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Effects of policies on patenting in wind power technologies

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Abstract

This paper explores factors driving innovation in wind power technologies in OECD countries by employing count data panel econometrics. Transnational patent data in wind power technologies serve as the indicator for innovation. In addition to classical supply side policies, the set of explanatory variables also reflects insights from the systems of innovation and policy analysis literature. The findings suggest that patenting is positively related to public R&D in wind power (reflecting *supply side regulation*), to the stock of wind capacity (*learning effects*), to the number of patents per capita (*innovation capacity*), to the share of Green party voters (*legitimacy of technology*), to *targets* for electricity from renewable energy sources, to the *stability* of the regulatory framework, and also to power prices (*profitability*). Feed-in-tariffs, which have been the predominant support mechanism for electricity from renewables, are not found to be positively related to patenting activity – unless they are implemented within a stable regulatory framework. These findings are robust to alternative model specifications and distributional assumptions.

Keywords: Innovation; supply-side regulation; demand-side regulation; wind power; patent analysis; count data econometrics;

Highlights

- Patenting in wind power is positively related to supply-side and demand-side policy
- Patenting is positively related to innovation capacity and technology legitimacy
- Patenting is positively related to target setting and a stable regulatory framework
- Feed-in-tariffs spur innovation in a stable policy environment only

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1 Introduction

Expanding renewable energy sources (RES) is considered to be a key strategy for tackling climate change, preserving resources, and securing energy supply. As a key component of decarbonising their power sectors, several countries, including Denmark, France and Germany, have recently passed “energy transition laws”, which mandate a sharp increase in RES over the next two to three decades. To achieve these targets at low cost, innovation efforts are needed to help increase performance and 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. Thus, in the absence of policy intervention, private innovation activities would be lower than socially desired. The importance of public policy in spurring environmental innovation (including RES innovations) has long been recognized (e.g. Rennings, 2000), and more recent work calls for innovation and environmental policies to be investigated jointly (e.g. del Río, 2009; Newell, 2010, Horbach et al., 2012; Costantini and Crespi, 2013; and del Río and Peñasco 2014).

To date, there is only scant empirical literature analysing the impact of policies on innovation in RES power technologies based on large samples. Notably, Johnstone et al. (2010), econometrically explore the effects of technology-specific expenditures on research and development (R&D) and of support mechanisms for electricity from RES on patenting activity in OECD countries between 1978 and 2003. Thus, apart from including various support mechanisms, the set of policies considered is rather narrow and does not reflect other policy factors which may impact patenting. In particular, the systems of innovation literature stresses the importance of innovation functions which have to be fulfilled, such as knowledge creation and exchange, entrepreneurial activities, guidance of search, early market formation, and legitimacy of technology (e.g. Smits and Kuhlmann, 2004; Bergek et al., 2008a; Heckert and Negro, 2009). In addition, the policy analysis literature points to the role of target setting and policy stability for innovation activities (e.g. Jänecke and Lindemann, 2010; Bergek et al, 2008a). Yet, the impact of these broader effects on innovation activities in RES power technologies has only been explored using case studies, which allow findings to be generalized in an analytical sense but not in a statistical sense.

In this paper, we econometrically analyse factors driving patenting activity in wind energy technologies, relying on data for 12 OECD countries over the time span of 1991 to 2011. In addition to traditional supply-side policies such as technology-specific R&D and demand-side policies such as support mechanisms for electricity generated by RES, we also include factors derived from the systems of innovation and the 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). Compared to previous analyses our sample captures the more recent and also more dynamic developments in wind power patenting.

The remainder of the paper is organized as follows. Section 2 describes the concepts and previous work. Section 3 provides an overview of wind power as a case. Section 4 presents the methodology, including a description of the data, the variables used in the empirical analysis, and the econometric approach. Results are presented and discussed in section 5. The final section summarizes the main findings and offers policy implications.

