Energy Policy 108 (2017) 684–695

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Effects of policies on patenting in wind-power technologies

Joachim Schleich[a,b,c,*], Rainer Walz[a], Mario Ragwitz[a]

[a] Fraunhofer Institute for Systems and Innovation Research, Breslauer Straße 48, 76139 Karlsruhe, Germany
[b] Grenoble Ecole de Management, 12, rue Pierre Sémard, BP 127, 38003 Grenoble Cedex 01, France
[c] Virginia Polytechnic Institute & State University, Blacksburg, 24061 VA, USA

ARTICLE INFO

Keywords:
Innovation
Supply-side regulation
Demand-side regulation
Wind power
Patent analysis
Count data econometrics

ABSTRACT

This paper explores the effects of policies and other factors driving innovation in wind power technologies in twelve OECD countries over more than two decades. Patent counts are used as an indicator for innovation. The factors considered are generally derived from the systems of innovation literature. Count data econometric model were used for the estimations. The suggest that patenting in wind power technology is positively related to public R & D in wind power (reflecting supply-side policy), the stock of wind capacity (reflecting learning effects), the number of patents per capita (reflecting a country's innovative capacity), and the share of Green party voters (reflecting the legitimacy of the technology). In particular, the presence of production or capacity targets for wind power or renewable energy sources and a stable policy environment (reflecting policy process) appear to be favourable for patenting wind power technologies. These results are robust to various model specifications, distributional assumptions, and alternative classifications of wind power technologies in the patent search.

1. Introduction

Expanding renewable energy sources (RES) is considered to be a key strategy for tackling climate change, preserving resources, and securing energy supply. For example, the European Union (EU) has set a binding target of 20% for the share RES in final energy consumption in 2020. For 2030, this share is 27% and current debates focus on the support of RES in the EU beyond 2020 (European Commission, 2015). As a key component of decarbonising their power sectors, several countries, including Denmark, France and Germany, have passed energy transition laws", which mandate a sharp increase in RES. To achieve these targets innovation efforts may enhance performance and help lower the costs of electricity generation from RES.

Policy support for innovation in RES technologies is typically justified by positive technology and knowledge spillovers and by RES's avoidance of external costs associated with the generation of electricity from conventional sources (e.g. Rennings, 2000). Because of these market failures, private innovation would be lower than socially optimal without policy intervention. Since environmental policies also act as demand-side innovation policies, more recent work calls for innovation and environmental policies to be investigated jointly (Horbach et al., 2012; Costantini and Crespi, 2013; del Río Gonzáles and Peñasco, 2014). Complementary to approaches which justify policy by market failures, the systems of innovation (SI) approach emphasizes the need for systemic innovation policies to improve the functioning of the innovation system and prevent "system failure" (Smits and Kuhlmann, 2004; Lundvall and Borras, 2005; Klein Woolthuis et al., 2013).

Only few studies have yet analyzed the impact of policies on innovation in RES technologies based on large samples (Lee and Lee, 2013, p. 415). Notably, Johnstone et al. (2010) econometrically explore the effects of public expenditures on research and development (R & D) and of support mechanisms for RES on patenting in OECD countries between 1978 and 2003. Yet, their analysis does not allow for other policy factors which have been identified as impacting patenting. The SI literature stresses the importance of specific innovation functions for innovation, in particular. Policy can influence the functionality of an innovation system by removing blocking and adding inducing mechanisms (Bergek et al., 2008a). In addition, the policy analysis literature points to the role of target setting and policy stability for innovation activities (e.g. Jänicke and Lindemann, 2010; Bergek et al., 2008a).

In this paper, we econometrically explore the factors driving patenting activity in wind energy technologies, relying on data for twelve OECD countries over the time span of 1991–2011. These factors include supply-side policies such as technology-specific R & D, and demand-side policies such as support mechanisms for electricity generated by RES. Relying on the comprehensive functions of innovation approach as a conceptual framework, we extend previous studies

* Corresponding author at: Fraunhofer Institute for Systems and Innovation Research, Breslauer Straße 48, 76139 Karlsruhe, Germany.
E-mail addresses: joachim.schleich@isi.fraunhofer.de (J. Schleich), rainer.walz@isi.fraunhofer.de (R. Walz), mario.ragwitz@isi.fraunhofer.de (M. Ragwitz).

http://dx.doi.org/10.1016/j.enpol.2017.06.043
Received 29 July 2016; Received in revised form 30 April 2017; Accepted 16 June 2017
0301-4215/

of patenting activities in RES power technologies - notably Johnstone et al. (2010) - by also including factors derived specifically from the SI and the policy analysis literatures, thereby complementing existing case-study based approaches in the SI and policy analysis literatures. We focus on wind energy because wind power is typically considered to exhibit the largest future potential among RES power technologies (IEA, 2014). Our sample also captures the more recent and also more dynamic developments in wind power patenting since the late 1990s. As a robustness check of our findings, we also allow for a more comprehensive classification of patents in wind-power technologies than previous studies.

Section 2 provides an overview of the literature and the conceptual framework used. Section 3 presents the methodology, including a description of the data, the variables, and the econometric approach. Results are shown and discussed in Section 4. Section 5 summarizes the main findings and offers policy implications.

2. Literature review

2.1. Conceptual framework

Since the 1990s, researchers have employed the SI heuristic to study innovation activities. In particular, the technological innovation systems literature has identified several functions that innovation systems need to fulfil to spur innovation (e.g. Jacobsson and Johnson, 2000; Smits and Kuhlmann, 2004; Hekkert et al., 2007; Bergek et al., 2008a; Heckert and Negro, 2009). These functions may be categorized as: creation and development of knowledge (F1); creation of positive external economies via exchange of information and knowledge between producers and along the value chain, including user-producer interaction (F2); guidance of the search for new technological solutions and markets (F3); creation of the legitimacy of a new technology and counteracting resistance to change (F4); facilitation of market formation (F5); supply of resources, especially for new technologies with a high risk of failure (F6); and diversity in experimentation and a variety of solutions (F7). These functions overlap and involve interactions and feedback loops. Recognizing that the actors who perform the functions respond to policies, the SI approach encompasses the traditional demand-pull and technology-push factors in a more systemic framework, but does not regard innovation as a linear process.

The policy instruments discussed in the innovation policy literature may affect the functionality of an innovation system by removing mechanisms which block the actors performing functions, or by adding mechanisms to support those actors. Supply-side regulation attempts to affect the innovation process per se and contributes to the creation and development of knowledge (F1). Traditional supply-side policies include technology-specific measures such as subsidies for R & D for particular technologies, cross-cutting policies such as the protection of intellectual property rights, and the standardisation of products and processes via norms (e.g. Blind, 2008). Subsidies for R & D, in particular, provide resources for the actors creating knowledge and developing new technologies (F1, F6) and facilitate the exchange of information (F2). Technology-specific R & D support also provides guidance of search (F3).

Demand for wind turbines is blocked, for example, because the costs of generating electricity from fossil fuels do not reflect the associated environmental damages so that electricity prices are lower than socially optimal. In this case, domestic demand-side policies enable market formation (F5) by providing support for production and, thus, for investment in technologies which are less harmful to the environment. There are various channels how this will foster innovation (e.g. Lundvall, 1988; von Hippel, 1996; Edler and Georghiou, 2007): The interaction between users and producers of an innovation transfers knowledge about preferences, customers and real-world operation conditions from the market to the technology providers. Thus, the exchange of knowledge (F2) is fostered. Furthermore, learning-by-doing in the production process of the innovation and utilizing economies of scale can improve product quality and drive down costs. In addition, demand-side policies may lead indirectly to the supply of resources (F6), as revenues from sales help to recover the costs of innovations.

Demand-side instruments for RES include measures supporting deployment such as feed-in tariffs (FITs), which make fixed payments to electricity generators for each kWh of electricity supplied from RES. Other support mechanisms include investment subsidies or tax exemptions, production tax credits (PTCs), quota obligations for the share of RES electricity generated or distributed, and tradable green certificate (TGC) schemes. Higher support levels generate higher profits which can then be used for additional innovation. By creating sufficient demand, these mechanisms help establish markets for high-cost RES technologies and overcome the technological fossil fuel lock-in in the energy sector (F5) (Unruh, 2002). Most theoretical and empirical studies consider market-based support mechanisms such as TGCs, FITs or PTCs to have stronger effects on innovation than command-and-control instruments like non-tradable obligations, since the latter provide lower financial incentives to advance technologies beyond the required standard (e.g. Jaffe et al., 1999). The thrust of the literature further suggests that FITs are more conducive to diffusion and innovation than TGC because they provide more predictable price incentives for investors (e.g. Schmidt et al., 2012; Bergek and Berggren, 2014). Such investment security is particularly relevant for investors in technologies like wind power, where capital costs account for a high share of total generation costs (e.g. Kleßmann et al., 2013).[1] FITs might therefore lead to a higher level of innovation than other mechanisms because they have a stronger effect on demand.

