, which results in the problem of overestimation of the significance of parameters. Therefore, negative binomial fixed effect regression model used in this paper is more appropriate than the Poisson fixed effect regression model.

Secondly, accounting for the different lag structures, the negative binomial fixed effect regression model to verify again was used. As shown in Table 5, the results after no lag and lagging all variables by two years are in line with those in Table 4. The coefficients of feed-in tariff policy, R&D spending, the interaction term (between R&D funding and feed-in tariff policy of wind power), cumulative installed capacity and electricity prices for households are all significantly positive. In other words, all variables under lag = 0 and lag = 2 have a significant positive impact on patent stock in wind power technologies. Additionally, according to the value of alpha, it means that negative binomial fixed effect regression model is suitable.

Third, in order to verify whether there exists policy endogeneity, like Schleich et al. [15], this paper also uses future policies as explanatory variables. The results for all parameter are in line with that of Table 4, which indicates that there is no evidence that the results in this paper suffer from endogeneity problem and reverse causality.

Forth, since FIT is a dummy variable, this variable can only reflect whether the implementation of feed-in tariff policy impacts the innovation capacity for wind power technologies, which is similar to verifying the innovation effect of feed-in tariff policy. Whereas, the dummy variable used to estimate the effect of feed-in tariff policy on patenting does not adequately capture policy features. Thus, the feed-in tariffs of wind power reported by National Energy Administration (NEA) [31] are used to substitute the dummy variable employed as a proxy for feed-in tariff policy. However, the feed-in tariffs (FITs) of wind power are published from 2013 to 2016, and the data for Beijing, Tianjin, Zhejiang, Guangdong, and Guangxi in individual years are not reported. Hence, the unreported data are estimated using the method of

Table 5
Results of robustness check (under lag = 0 and lag = 2).

	Model 3 lag = 0	Model 4 lag = 0	Model 5 lag = 2	Model 6 lag = 2
FIT	0.5741***	0.9570***	0.4896***	0.6178***
	(0.0977)	(0.1493)	(0.0542)	(0.0898)
lnRD	0.7317***	0.7141***	0.3468***	0.3513***
	(0.1247)	(0.1257)	(0.0697)	(0.0720)
lnRD*FIT		0.7472***		0.2487*
		(0.2082)		(0.1480)
lnCIC	0.1391***	0.0967**	0.1062***	0.0894***
	(0.0442)	(0.0447)	(0.0282)	(0.0309)
lnEP	1.8486***	1.6134**	1.5738***	1.5001***
	(0.6425)	(0.6804)	(0.3123)	(0.3403)
Constant	−12.0426***	−10.5427**	−7.0460***	−6.6185***
	(4.2661)	(4.5042)	(1.9599)	(2.1372)
Log likelihood	−1368.3684	−1355.3254	−1064.5382	−1061.5654
alpha	0.0574***	0.0519***	0.0237***	0.0230***
Sample size	279	279	221	221

Note: ***, ** and * indicate the significance at the 1% level, 5% level and 10% level, respectively. The standard error is reported in the parentheses.

Lin and Chen [31], which refers to the method of Lin and Li [54]. The values estimated by the levelized cost of electricity (LCOE) of renewable energy with a reasonable profit rate lay the foundation for reasonable feed-in tariffs and are close to the real feed-in tariffs [54–55]. The Eq. (3) is described as follows:

$$C_w = \frac{r(1 = r)^n}{(1 = r)^n - 1}(1 + \omega)(1 + \tau)(1 + \mu)\frac{C}{\alpha T(1 - \lambda)} \tag{3}$$

Except for T, the sources of the above parameters are based on Lin and Li [54]. Hence, the parameters and values for the estimation of feed-in tariffs are summarized as follows (See Table 6):