Similar to domestic regulation, foreign regulation may also enable market formation (F5), which indirectly facilitates the supply of resources (F6), user-producer interactions and learning effects (F2) (e.g. Wagner, 2007; Wei Yingqi et al., 2008). Likewise, a greater number of innovations may induce higher exports in the future, reinforcing the positive relation between exports and innovation (e.g. Fagerberg, 1988; Dosi and Soete, 1988; Sanyal, 2004; Madsen, 2008).

The SI literature stresses, in particular, the importance of learning, of a country's innovative capacity, and of technology legitimacy for innovation. Accordingly, learning-by-doing, learning-by-using, and learning-by-interacting (user-producer interaction) (F2) lead to patenting of new products and processes (e.g. Smits and Kuhlmann, 2004; Lundvall, 1988; von Hippel, 1996). Learning effects are also linked with market formation. In particular, incorporating user knowledge into the design process may be conducive to innovation, allowing for knowledge to spill over to domestic actors through various channels, including “reverse engineering” in cases where technologies are imported (e.g. Boon et al., 2011; Nahuis et al., 2012; Peine and Hermann, 2012). Technology diffusion further signals commercial opportunities for (potential) domestic technology producers and may also stimulate domestic innovation activities eventually leading to patenting. A country's higher scientific and technological know-how also nurtures innovation activities by companies (F1) (e.g. Nelson, 1993). Finally, a higher perceived legitimacy of technology translates into the greater market success of a new technological paradigm (F4). Similarly, the greater potential and performance ascribed to a technology facilitates legitimacy and increases further innovation activities (Bergek et al., 2008b). A second aspect of legitimacy relates to the power to change existing rules and institutions, e.g. via the ability to influence public policy (Hekkert and Negro, 2009) and to challenge existing technological regimes (Walz and Köhler, 2014).

The policy analysis literature stresses the importance of target

[1] Capital costs account for about 80% of the levelized costs of wind power generation (IRENA, 2012).

setting and of the stability of the regulatory framework for innovation in RES (e.g. Jänicke and Lindemann, 2010; Bergek et al., 2008a). Given the time needed to bring innovations to the market, and the dependence of market development on political measures, innovators are deterred by prospects of stop-and-go policies (Nemet, 2009). Enacting policy targets and ensuring a stable regulatory framework reduce this blocking mechanism and support the functions of an innovation system such as guiding innovative search processes (F3) and promulgating the legitimacy of RES for innovation (F4) (e.g. Smits and Kuhlmann, 2004; del Río Gonzáles and Bleda, 2012; Bergek and Berggren, 2014). Likewise, the emerging policy mix literature stresses the need to broaden the perspective and go beyond merely analysing the features of single policy instruments (Rogge and Reichardt, 2016). Existing empirical analyses rely almost exclusively on case study interviews involving a limited number or actors. Case studies are well suited to gain profound insights into complex decision-making processes and structures within organizations, but their findings are usually limited to an analytical generalization, where observed outcomes of decision-making processes are explained by identifying the relevant causal mechanisms (Yin, 1994, p. 45 f). But they have a weak basis for generalizing the findings in a statistical sense. The low number of observations does not allow for statistical inference.

2.2. Findings from econometric analyses

The few econometric studies exploring the impact of public policies on innovation activities in technologies for RES employ country-level panel data, and use patent counts over time as indicators for innovation. Johnstone et al. (2010) focus on the effects of different support mechanisms by drawing on data for five RES in 25 OECD countries between 1978 and 2003. They find that FITs increase patenting activity in high-cost technologies used in RES (i.e. solar), but not for more cost-competitive technologies. FITs were found to negatively affect patenting in wind-power technologies. For most specifications, patenting is not related to the support levels per se, but to whether a policy is in place or not. In addition, Johnstone et al. (2010) further find that public R & D boosts patenting in wind-power. They further conclude that policies rather than electricity prices are driving innovation in RES.

Costantini et al. (2015) draw on data from 36 OECD and non-OECD countries between 1990 and 2010 to analyse the factors driving patenting in biofuel-related technologies. Accordingly, public R & D and to a country's innovative capacity increase patenting in biofuel technologie. They further find patenting in mature technologies to be mainly related to demand-side policies. In comparison, patenting for less-mature technologies is related to supply-side and demand-side policies.

Johnstone et al. (2010) and Costantini et al. (2015) both focus on the effects of the different types of support mechanisms, particularly on FITs. In comparison, the impact of other demand-side factors has only been explored in case studies, where identification of the effects was difficult (e.g. Hekkert and Negro, 2009). The majority of empirical studies explore the effect of support mechanisms on the deployment of RES rather than on innovation, e.g. Polzin et al. (2015) or del Río Gonzáles and Peñasco (2014).

Nesta et al. (2014) and Nicolli and Vona (2016) study the effect of market liberalization on patenting for renewable technologies in EU countries. Market liberalization enabled the entry of electricity suppliers who typically relied on small, decentralized units such as wind mills, thus challenging the incumbent utilities, which typically relied on centralized fossil-fuel or nuclear units. The market entry of these new suppliers increased the incentives for technology providers to innovate in decentralized RES technologies. The results of Nesta et al. (2014) and Nicolli and Vona (2016) confirm that reducing entry barriers induces innovation. Analysing RES patenting activities in OECD and non-OECD countries, Bayer et al. (2013) conclude that democratic institutions spur patenting. They argue that democratic governments are more likely than autocracies to provide public goods like infrastructure or education for their citizens' benefit, which in turn spur patenting. Dechezleprêtre and Glachant (2014) explored the impact of foreign policies on domestic innovation. Using wind power generation abroad as a proxy for the demand-pull effects of foreign policies, they conclude that patenting is positively related to foreign policies.

Our empirical study is closest to Johnstone (2010) and Costantini et al. (2015). Like Johnstone et al. (2010), our analysis includes R & D expenditures, and allows for different support mechanisms. Similar to Costantini et al. (2015), we allow for learning effects and the country's innovative capacity. In addition, and complementary to the case study analyses relying on the SI and policy studies frameworks, our empirical model accounts for other factors identified by the functions of innovation literature such as technological legitimacy, target setting and the stability of the regulatory framework. Our specification generally includes a broader set of explanatory and control variables than the extant empirical literature. The analyses by Johnstone et al. (2010), Nesta et al. (2014) and Nicolli and Vona (2016) use wind technology patents retrieved for the sub-class F03D, which relates to the main focus of wind power plants such as motors, masts and rotors. In addition to also using F03D, we further employ a more comprehensive classification, which comprises patents related to electric and electronic components, for example.

3. Methodology

3.1. The case of wind power

Wind energy plays an important role for decarbonising the electricity sector in many countries. By the end of 2015 about 432 GW of wind power had been installed globally (GWEC, 2015), 176 GW in Asia, 148 GW in Europe and 89 GW in North America. Until about 2006, the development was driven by European countries, particularly Denmark and, later, Germany and Spain. The markets in Asia exhibited high growth rates in recent years, with an annual installed capacity of 34 GW in 2015. Since 2012, capacity growth in Europe has stabilized at about 11–14 GW per year, and varied in North America between 3 and 15 GW. About 98% of the globally installed wind capacity is onshore wind. Only about 12 GW of offshore wind capacity had been constructed in 2015.

All large markets are strongly policy driven. The types and design of the support mechanisms differ across countries over time.[2] For example, the US has traditionally implemented federal PTCs for power generated from certain RES (including wind). In addition, several states have renewable portfolio standards (RPS) in place. In the EU, wind energy was initially driven by FITs introduced at the member-state level, e.g. in Denmark, France, Germany, Portugal and Spain. Some countries, including Belgium, Poland, Sweden and the UK, primarily relied on TGCs based on quota obligations. Germany replaced its technology-neutral power purchase agreements with a technology-specific FIT in 2000, specifying a fixed remuneration level for 20 years. Since then, FITs have become the dominant support mechanism in most countries, but design features differ across countries. For example, Spain's FIT, in place from 1997 until 2012, fixed the remuneration for only five years. Several countries have switched mechanisms over time, primarily from FIT and TGC to feed-in premium (FIP) systems. Germany, Italy, the Netherlands and the UK recently introduced FIPs to improve compatibility with the electricity market.[3] In early 2014, the EU adopted the "Environmental and Energy State Aid Guidelines for 2014–2020" (European Commission, 2014), effectively making FIPs based on bidding systems the central RES support mechanism.

[2] For further details we refer to the IEA 'Renewable Energy Policies and Measures Database' (http://www.iea.org/policiesandmeasures/renewableenergy/).

[3] Under a FIP, electricity producers receive a premium on top of the wholesale price. To prevent under- and overcompensation, FIPs are typically combined with predetermined price floors and caps or minimum and maximum levels of total remuneration. Alternatively, floating FIPs are used. Here, the total remuneration is fixed at a "strike price" if a predefined benchmark for market revenues is reached.

Over the last three decades, wind-power technology has made substantial progress, resulting in significant cost reductions. Estimating learning curves between 1981 and 2004, Nemet (2009) finds a progress ratio of 89%. Cost reductions were driven mainly by economies of scale, the development of new technology concepts and materials, and the standardisation and automation of manufacturing processes. For example, over the last two decades, the capacity of a standard turbine increased by a factor of ten.

3.2. Empirical analysis

We employ panel econometrics to estimate the impact of policy and other factors on patenting, relying on a time series of cross-sectional data for twelve OECD countries: Austria (AT), Denmark (DK), France (FR), Germany (DE), Italy (IT), Japan (JP), the Netherlands (NE), Spain (SP), Sweden (SE), Switzerland (CH), the United Kingdom (UK) and the United States (US). Country choice was motivated by their importance for patenting in wind-power technologies, as well as data availability. Our sample includes countries with relatively low patenting such as Switzerland or Austria and also countries such as Denmark and Germany with relatively high patenting. In total, the countries included in our sample account for 75–90% of global wind-power patents in any given year. Of the countries which have very recently become more relevant for wind power patenting, only China and Korea are missing from our sample.

3.2.1. Dependent variable

Although extensively employed in the empirical literature, using patent data to reflect innovation has been critically discussed (Pavitt, 1985; Griliches, 1990; Archibugi and Pianta, 1996; Jaffe and Trajtenberg, 2002; Nagaoka et al., 2010). Patents incorporate information on relevant aspects of the innovative process, but not all of the generated innovation is actually patented. Patents can only capture codified knowledge but cannot capture tacit knowledge. In addition, inventors may protect their technological innovations using other methods such as secrecy or lead time (e.g. Hall et al., 2014). Also, patents may not adequately reflect commercial value and frequently fail to yield significant value to their owners (Harhoff et al., 1999). For example, companies may use patents to prevent competitors from patenting related inventions, or to avoid law suits (Cohen et al., 2000). However, since alternative appropriate data (e.g. private R & D on wind-power technologies) are often lacking, patent information is often the only available option. In this sense, we follow the thrust of the empirical literature and use the number of patents *(patents*) as the dependent variable for the econometric panel estimation.

Among renewable energy technologies, wind-power technologies are particularly well classified: they form the patent sub-class F03D. This sub-class comprises mechanisms for converting the energy of wind into useful mechanical power: (i) wind motors with rotation axis substantially parallel to the flow of air entering the machine; (ii) wind motors with rotation axis substantially at a right angle to the flow of air entering the machine; (iii) other wind motors; (iv) controlling wind motors; (v) adaptations of wind motors for special use; (vi) combinations of wind motors with apparatus driven thereby; and (vii) other details, component parts, or accessories of wind motors. Thus, F03D relates to the main focus of wind power plants such as motors, masts and rotors, but does not cover the electrical power generation or distribution aspects of wind power plants.[4] Furthermore, we do not include off-shore wind technologies, since they have become prominent only recently.

The patent data refers to patent applications and country assignment based on the country where the inventor lives rather than at the location of the headquarters of the company filing the patent. Thus, the data likely indicates the country where the new knowledge has been acquired. Patent data is collected relying on the transnational patent approach described by Frietsch and Schmoch (2010).[5] Accordingly, we count all patent applications filed under the Patent Cooperation Treaty (PCT), independent of whether they are transferred to EPO or not. Furthermore, we take EPO applications into account. To avoid double counting, we only count the direct EPO applications without precursor PCT application. Thus, all patent families with at least a PCT application or an EPO application are taken into account.[6] The data was retrieved from the Questel database (www.questel.com) using the International Patent Classification (IPC). A total of 6527 patents were identified for the time period 1991–2011. The data indicate a strong increase in total patenting of wind-power technologies over that period (see Fig. 1 and also Annex Table A1). Until 1998, patenting was relatively low. The average number of patents per country was between 1 and 2 for the first years of the time period considered. It then started to increase, in particular in the USA, Denmark, and Germany. After 2005, patenting also took off in Japan, the UK, and Spain.[7] In sum, patenting activity increased in all twelve countries since the early 1990s, but the levels and the development of *patents* differs across countries.

3.2.2. Explanatory variables

We include public R & D expenditures for wind-power technologies (see Table 1).[8]As a supply side policy $r\&d$ is expected to increase patenting activity. We further include a dummy variable, *FIT*, which takes on the value of one if a FIT was in place in a specific year.[9] Similarly, *NOFIT* is equal to one if other-than-FIT support mechanisms were implemented. Practically, *NOFIT* mostly means quota systems with TGCs.[10] *FIT* and *NOFIT* only capture differences in the types of support mechanisms, but not in the support levels.[11] Both, *FIT* and *NOFIT* reflect domestic demand-side policies and should be positively related with patenting. Since FIT is thought to provide higher investment security than other support measures, and because it might enable higher supply of resources, the effect of *FIT* should be larger than of *NOFIT*. We include the export volume of wind-power technol-

[4] Employing an alternative retrieval methodology, we additionally allow for a more comprehensive classification of wind power technologies, which also includes patents related to the electric and electronic components of wind power technology, for example. Further details and results are reported in Section 4 under the subheading "robustness checks".

[5] In general, the choice of patent offices from which patent applications are taken matters. Since patents are also a means to protect markets, there is a country bias in favour of domestic applicants. To address this country bias, the triadic patent approach was developed in the 1990s. This approach only considers patents which are simultaneously applied for at the EPO, USPTO and JPO. As a drawback, however, it does not allow analysing patent applications before 2001, since until then the USPTO only published data for the patents granted, i.e. not for all the patents applied for. In addition, for countries other than Japan, the outcome under the triadic approach is de facto defined by the application at the JPO. In light of the low relevance of Japan as a destination of wind turbine exports for the period covered in this study, the triadic patent approach does not appear appropriate for our study.

[6] Frietsch and Schmoch (2010) conclude that this transnational approach provides larger samples than the Triadic approach for the analysis of specific fields and is highly capable of reliably capturing the relations between different countries.

[7] In 2003, the last year in the analysis by Johnstone et al. (2010), the average number of patents is 20 (for the 12 OECD countries in our sample). By 2011, the last year in our analysis, this figure has increased to 100.

[8] Private R & D expenditures for wind power technologies could not be included due to lack of data. To the extent that private R & D efforts are correlated with explanatory variables in the model, the estimated coefficients may suffer from an omitted variable bias.

[9] *FIT* also equals one if a FIP was in place in Spain (from 2007 on) or Denmark (from 2009 on), since the incentives of these FIPs for investors are similar to those of FITs. For similar reasons, *FIT* was set to one when a PTC was in place in the USA. This approach is supported, among others, by May (2015).

[10] Other support mechanisms were implemented for a few years only, and did not justify including a separate variable. For example, the UK had a tender system for renewable wind power for five years only 1997–2001).

[11] Similar to Johnstone et al. (2010), we abstract from the fact that policies may be implemented or adjusted in response to patenting activity (e.g. Downing and White, 1986). Policy endogeneity is difficult to address in the given context, in particular since there is not much variation in the variables capturing support mechanisms. We further explore policy endogeneity in the sub-section on robustness checks.

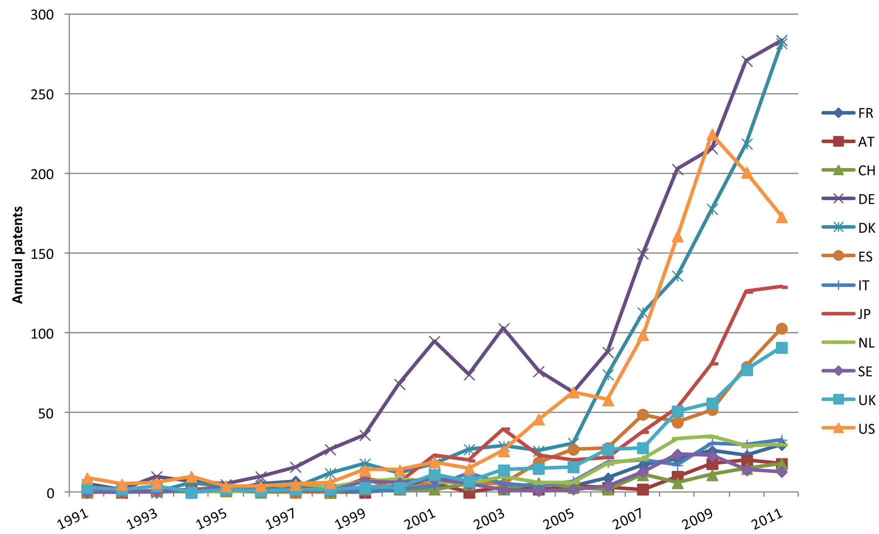

Fig. 1. Annual transnational patents in wind-power technology for twelve OECD countries.

ogies (*export),* which is meant to roughly capture the impact of export demand (e.g. via foreign support mechanisms) on domestic patent activity. *Export* is expected to be positively related with patenting.