As mentioned above, the data on feed-in tariffs at the provincial level in China are only published from 2013 to 2016. Additionally, the results under no lag presented in Table 5 are similar to those under lag = 1 shown in Table 4. Therefore, to avoid losing too much freedom, this paper employs negative binomial fixed effect regression model and all variables under no lag, but the values of alpha are not statistically significant indicating that there is no problem of over-dispersion. The Poisson fixed effect regression model with cluster-robust standard errors for the estimation was used, and the findings are presented in Table 7. Based on Pearson's correlation coefficient, there is no multicollinearity between the feed-in tariffs, the R&D expenditure and interaction effect between the feed-in tariffs and R&D funding. When the interaction term was introduced into Model 7, the values of VIF for all variables are far lower than 10, and the mean value of VIF is 1.4, indicating that the problem of multicollinearity does not exist. Hence, this paper includes the interaction term in Model 8. As shown in Table 7, the feed-in tariffs of wind power are positive and statistically significant, which shows that higher feed-in tariffs of wind power promote the patent stock in wind power technologies. The significance of FITs is at 1% level. A 1% increase in feed-in tariffs brings a 0.12%-0.18% increase the in the mean patent stock of wind power technologies. Although this result is in contrast to the results shown in Johnstone et al. [12] and Nicolli and Vona [13], it is in line with the result of Lindman and Söderholm [16]. There are two reasons as follows: (1) the government employs higher feed-in tariffs of wind power to induce investment in wind power at high-cost sites [44], which are close to electricity consumption centers with not only relatively sufficient consumptive ability

Table 7
Results of robustness check (under feed-in tariffs).

	Model 7	Model 8
lnFITs	0.3303***	0.3470***
	(0.1102)	(0.1207)
lnRD	0.2989*	0.3036*
	(0.1709)	(0.1707)
lnRD*lnFITs		0.8092
		(1.1303)
lnCIC	0.2669***	0.2653***
	(0.0475)	(0.0475)
lnEP	0.9712	1.0128
	(0.6520)	(0.6638)
Log likelihood	−398.9808	− 398.4599
Sample size	116	116

Note: ***, ** and * indicate the significance at the 1% level, 5% level and 10% level, respectively. The standard error is reported in the parentheses.

Table 6
Parameters and values for estimation of feed-in tariffs.

Parameter	Definition	Value
C	Cost of wind power generator (CNY/kW)	5000 CNY/kW (2013; 2014) 4800 CNY/kW (2015; 2016)
r	Discount rate	10%
n	Service time	20
ω	Ratio between operating cost and initial investment	12%
τ	Profit rate	10%
μ	Value-added tax rate	8.5%
α	Proportion of generation's cost in initial investment	70%
λ	Auxiliary power rate	2.5% (2013; 2014) 3% (2015) 2.9% (2016)
T	Equivalent hours	The values are from Renewable Energy Data Manual and the Notification on National Electricity Price Regulation in the Electric Power Enterprises published by National Energy Administration.
C_w	Feed-in tariffs of wind power (CNY/kWh)	The values are calculated by Eq. (3).

but also difficult exploitation conditions for wind power. Hence, these sites require more innovation in wind power technologies. (2) Though the benchmark feed-in tariffs of wind power have been constantly reduced, and are expected to be equal to those of thermal power in 2020, it does not mean that government has no interest or motivation in wind power. Because wind power technologies have become more commercial and mature, innovation in wind power technologies will not only depend on higher feed-in tariffs of wind power [56]. In addition, the gap in renewable energy subsidies becomes bigger than before, which makes the Chinese government face great financing pressure. At present, the Chinese government also advocates that demand-pull policies (e.g. feed-in tariffs) should be connected with R&D spending, deployment strategy, carbon trading market system and so on to promote the innovation of wind power technologies [57–58]. Thus, although higher feed-in tariffs foster higher patent counts, the feed-in tariffs of wind power do not need to keep as high as in the past. Besides, R&D funding and cumulative installed capacity have significantly positive impacts on wind power technological innovation, which is similar to the results in Table 4. A 1% increase in R&D funding raises the mean patent stock of wind power technologies by 0.12%. However, the coefficients of the interaction term and electricity price are not statistically significant. Though increasing feed-in tariffs promote patent stock of wind power technologies, it may not play a role in stimulating R&D funding to drive wind power technological innovation.