Similar to Costantini et al. (2015), learning effects (are assumed to be captured by the cumulative capacity of wind power installed in a particular country (*windcap*). If domestically installed capacity is also generated by domestic producers, learning effects especially relate to economies of experience on the production side and to user-producer interactions. Furthermore, knowledge obtained from experience with imported wind turbines might spill over to other domestic technology providers. Since the effects of the capacity installed in a particular year are likely to fade over time, we follow the empirical literature and apply an annual decay rate. We use a rate of 10%, which is in the range of rates typically employed for the depreciation of the knowledge stock.

To reflect a country's innovative capacity, we follow Costantini et al. (2015) and include the number of total patents (net of patents for RES) per capita (*patents_all_pc). Patents_all_pc* may also account for cultural differences across countries concerning the propensity to patent. Thus, *patents_all_pc* should be positively related with patenting.

The legitimacy of technology has been empirically analyzed in case studies by looking at the increase in interest groups, lobbying activities, and debates in parliament and the media (Bergek et al., 2008a; Hekkert and Negro, 2009). There is no single indicator available which covers all of these aspects across countries over time. As a proxy for the legitimacy of technology, we include the share of votes for green parties at national level during the most recent election (*greenvote).* To be considered a green party, it had to be a member of the Global Greens, the European Green Party or the parliamentary group of the Greens in the European Parliament. The share of green party voters is supposed to reflect the social acceptance of renewable energy technologies in the eyes of the relevant stakeholders. Green party programmes typically foresee, as a core element, a strong increase in renewable electricity. Competition for voters also means that other parties may adjust their programmes to adopt green issues if these attract voters. Voter support for a green party is therefore assumed to be positively correlated with support for an energy transition in a country.[12] Thus, *greenvote* primarily relates to one aspect of legitimacy: the power to change existing rules and institutions, e.g. via the ability to influence public policy (Hekkert and Negro, 2009).

To capture factors of innovation which feature prominently in the policy analysis literature, and which are also linked to innovation functions, we construct two variables (see also Annex Table A2). First, *target* takes the value of one if a national target is in place for electricity generated from wind power or from renewable energies in general. For example, Germany was the first of the sample countries to introduce targets for wind in 1989, i.e. installing 250 MW between 1989 and 1996. The federal German Renewable Energy Act, which came into force in 2000, aimed at doubling the electricity generated by RES until the year 2010. Similarly, in 1996, Japan implemented legislation aiming to have 3 GW of wind power installed by 2010. In 2003, Japan then introduced the target for 16 TWh to be generated by all RES in 2014. In the US, individual states introduced RPSs in the 1990s. For the US, *target* was set to one, if states accounting for more than half the US population had targets in place. This was the case since 2004. Such an official target signals that the technology is seen as very important. *Target* is expected to increase patenting activity. Second, and somewhat more exploratively, we attempt to capture the impact of the stability of the regulatory framework. To do so we construct *stability,* which equals one if there is a stable regulatory framework in place *and* a supportive regulatory framework exists (e.g. provisions for integration of power from RES into the grid, building codes, standards) *and* if there are information and education programmes in place. For the US, for example, the short duration and fast changes in legislation led to a score of zero for most of the 1990s. The federal PTCs were extended several times for only two additional years, and by a narrow margin of votes (Bird et al., 2005). In the UK, legislation governing wind energy started relatively late. A renewable obligation plan has existed since 2000 (updated in 2002). In 2001, a climate change levy was introduced, which is still in place. From 2002 on, when the offshore wind capital grants scheme and the renewable obligations were introduced (both are still in place), the regulatory framework in the UK was judged to be stable.[13] Denmark started to foster RES in the mid-1970s, passed the Electricity Supply Act in 1976 (still in place), implemented a technical certification scheme for the design, manufacture and installation of wind turbines during the 1980s, and passed the green tax package in 1995. Stability of the regulatory framework in Denmark was deemed to be further strength-

[12] By choosing country-level measures to reflect legitimacy, we ignore that legitimacy may also materialize at the regional or local level, in particular for wind power (e.g. Spiess et al., 2015). Detrimental effects of wind power at the local level may include noise disturbance or visual impact on the landscape. On the benefit side, wind power may boost local employment.

[13] A detailed description of the country-specific assessment and the sources used is beyond the scope of this paper, but is available from the authors upon request.

Table 1
Definition of variables.

	Definition	Functions of Innovation addressed	Expected sign	Data sources
Dependent variable				
Patents	Number of international patents for wind technologies.			Patent families with at least a PCT application or an EPO application; EPO and WIPO data, retrieved with Questel.
Explanatory variables				
r & d	Public R & D for wind power including onshore and offshore technologies and wind energy systems and other technologies (Group 32) (million $2013).	F2, F2, F3, F6	+	IEA RDD online data service: http://www.iea.org/statistics/RDDonlinedataservice/
FIT	Dummy, value of 1 if a FIT or FIP is implemented.	F5	+	IEA/JRC Global Renewable Measures Database, data for instrument were taken primarily from European Renewable Energies Federation and the literature.
NOFIT	Dummy, value of 1 if another support measure aside from a FIT or a FIP is implemented.	F5	+	IEA/JRC Global Renewable Measures Database, data for instrument were taken primarily from European Renewable Energies Federation and the literature.
Export	Export volume of wind power technologies (10e9 $2013).	F5	+	UN-COMTRADE for HS classification number 850231 "Electric generating sets and rotary converters - Wind-powered".
windcap	Accumulated installed wind power capacity (GW = 1000 MW); decay rate of 10% p.a. is applied.	F2	+	Global Wind Energy Council Global Statistics.
patents_all_pc	Number of international patents (net of *patents* and *patents_reg*) per million inhabitants.	F1	+	Patent families with at least a PCT application or an EPO application; EPO and WIPO data, retrieved with Questel.
Greenvote	Share of votes of Green party (in %).	F4	+	For EU countries, outcomes of the most recent EU Parliament elections were used. For other countries and for EU countries prior to their joining the EU, data were taken from the elections of national parliaments.
Target	Dummy, value of 1 if target for wind energy or capacity exists	F3, F4	+	Reports by IEA, IRENA, national agencies, academic and grey literature.
Stability	Dummy, value of 1 regulatory environment considered stable	F3, F4	+	Reports by IEA, IRENA, national agencies, academic and grey literature.
Control variables				
Powerprice	Electricity price for households including excise taxes and other taxes and surcharges ($ 2013/MWh).		+	IEA Energy Prices and Taxes Database.
patents_reg	Number of international patents for all renewable technologies (excluding wind).		+	Patent families with at least a PCT application or an EPO application; EPO and WIPO data, retrieved with Questel.

ened by the wind energy co-operative tax incentive of 1997 and the offshore wind agreement in 1998. But the regulatory framework became unstable in the wake of liberalization of the energy markets in the late 1990s and the change in government in 2001. In particular, legislation was passed in 1999 foreseeing a switch from a FIT-type support system to a TGC system, with a transition period to 2005. In 2004, however, new legislation was passed which introduced FITs, a replacement scheme for on-shore wind turbines (still in place), and a long-term energy strategy.[14] *Stability* should be positively related with patenting in wind-power technologies.

3.2.3. Control variables

Following the literature (e.g. Johnstone et al., 2010; Nicolli and Vona, 2016), we include the price of electricity (*powerprice*). As pointed out by the induced innovation literature (e.g. Popp, 2002), an increase in the price of electricity is expected to amplify the incentives for innovation in renewable energies. This may be because the remuneration for renewable electricity is tied to the power price (as was the case in Germany until 2000, for example). Likewise, technology providers may interpret increasing electricity prices as a signal for the higher profitability of their products in the future. The data on end-use prices provided by the IEA include excise taxes as well as other taxes and surcharges such as municipal taxes, and surcharges for renewable energy and combined heat and power. Thus, *powerprice* may also capture the effect of support mechanisms for RES (policy-induced innovation). Similarly, end-users' electricity prices may also include energy and environmental taxes or the costs of greenhouse gas certificates (e.g. for allowances in the EU Emissions trading systems since 2005). In this sense, *powerprice* also reflects the stringency of environmental regulation.[15]

Finally, we include the number of patents in RES technologies (net of patents for wind-power technologies) to control for changes in the propensity to patent in RES over time and across countries.[16] To calculate *patents_reg,* we use patents for solar energy (including photovoltaic and concentrated solar thermal power), ocean energy (including tidal and wave energy and salinity gradient power), biofuels (including liquids, solids and biogases), geothermal (including hydrothermal and hot, dry rock resources), and hydroelectricity (including large and small hydroelectricity).[17] Together with wind power, these RES also form the patent class Y02E 10/00. *Patents_reg* dominated by photovoltaic patents (IPC class H01L-03).

Table 1 provides an overview of the variables, references to the data sources and expected signs in the econometric analysis. It also includes a column indicating which of the SI functions of innovation the policy variables and factors are supposed to address. The descriptive statistics of the dependent and explanatory variables (in levels) appear in Table 2.

3.2.4. Econometric model

To analyse the factors driving innovation activity in wind-power technologies, we employ a similar panel econometrics model as previous studies:

Table 2
Descriptive statistics of dependent and explanatory variables (1991–2011).

Variable	Unit	Obs.	Mean	SD	Min	Max
patents	count	252	25.90	49.94	0.00	284
r&d	million $2013	250	13.81	20.23	0.19	197.21
FIT	dummy	252	0.47	0.50	0.00	1.00
NOFIT	dummy	252	0.24	0.43	0.00	1.00
export	10e9 $2013	252	0.14	0.37	0.00	2.20
windcap	GW	252	1.89	4.10	0.00	30.14
patents_all_pc	per million inhabitants	252	204.19	132.57	8.34	651.29
greenvote	percent	252	4.27	3.51	0.00	13.04
target	dummy	252	0.62	0.49	0.00	1.00
stability	dummy	252	0.51	0.50	0.00	1.00
powerprice	US 2013$/MWh	252	190.11	54.89	94.20	387.88
patents_reg	count	252	89.24	165.89	0.00	1061

$$\begin{aligned} patents_{i,t} = {} & constant + \beta_1 r\&d_{i,t-1} + \beta_2 FIT_{i,t-1} + \beta_3 NOFIT_{i,t-1} \\ & + \beta_4 export_{i,t-1} + \beta_5 windcap_{i,t-1} + \beta_6 patentsallpc_{i,t} \\ & + \beta_7 greenvote_{i,t-1} + \beta_8 target_{i,t-1} + \beta_9 stability_{i,t-1} \\ & + \beta_{10} powerprice_{i,t-1} + \beta_{11} patentsreg_{i,t} + \alpha_i + \varepsilon_{i,t} \end{aligned} \quad (1)$$

where $I = 1,...,12$ indexes the cross-sectional units (countries) and $t = 1991,..., 2011$ indexes time; α_i represents an unobserved country-specific effect, and $\varepsilon_{i,t}$ is the usual idiosyncratic error term. The coefficient β_i may be interpreted as a semi-elasticity. If variable i increases by one unit, $100{*}\beta_i$ is the percentage change in the mean number of patents. In the estimated specification, most explanatory variables enter with a lag of one period, recognizing that companies take time to mobilize the resources to respond to policy and market factors.[18] Lagging explanatory variables is also expected to reduce potential endogeneity problems related to the policy variables. Since *patents_reg* is supposed to control for general trends in the propensity to patent for renewables, it is not lagged.

As is common in patent analysis (Hausman et al., 1984; Hall et al., 1986), we use a negative binomial model to reflect the count nature of the dependent variable.[19]

Compared to a purely cross-sectional analysis, a panel analysis allows for more general heterogeneity across countries. In particular, omitted country characteristics which affect a country's propensity to patent and which are correlated with other regressors do not result in inconsistent parameter estimates in panel data models as long as these unobserved effects (i.e. α_i in Eq. (1)) are roughly constant over the period in question. Like Nesta et al. (2014), Costantini et al. (2015), or Nicolli and Vona (2016), we employ a fixed-effects estimator to estimate Eq. (1). The fixed effects estimator uses variation within countries (i.e. deviation of variables from country means). In our estimations of Eq. (1), all variables are transformed into the natural logarithm except for the dummy variables, *greenvote* and the count variables.[20] Thus, the coefficients for the log-transformed variables may be interpreted as elasticities, the coefficients for the dummies and for *patentsall* as semi-elasticities.

[14] Typically, target setting precedes the implementation of other supportive measures, but this is not necessarily the case. One example of a case where a stable regulatory framework existed without an official target was Germany during the late 1990s. No formal government target existed at that time but the so called "Stromeinspeisegesetz" provided a stable regulatory framework (combined with a feed-in type support system).

[15] For the nine EU Member States in our data set, end-use prices without taxes and levies were available from Eurostat. Additional analyses for the restricted sample using these prices corroborate the findings reported in Section 4. We provide more details on this additional analysis in the subsection on robustness checks.

[16] Johnstone et al. (2010) use patents across all technologies (not just RES) as a control variable. Thus, our specification allows distinguishing between the general technological capacity of a country (*patents_all_pc*) and cyclical effects over time which are specific to the RES domain (*patents_reg*).

[17] We generally used IPC. For technologies, where IPC is too broad (e.g. biofuels), we combined IPC with key words.

[18] This specification follows, among others, Hall et al. (1986) and Costantini et al. (2015). In Johnstone et al. (2010), the explanatory variables are entered without lags, implying that patenting activities respond instantaneously to market and policy signals. We report the results of alternative lag structures in the sub-section on robustness checks. Allowing different lag structures also helps to capture the potential effects of reverse causality.

[19] Unlike a Poisson model, the negative binomial model does not assume that the conditional mean is equal to the conditional variance (equidispersion). The conditional probability function of the negative binomial models includes an additional term reflecting unobserved heterogeneity, which is assumed to follow a gamma distribution.

[20] Since the natural log of zero is not defined, we set the data to a small number (0.00001) when *windcap* or *r&d* was zero. This was the case for a total of 13 observations. Results were virtually the same when these observations were dropped.

Table 3
Results for negative binomial fixed-effects estimator (standard errors in parentheses).

r & d (t−1)	0.135	***
	(0.0427)	
FIT (t−1)	−0.186	
	(0.157)	
NOFIT (t−1)	−0.137	
	(0.192)	
export(t−1)	0.00371	
	(0.0214)	
windcap(t−1)	0.0885	**
	(0.0346)	
patents_all_pc (t−1)	0.507	***
	(0.157)	
greenvote (t−1)	0.0670	***
	(0.0247)	
target (t−1)	0.563	***
	(0.129)	
stability (t−1)	0.714	***
	(0.116)	
powerprice (t−1)	0.342	
	(0.287)	
patents_reg (t)	0.00187	***
	(0.000220)	
Constant	2.557	
	(2.209)	
Log likelihood	−688.9	
Sample size	238	

** indicates individual significance in two-tailed *t*-test at p=5%.
*** indicates individual significance in two-tailed *t*-test at p=1%.

4. Results

Table 3 displays the results from estimating Eq. (1) via maximum likelihood methods. We first note that the findings support most of our predictions.[21] The coefficients of *r & d, windcap, patents_all_pc, greenvote, target*, *stability* and *patents_reg* exhibit the expected positive sign and are statistically significant.[22]

The findings for our supply-push policy, *r & d*, are similar to Johnstone et al. (2010), Dechezleprêtre and Glachant (2013) and Nicolli and Vona (2016). The point estimate of the coefficient suggests that an increase in public R & D for wind technologies by 1% is associated with, on average, about 2.5 more patents in the following year (0.0925*27.16[23]).

Turning to the domestic demand-pull policy design, we find that *FIT* and NOFIT exhibit a negative sign, but are not statistically significant. The result for FIT is consistent with Johnstone et al. (2010), but for a more updated sample, and a much richer set of explanatory and control variables. This finding is also consistent with Nicolli and Vona (2016), but for different countries and explanatory and control variables. While consistent with the previous econometric work, the findings for *FIT* are not consistent with the thrust of the case study analyses. Arguably, the dummy variable employed to reflect the impact of FITs in our econometric analysis does not adequately capture design features which are relevant for patenting activities such as the duration or level of support (the stringency), or digression in FIT rates. Thus, similar to the results for the effectiveness of support schemes on the deployment of renewable electricity (IEA, 2008), the innovation effects of support schemes are as likely to depend on these design features as on the specific instrument applied (Ragwitz et al., 2007; Davies and Diaz-Rainey, 2011). Finally, del Río Gonzáles et al. (2014) note that FITs in EU Member States have been associated with lower levels of support than other instruments, implying lower financial incentives to innovate.