Fifth, this paper used provincial R&D expenditure as a proxy for technology-push policies rather than R&D funding investment of industrial enterprises above designated size. Like R&D funding investment of industrial enterprises above designated size, the data on the provincial R&D funding are also available, as a whole, which also has the same trend with the data on R&D investment in wind power. The data on provincial R&D funding include the R&D expenditure for industrial enterprises, the universities and public research institutes. Moreover, the data on R&D expenditure also contains R&D spending from industry and government. Therefore, our study uses provincial R&D investment (PRD) as a proxy for technology-push policies (e.g., R&D spending). It has been deflated by CPI (2006 = 1). Table 8 indicates that the provincial R&D investment has a significantly positive impact on patenting in wind power technologies. A 1% increase in R&D expenditure raises the mean patent stock by about 10.23% −10.76%. The feed-in tariff policy has a positive and statistically significant impact on innovation in wind power technologies. The existence of a feed-in tariff policy of wind power raises the mean patent stock by about 30.87%-49.23%. However, there is no interaction effect between the feed-in tariff policy and R&D funding, which shows only the interaction effect between the feed-in tariff policy and R&D funding from industrial enterprises can impact innovation in wind power technologies. The enterprises of the wind power industry are gainers for feed-in tariff policy, but the universities and public research institutes are not. The enterprises are the main bodies for innovation in wind power technologies. Although R&D spending of wind power enterprises from government plays the most effective role in the short and medium term [59–60], promoting government and enterprises investing on R&D activities can induce wind power technological innovation in the long run. Encouraging the R&D funding investment in wind power industry enterprises from government and enterprises should be both paid attention to.

Table 8
Results of robustness check (under provincial R&D spending).

	Model 9	Model 10
$FIT_{(t-1)}$	0.3087^{***}	0.4923^{**}
	(0.0658)	(0.2238)
$lnPRD_{(t-1)}$	1.1306^{***}	1.0744^{***}
	(0.1714)	(0.1900)
$lnPRD*FIT_{(t-1)}$		0.3867
		(0.4535)
$lnCIC_{(t-1)}$	0.0601	0.0539
	(0.0428)	(0.0412)
$lnEP_{(t-1)}$	0.5790	0.7634^{*}
	(0.4084)	(0.4205)
Constant	-10.7976^{***}	-11.4853^{***}
	(3.1977)	(2.9842)
Log likelihood	−1203.1323	−1201.0595
alpha	0.0335^{***}	0.0332^{***}
Sample size	250	250

Note: ***, ** and * indicate the significance at the 1% level, 5% level and 10% level, respectively. The standard error is reported in the parentheses.

Table 9
Results of robustness check (annual patent counts as explained variable).

	Model 11	Model 12
$FIT_{(t-1)}$	0.6279^{***}	0.5528^{***}
	(0.0930)	(0.1313)
$lnRD_{(t-1)}$	0.1757^{**}	0.1776^{**}
	(0.0859)	(0.0839)
$lnRD*FIT_{(t-1)}$		−0.1466
		(0.2271)
$lnCIC_{(t-1)}$	0.0804^{**}	0.0895^{**}
	(0.0350)	(0.0407)
$lnEP_{(t-1)}$	0.8680^{**}	0.9104^{**}
	(0.4438)	(0.4482)
Constant	−2.8066	−3.0771
	(2.4742)	(2.4862)
Log likelihood	−1026.421	−1026.102
alpha	0.0733^{***}	0.0730^{***}
Sample size	250	250

Note: ***, ** and * indicate the significance at the 1% level, 5% level and 10% level, respectively. The standard error is reported in the parentheses.

Finally, the paper used the annual patent counts for wind power technologies to replace the stock of patent for wind power technologies. As shown in Table 9, the variables except interaction term have significant positive relationships with the innovation of wind power technologies, which is similar to the results of Table 4. In other words, the feed-in tariff policy and R&D funding both promote patent counts of wind power technologies, but there is no interaction effect between the feed-in tariff policy and R&D funding on patent counts of wind power technologies. A 1% increase in R&D expenditure raises the mean patent counts by about 0.83% −0.84%. Moreover, the existence of feed-in tariff policy of wind power raises the mean patent counts by about 55.28%-62.79%.

Therefore, a series of different model specifications and an alternative classification of variables verify our findings, to a certain extent, are robust, and obtain new findings.

5. Concluding remarks and policy suggestions

Based on negative binomial fixed effect regression model and provincial panel data from 2006 to 2016, we investigate the effects of policies (feed-in tariffs and R&D spending), their interaction, deployment of wind power and electricity prices on wind power technology innovation at the provincial level in China. The following conclusions are drawn from the findings: (1) demand-pull policies through feed-in tariff policy promote innovation in wind power technologies; (2) higher feed-in tariffs of wind power induce greater stock of patents in wind technologies; (3) technology-push policies through R&D spending support wind power technological innovation; (4) only R&D funding investment in industrial enterprises under the implementation of feed-in tariff policy can stimulate greater patent stock due to the fact that the wind power industry enterprises are gainers for feed-in tariff policy, indicating that there is interaction effect; (5) improving the wind power deployment drives wind power technology patents; (6) increasing electricity prices will incentivize innovation of wind power manufacturers in order to reduce cost and obtain more profit.

Fossil fuel produces not only carbon emissions, but also SO_2 and

NO_x which pollute the environment [61]. Renewable energy with rational exploitation is beneficial to solve environmental problems and obtain economic returns [62]. The Chinese government makes an effort to increase the share of non-fossil energy consumption by about 20% in 2030. The wind power industry in China will keep expanding, which is a strategic choice to change the mode of economic development and adjust the energy structure. Technological innovation is also key to promoting clean power, like wind power, to substitute for fossil fuel [63]. As a strategic industry, the patents of wind power already have obvious strategic significance. Moreover, the complementarities between policies can play an important role in the innovation of wind power technologies [64].

From the above findings, we suggest that demand-pull policies (e.g. feed-in tariffs) should combine with technology-push policies (e.g. R&D spending), deployment strategy and incentive from electricity price to promote the innovation in wind power technologies. Secondly, the feed-in tariff policy not only plays a direct role in driving innovation in wind power technologies, but also indirectly affects patent stock through R&D spending, especially through R&D funding from wind power industry enterprises. Therefore, wind power technological innovation in China is spurred by both demand-pull policies (e.g. feed-in tariffs) and technology-push policies. Thirdly, feed-in tariff instrument has a great effect on patenting. The government should employ higher feed-in tariffs of wind power to induce investment in wind power at high-cost sites, which are close to electricity consumption centers with not only relatively sufficient consumptive ability but also difficult exploitation conditions for wind power. Forth, the benchmark feed-in tariffs of wind power should be constantly adjusted, and are expected to be equal to those of thermal power in 2020. Reforming the feed-in tariff policy will induce wind power investors to pay attention to the production cost [65].

Finally, promoting R&D spending is a key way for patenting in wind power technologies. First of all, encouraging the R&D funding investment in wind power industry enterprises from government and enterprises should be both paid attention to. Promoting R&D expenditures by government and enterprises are conducive to wind power technological innovation in the long term due to the fact that enterprises are the main body of R&D activities. Next, the market stimulus is a major means of promoting innovation, but there is also a market failure [54]. For instance, insufficient information may lead to uncertainties in the value of R&D expenditures, and even make the actual value of R&D spending below the optimal level, and information constraints will also impair private investors' decisions [66]. Therefore, government funds to support wind power technologies should be utilized more efficiently in order to achieve the technology transition under the improvement of marketization [67]. Besides, improving the attractiveness of the green industry is beneficial to broadening the green investment [68]. Further, adequate government funds to support wind power technologies signal the emphasis on wind power technologies, which also makes enterprises of wind power invest more R&D activities for wind power technologies. Additionally, especially for regions with backward technology, more financial support measures should be applied to renewable energy technologies. Above all, R&D investment supported by financial support measures, targets for emissions reduction and price-based policies can play a better role in fostering innovation in wind power technologies.

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