Unlike predicted, our proxy for foreign demand-pull is not found to be statistically significant. Arguably, *export* only coarsely captures the effects of foreign regulation on domestic patenting. This insignificant result may further be explained by the dominant role of domestic markets in almost all countries. Before 2000, only Denmark exhibited considerable exports in the order of magnitude of three-digit level of million $ per year, amounting to roughly 90% of world exports. Germany was a distant second with roughly 5% of world trade share. Similarly, Dechezleprêtre and Glachant (2013) argue that the effects of foreign policies on patenting activity in wind-power technologies are dwarfed by domestic policies.

Similar to Costantini et al. (2015) for biofuel technologies, the findings for *windcap* and *patents_all_pc* support our predictions that innovation activity in wind-power technologies is positively related with learning effects and a country's innovative capacity. Increasing the installed wind capacity by 1% raises the mean number of patents in wind technologies by about 3.6 in the following year. However, our results do not suggest which of the various effects which link diffusion of technology to innovation activity is responsible for this result. This will be a research task taken up by future work, perhaps using other methodologies than econometrics (e.g. case studies using an event history approach).

The estimation results for *greenvote* support our prediction that a higher legitimacy of technology spurs patenting activity. An increase in the share of green voters by one percentage point changes the mean number of wind patents by 5.8% (exp(0.0561)−1), i.e. by 1.6 patents.

Finally, our findings for *target* and *stability* imply that target setting and stability of the regulatory framework are conducive to patenting in wind-power technologies. The existence of a wind energy target increases the mean number of patents by about 56%, i.e. by about 15 patents. Similarly, a stable policy environment raises the mean number of patents by about 71%, i.e. by about 19 patents.

Turning to the control variables, the coefficient for *powerprice* is positive but not statistically significant, which is similar to Johnstone et al. (2010). As expected, patenting activity in other renewable electricity technologies (*patents_reg*) is positively and statistically significantly related with patenting in wind-power technologies. One more patent in non-wind renewable energy technologies leads to an increase in the mean number of wind patents by about 0.2% (exp(0.00187)−1) or 0.05 patents.

In sum, most of our results confirm the relevance of supply-side and demand-side factors for patenting in wind-power technologies. Extending the existing empirical literature to more explicitly and more comprehensively account for factors identified by the SI and policy analysis literatures provides additional insights. Similar to Costantini et al. (2015) for biofuels, we find learning effects and a country's innovation capacity to be positively related with patenting in wind technologies. In addition though, we observe such a positive relation also for the share of green party votes, i.e. our proxy for the legitimacy of technology. Moreover, target setting and the stability of the regulatory framework turned out to be significantly correlated with patenting activity in wind-power technologies. Thus, our econometric results generally support and complement the insights from the conceptual and predominantly case-study based system of innovation and policy analysis literature on the factors driving innovation activities.

4.1. Caveats

While our analysis includes a more comprehensive set of factors

[21] To assess whether collinearity may be a problem, variance inflation factors (VIF) were calculated (by regressing patents on the set of explanatory variables in Table 3). The average VIF is 2.14 and all VIFs are below 3. In light of the standard cut-off point of 10, the variables do not appear to be highly inter-correlated.

[22] For the remainder of this section "statistically significant" means p-value ≤ 0.1.

[23] 27.16 is the mean patent count of the observations used in the analysis. This figure is slightly higher than the mean reported in Table 1 because lagging of explanatory variables implies that data on *patents* for 1991 is not used. Since patent activity in 1991 was lower than in subsequent years, the mean patent count increases if observations for 1991 are dropped.

than previous studies, not all factors that might affect innovation in wind-power technologies could be included. Notably, due to the lack of data, we could not explore the role of competition among technology providers. In addition, our analysis of policy stability was rather exploratory and the indicator employed may only be a crude proxy. Our indicator may not properly reflect market regulation (e.g. conditions for access to the grid for electricity from renewables), the availability and quality of the grid infrastructure, the effects of permitting and planning procedures, or zoning laws. Our econometric analysis may also not adequately capture the dynamic nature of innovation systems and their differential impacts on innovation, including leader-follower relations across countries (e.g. Bento and Fontes, 2015). Finally, in contrast to the way it was modelled in this study, the role of policy stability (and support scheme type) in innovation may depend on the life cycle of the technology (e.g. Huenteler et al., 2016). For example, the stability of the regulatory framework (and remuneration) may be more relevant when a technology is less mature.

4.2. Robustness checks[24]

To verify the robustness of the results presented in Table 3, we tested a series of alternative model specifications and also allowed for an alternative classification of wind technology patents. First, we also estimated Eq. (1) using the Poisson specification. In general, the results are quite consistent with the findings for the negative binomial models. Unlike the negative binomial model though, the coefficient associated with NOFIT was negative and statistically significant at $p < 0.01$, the coefficient associated with *export* was positive and statistically significant at $p < 0.01$. Inappropriate use of the Poisson model means, however, that standard errors and p-values are too low, thus overstating the significance of the parameters. A standard likelihood-ratio test, provided evidence in favour of the negative binomial model and against the Poisson model at $p < 0.01$).

Second, the fixed effects estimator for negative binomial models as developed by Hausman et al. (1984) and implemented in the Stata xtnbreg command, has been criticized for its lack of controlling for all stable covariates when maximizing the conditional likelihood (Allison and Waterman, 2002; Greene, 2005). We therefore use the unconditional FE negative binomial estimator by including dummy variables for all countries. This also allows calculating robust and cluster robust standard errors. The results were very similar to those presented in Table 3. Qualitatively, noticeable differences were found for *powerprice*, which was found to be positively and statistically significantly related to patenting. In addition, employing the generalized Poisson model, which allows for under- and overdispersion, we qualitatively found very similar results as the unconditional FE negative binomial model.

Third, we also explored the effects of different lag structures for the explanatory variables. Lagging *powerprice* by two rather than one year renders *powerprice* statistically significant in all models. The findings for the other variables were similar to those reported in Table 3. As expected though, the loss in degrees of freedom negatively affected the p-values of most parameter estimates. Lagging all explanatory variables by one or by two years more than specified in Eq. (1) yielded similar results to those presented in Table 3. Probably because of lower degrees of freedom, the coefficients associated with *R & D* and *greenvote* were no longer statistically significant in both additional analyses.

Fourth, to further address concerns about policy endogeneity, we also employed future (rather than past) policies as explanatory variables and then explored whether the parameters estimated in Eq. (1) differ. The results for all parameter estimates and significance levels are very similar to those reported in Table 3. These findings provide no evidence that our results may suffer from endogeneity or reverse causality.

Fifth, since *powerprice* also includes taxes and levies, this variable may not adequately reflect the investment incentives for suppliers. Using wholesale electricity prices may therefore be preferable. We could not find data on wholesale electricity prices for the time frame of our study for the 12 countries in our sample. Instead, we estimated the model for the nine EU countries only, using the end-use prices without taxes and levies available from Eurostat. The findings for this restricted sample are very similar to those reported in Table 3 for the full sample of countries, i.e. the coefficients of *r & d*, *windcap*, *greenvote*, *target*, *stability* and *patents_reg* turn out to be statistically significant. In addition, the coefficient associated with *powerprice* becomes statistically significant.

Sixth, since there was some discretion on the side of the authors when constructing *stability*, we also estimated Eq. (1) excluding *stability*. We find that excluding *stability* barely affects the findings.

Seventh, we used the stock of past patents in wind technologies rather than the total patents per capita to reflect a country's innovation capacity.[25] Arguably, the former may more adequately reflect sector-specific effects such as wind technology suppliers' learning-by-inventing. Since the effects of patents in the past are likely to fade over time, we depreciate the knowledge stock at a rate of 10%. For this alternative specification, we found the knowledge stock to be positively related to patenting ($p < 0.01$). The findings for the other variables were virtually the same as those presented in Table 3, although the values of the Bayesian and Akaike information criteria (BIC and AIC) were somewhat higher, thus supporting the use of total patents per capita rather than the stock of past patents in wind technologies.

Finally, we conducted a new patent search to consider a broader set of wind-power technologies. Instead of F03D, we used patent class Y02E10/70 and sub-classes. In contrast to F03D, this new classification also includes additional patents related to the electric and electronic components of wind-power technology, for example. The class Y02E10/70 contains all patents considered wind energy patents by the patent office and should therefore comprehensively cover wind-power technologies. For AT, CH, DE, ES, IT, and SE, this new classification resulted in a total patent count for the period considered, which was at most 10% higher than for the F03D classification. The largest increase is observed for the UK (+20%), France and the US (+28% each). Results from estimating Eq. (1) for this alternative classification of wind-power technologies are qualitatively identical to those presented in Table 3. Hence our findings are robust to this alternative, more comprehensive classification of the technologies underlying the dependent variable.

5. Conclusions and policy implications

The results of our econometric analysis of international patents in wind-power technologies using a panel of twelve OECD countries over a period of more than two decades generally supported the predictions derived within the comprehensive functions of innovation framework. Additional to traditional supply-side and demand-side factors, this framework also comprises factors identified by the SI and policy analysis literatures. Our findings are robust to a series of different model specifications, distributional assumptions and alternative classifications of wind-power technologies in the patent search. They also provide insights for policy making.

Similar to the scant empirical literature on innovation in RES technologies, patenting activity was found to be positively related with public R & D spending on wind-power technologies and learning effects

[24] All results not shown to save space are available from the authors.

[25] To capture capacity, Costantini et al. (2015) also considered the stock of past patents of their dependent variable, but also prefer a specification with total patents per capita based on the BIC.

(as proxied by the stock of wind power capacity). Thus, increasing the level of public R & D spending and designing policies to increase the diffusion of RES appear to be important policies for increasing innovation.

On the one hand, our empirical results do not support the view that the effects of feed-in-tariffs on patenting activities differ from those of other support mechanisms (notably tradable green certificates). On the other hand, we find strong evidence that the policy process affects innovation. Notably, patenting in wind power is positively related to the presence of production or capacity targets for wind power. We further observed that a more stable policy environment is favourable for patenting. Thus, our findings support the view that providing a long-term, stable regulatory framework is more relevant for patenting in wind-power technologies than the actual type of support scheme applied. Such support schemes may even be detrimental if embedded in an unstable regulatory framework such as the stop-and-go cycles in the US federal PTC, or the frequent changes to the Dutch FIT support system. Together with the results for learning effects, our findings for target setting and stability of the regulatory framework emphasise the importance of a strong domestic market based on a stable regulatory framework for patenting in wind-power technologies. The current discussion about the future support for renewable electricity in the EU beyond 2020 revolves around the need for national targets and support schemes in particular for mature technologies like wind onshore (Held et al., 2015). In light of this debate, we conclude that Member States' commitments to credible wind power expansion trajectories as an integral part of their energy and climate plans would be conducive to innovation.

With regard to broader factors which cannot be influenced by domestic RES policies, we found that patenting is positively related to a country's innovation capacity (either measured as patents per capita or as stock of past patents in wind technologies) and to share of green party votes (as a proxy for aspects of political economy and the ability to change existing rules and institutions). In contrast to our prediction, export demand did not exhibit a statistically significant effect on patenting in most models estimated. Arguably, in light of the ongoing globalisation of renewable technology markets, foreign demand-pull factors will become more relevant for domestic innovation in RES technologies in the future.

In some model specifications, patenting in wind power was also positively related to electricity prices, in particular when lagged by two years rather than one. Thus, it may take firms longer than implied in the extant literature to respond to prices and mobilize the resources leading to new patents. Finally, we found that the patenting of wind-power technologies was positively associated with general patenting activity in renewable energy technologies in a country. This may reflect general country-specific tendency and trends to patent in renewable technologies, or positive innovation spillovers across different RES technologies.

Finally, our general findings on the role of policies for innovation in wind-power technologies in OECD countries also provide insights for policy design in countries such as China or India, which are striving to become leading renewable energy technology providers. Our results suggest that traditional supply-side and demand-side policies will be effective for building up domestic innovation capabilities in these technologies, especially if they are combined with policies which strengthen the innovative capacity of the country and set clear targets in stable policy environments.

Acknowledgements

The authors would like to thank three anonymous reviewers their many critical and helpful comments, Isabelle-Maria Bodas-Freitas, Rainer Frietsch, David Grover and Jojo Jacob for their insightful feedback on methodological issues, Rouven Emmerich for his thorough research assistance, and Frank Marscheider-Weidemann for his help in retrieving patent data. The paper further benefitted from comments made by participants at the 2016 Annual IAEE International Conference in Bergen, Norway.

Annex A

Tables A1 and A2

Table A1
Descriptive statistics of dependent variable (number of patents) by country for 1991–2011.

Country	Obs	Mean	Std. Dev.	Min	Max	Total
US	21	55.38	72.01	4	225	1163
DE	21	86.14	89.00	2	284	1809
JP	21	28.71	38.79	0	129	603
FR	21	8.38	9.26	0	30	176
UK	21	19.76	26.61	0	91	415
IT	21	9.10	11.24	0	33	191
NL	21	10.90	11.81	0	35	229
CH	21	4.19	5.25	0	18	88
SE	21	6.29	7.18	0	24	132
AT	21	4.48	6.35	0	20	94
ES	21	20.67	29.13	0	103	434
DK	21	56.81	81.35	0	282	1193

Table A2
Values for the policy variables *target* (T) and *stability* (S).

	US		DE		JP		FR		UK		IT		NE		CH		AT		SE		ES		Dk	
year	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S	T	S
1991	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1996	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1997	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
1998	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
1999	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
2000	0	1	1	1	1	0	1	1	1	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0
2001	0	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1	0	1	0	1	0	1	0
2002	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	0	1	0
2003	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0
2004	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0
2005	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
2006	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2007	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2008	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2009	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2010	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2011	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

References

Allison, P.D., Waterman, R., 2002. Fixed effects negative binomial regression models. In: Stolzenberg, R.M. (Ed.), Sociological Methodology. Basil Blackwell, Oxford.

Archibugi, D., Pianta, M., 1996. Measuring technological change through patents and innovation surveys. Technovation 16 (9), 451–468.

Bayer, P., Dolan, L., Urpelainen, J., 2013. Global patterns of renewable energy innovation, 1990–2009. Energy Sustain. Dev. 17 (3), 288–295.

Bento, N., Fontes, M., 2015. The construction of a new technological innovation system in a follower country: wind energy in Portugal. Technol. Forecast. Social. Change 99, 197–2010.

Bergek, A., Hekkert, M., Jacobsson, S., 2008a. Functions in innovation systems: a framework for analysing energy system dynamics and identifying system building activities by entrepreneurs and policy makers. In: Foxon, T., Köhler, J., Oughton, C. (Eds.), Innovations in Low-Carbon Economy. Edward Elgar, 79–111.

Bergek, A., Jacobsson, S., Sandén, B., 2008b. Legitimation and development of positive external economies: two key processes in the formation phase of technological innovation systems. Technol. Anal. Strateg. Manag. 20 (5), 575–592.

Bergek, A., Berggren, C., 2014. The impact of environmental policy instruments on innovation: a review of energy and automotive industry studies. Ecol. Econ. 106, 112–123.

Bird, L., Bolinger, M., Gagliano, T., Wiser, R., Brown, M., Parson, B., 2005. Policies and market factors driving wind power development in the United States. Energy Policy 33, 1397–1407.

Blind, K., 2008. Regulatory foresight: methodologies and selected applications. Technol. Forecast. Social. Change 75, 496–516.

Boon, W., Moors, E., Kuhlmann, S., Smits, R., 2011. Demand articulation in emerging technologies Intermediary user organisations as co-producers. Res. Policy 40, 242–252.

Cohen, W., Nelson, R., Walsh, J., 2000. Protecting their intellectual assets: appropriability conditions and why U.S. Manufacturing firms patent (or Not). NBER Working Paper No. 7552.

Costantini, V., Crespi, F., 2013. Public policies for a sustainable energy sector: regulation, diversity and fostering of innovation. J. Evolut. Econ. 23, 401–429.

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

Davies, S.W., Diaz-Rainey, I., 2011. The patterns of induced diffusion: evidence from the international diffusion of wind energy. Technol. Forecast. Social Change 78, 1227–1241.

Dechezleprêtre, A., Glachant, M., 2013. Does foreign environmental policy influence domestic innovation? Evidence from the wind industry. Environ. Resour. Econ. 58, 391–413.

del Río Gonzáles, P., Bleda, M., 2012. Comparing the innovation effects of support schemes for renewable electricity technologies: a function of innovation approach. Energy Policy 50, 272–282.

del Río Gonzáles, P., Peñasco, C., 2014. Innovation effects of support schemes for renewable electricity. Univers. J. Renew. Energy 2, 45–66.

del Río Gonzáles, P., Tarancón, M.A., Peñasco, C., 2014. The determinants of support levels for wind energy in the European Union. An econometric study. Mitig. Adapt. Strateg. Glob. Change 19 (4), 391–410.

Downing, P., White, L., 1986. Innovation in pollution control. J. Environ. Econ. Manag. 13, 18–29.

Dosi, G., Soete, L., 1988. Technical change and international trade. In: Dosi, G. (Ed.), Technical change and economic theory. Pinter, London.

Edler, J., Georghiou, L., 2007. Public procurement and innovation – resurrecting the demand side. Res. Policy 36, 949–963.

European Commission, 2014. Guidelines on state aid for environmental protection and energy 2014-2020, 2014/C 200/01. 2014. ⟨http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52014XC0628%2801%29&from=EN. (Accessed 6 Jun 2016).

European Commission, 2014. Guidelines on state aid for environmental protection and energy 2014-2020, 2014/C 200/01. 2014. ⟨http://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52014XC0628%2801%29&from=EN⟩. (Accessed 6 June 2016).

Fagerberg, J., 1988. International competitiveness. Econ. J. 98, 355–374.

Frietsch, R., Schmoch, U., 2010. Transnational patents and international markets. Scientometrics 82, 185–200.

GWEC, 2015. Global Wind Energy Report 2015. Global Wind Energy Council.

Greene, W., 2005. Functional form and heterogeneity in models for count data. Found. Trends Econ. 1, 113–218.

Griliches, Z., 1990. Patent statistics as economic indicators: a survey. J. Econ. Lit. 28, 1661–1707.

Hall, B.H., Griliches, Z., Hausman, J., 1986. Patents and R&D: is there a lag? Int. Econ. Rev. 27, 266–283.

Hall, B., Helmers, C., Rogers, M., Vania, S., 2014. The choice between formal and informal intellectual property: a review. J. Econ. Lit. 52 (2), 375–423.

Harhoff, D., Narin, F., K. Vopel, K., 1999. Citation frequency and the value of patented inventions. Rev. Econ. Stat. 81 (3), 511–515.

Hausman, J., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patents–R&D relationship. Econometrica 52, 909–938.

Held, A., Ragwitz, M., Resch, G., Genoese, F., Liebmann, L., Pató, Z., Szabo, L., 2015. Implementing the EU 2030 climate and energy framework – a closer look at renewables and opportunities for an Energy Union. Issue Paper, Towards 2030 project.

Hekkert, M.P., Suurs, R.A.A., Negro, S.O., Kuhlmann, S., Smits, R.E.H.M., 2007. Functions of an innovation system: a new approach for analysing technological change. Technol. Forecast. Social. Change 74, 413–432.

Hekkert, M.P., Negro, S.O., 2009. Functions of innovation systems as a framework to understand sustainable technological change: empirical evidence for earlier claims. Technol. Forecast. Social. Change 76, 584–594.

Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact–the role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122.

Huenteler, J., Schmidt, T.S., Ossenbrink, J., Hoffmann, V.H., 2016. Technology life-cycles in the energy sector — technological characteristics and the role of deployment for innovation. Technol. Forecast. Social Change 104, 102–121.

International Energy Agency (IEA), 2008. Deploying Renewables. Principles for Effective Policies OECD/IEA, Paris.

International Energy Agency (IEA), 2014. Energy Technology Perspectives 2014. OECD/IEA, Paris.

IRENA, 2012. Renewable energy technologies: Cost analysis series, volume 1, Power Sector. International Renewable Energy Agency (IRENA) Working Paper. June.

Jacobsson, S., Johnson, A., 2000. The diffusion of renewable energy technology: an analytical framework and key issues for research. Energy Policy 28 (9), 625–640.

Jaffe, A.B., Newell, R.G., Stavins, R.N., 1999. Technological change and the environment.

Resources for the future. Discussion Paper 00-47. Washington, D.C.
Jaffe, A., Trajtenberg, 2002. Patents, Citations, and Innovations: a Window on the Knowledge Economy. MIT Press, Cambridge, Massachusetts.
Jänicke, M., Lindemann, S., 2010. Governing environmental innovations. Environ. Polit. 19 (1), 127–141.
Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Klein Woolthuis, R., Lankhuizen, M., Gilsing, V., 2013. A system failure framework for innovation policy design. Technovation 25 (6), 609–619.
Kleßmann, C., Held, A., Rathmann, M., de Jager, D., Gazzo, A., Resch, G., Busch, S., Ragwitz, M., 2013. Policy options for reducing the costs of reaching the European renewables target. Renew. Energy 57, 390–403.
Lee, K., Lee, S., 2013. Patterns of technological innovation and evolution in the energy sector: a patent-based approach. Energy Policy 59, 415–432.
Lundvall, B.A., 1988. Innovation as an interactive process: from user-producer interaction to the national system of innovation. In: Dosi, G. (Ed.), Technical Change and Economic Theory. Pinter, London, 349–369.
Lundvall, B.A., Borras, S., 2005. Science, technology, and innovation policy. In: Fagerberg, J., Mowery, D.C., Nelson, R.R. (Eds.), Oxford Handbook of Innovation. Oxford University Press, 599–631.
Madsen, J.B., 2008. Innovations and manufacturing export performance in the OECD countries. Oxf. Econ. Pap. 60 (2008), 143–167.
May, N., 2015. The Impact of Wind Power Support Schemes on Technology Choices. DIW, Berlin, (DIW Discussion Papers # 14851485).
Nagaoka, Motohashi, and Goto, 2010. Patent statistics as an innovation indicator. In: Hall and Rosenberg (eds.), Handbook of Economics of Innovation.
Nahuis, R., Moors, E., Smits, R., 2012. User producer interaction in context. Technol. Forecast. Social Change 79, 1121–1134.
Nelson, R.R. (Ed.), 1993. National Innovation Systems: a Comparative Analysis. Oxford University Press, New York.
Nemet, G., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38, 700–709.
Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. J. Environ. Econ. Manag. 67, 1–16.
Nicolli, F., Vona, F., 2016. heterogeneous policies, heterogeneous technologies: the case of renewable energy. Energy Econ. 56, 190–204.
Pavitt, K., 1985. Patent statistics as indicators of innovative activities: possibilities and problems. Scientometrics 7, 77–99.
Peine, A., Herrmann, A., 2012. The sources of use knowledge: towards integrating the dynamics of technology use and design in the articulation of societal challenges. Technol. Forecast. Social. Change 79, 1495–1512.
Polzin, F., Migendt, M., Täube, F., von Flotow, P., 2015. Public policy influence on renewable energy investments — A panel data study across OECD countries. Energy Policy 80, 98–111.
Popp, D., 2002. Induced innovation and energy prices. Am. Econ. Rev. 92, 160–180.
Ragwitz, M., Huber, C., Resch, G., 2007. Promotion of renewable energy sources: effects on innovation. Int. J. Public Policy 2 (1/2), 32–56.
Rennings, K., 2000. Redefining innovation - eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32, 319–332.
Rogge, K., Reichardt, K., 2016. Towards a more comprehensive policy mix conceptualization for environmental technological change: a literature synthesis. Res. Policy 45 (8), 1620–1635.
Sanyal, P., 2004. The role of innovation and opportunity in bilateral OECD trade performance. Rev. World Econ. 140 (4), 634–664.
Schmidt, T., Schneider, M., Rogge, K., Schuetz, M., Hoffmann, V., 2012. The effects of climate policy on the rate and direction of innovation: a survey of the EU ETS and the electricity sector. Environ. Innov. Soc. Transit. 2, 23–48.
Smits, R., Kuhlmann, S., 2004. The rise of systemic instruments in innovation policy. Int. J. Foresight Innov. Policy 1 (1), 1–26.
Spiess, H., Lobsiger-Kägi, E., Carabias-Hütter, V., Marcolla, A., 2015. Future acceptance of wind energy production: Exploring future local acceptance of wind energy production in a Swiss alpine region. Technoolgical Forecast. Social Change 101, 263–274.
Unruh, G., 2002. Escaping carbon lock-in. Energy Policy 30, 317–325.
von Hippel, E., 1996. Lead users: a source of novel product concepts. Manag. Sci. 32 (7), 791–805.
Wagner, J., 2007. Exports and productivity: a survey of the evidence from firm-level data. World Econ. 30, 817–838.
Walz, R., Köhler, J., 2014. Using lead market factors to assess the potential for a sustainability transition. Environ. Innov. Soc. Transit. 10, 20–41.
Wei Yingqi, Y., Xiaming Liu, X., Wang, C., 2008. Mutual productivity spillovers between foreign and local firms in China. Camb. J. Econ. 32, 609–631.
Yin, R.K., 1994. Case study research: design and methods. Sage Publications, London.