2 Concepts and previous work

Conceptually, the literature typically distinguishes between supply-side (alias supply-push or technology-push) policy instruments and demand-side (alias demand-pull or market-pull) policy instruments. Supply side regulation attempts to affect the innovation process per se, contributes to the creation and development of knowledge and supplies resources for the development of new technologies. Traditional supply side policies include technology-specific measures such as subsidies for R&D for particular technologies, cross-cutting policies such as protection of intellectual property rights, and the standardisation of products and processes via technology norms (e.g. Blind, 2008).

In comparison, demand-side policies enable market formation, which indirectly leads to the supply of resources, exchange of information, and market growth, facilitating user-producer interactions and learning (e.g. Edler and Georghiou, 2007). Demand-side instruments for RES include measures supporting deployment, such as feed-in-tariffs (FITs), which involve 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 (PTC), quota obligations for the share of RES electricity generated or distributed, and tradable green certificate (TGC) schemes. Consequentially, the level of support for innovation may be determined administratively or by market forces. By creating sufficient demand these mechanisms help establish markets for high-cost RES technologies and help overcome the technological lock-in into fossil fuel technologies in the energy sector (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 incentive 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 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 technologies like wind power, where capital costs account for a high share of total generation costs[1]. Systematically reviewing the empirical literature on national RES support policies, del Río and Peñasco (2014) conclude that FITs are the most appropriate promotion instrument to spur innovation and early diffusion in RES for electricity generation. Recent conceptual and empirical work suggests that the innovation effects of support measures are not just driven by the type of measure and the support level (e.g. Davies and Diaz-Rainey 2011), but also by particular design features of the measures: the duration of support, decline of support levels over time, the quantitative limits for installed capacities (e.g. in GW per year), or the differentiations made intra-technology (e.g. by size, specific technologies used, location) (e.g. del Río, 2012; Hoppmann et al. 2013). For photovoltaics, Hoppmann et al. (2013) further conclude that policy-induced market growth increases innovation activities in companies.

The systems of innovation (SI) and the policy analysis literatures bring in policy factors which complement these traditional supply and demand side impacts or policy. More specifically, SI stresses the importance of learning, of a country's innovative capacity, and of technology legitimacy on innovation. Accordingly, learning-by-doing, learning-by-using, or learning by-interacting (user-producer interaction) lead to innovations such as patenting of new products and processes (e.g. Smits and Kuhlmann 2004). Likewise, a country's higher scientific and technological know-how nurture innovation activities by companies (e.g.

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

Nelson 1993). Finally, a higher perceived legitimacy of technology translates into higher market success of a new technological paradigm. 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). Providing investment security and stability, enhancing the legitimacy of technology, offering search guidance, and offering a long-term perspective for investment priority setting are key functions of an innovation system (e.g. Smits and Kuhlmann 2004, del Río and Bleda 2012, Bergek and Berggren 2014).

The policy analysis literature notes that target setting and the stability of the regulatory framework affect innovation in RES (e.g. Jänicke and Lindemann 2010, Bergek et al., 2008a).[2] Enacting policy targets and ensuring a stable regulatory framework are likely to support the functions of an innovation system such as guiding innovative search processes and promulgating the legitimacy of RES on innovation. Likewise, the emerging policy mix literature stresses the need to broaden our collective perspective and go beyond merely analyzing the features of single policy instruments (Rogge and Reichardt, 2013). Existing analyses, however, rely almost exclusively on case studies.

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 activity. Johnstone et al. (2010) focuses on the effects of different support mechanisms by drawing on data for five RES (wind, solar, geothermal, ocean, and biomass plus waste) in 25 OECD countries between 1978 and 2003. They find that FITs are positively related to patenting activity in high-cost technologies used in RES (i.e. solar), but, somewhat surprisingly, not for more cost-competitive technologies. In fact, for wind power technologies the coefficient associated with the FIT policy variable is, statistically, significantly negative. For most specifications though, patenting is not related to the support levels per se, but rather to whether a policy is simply in place or not. In addition, Johnstone et al. (2010) find that public R&D expenditures exhibit a positive effect on patenting in wind- and solar-power technologies. Since they observe a statistically significant positive rela-

2 The impact of regulatory uncertainty on firms' innovation activity has also been explored in the management literature, e.g. (Marcus 1981, 2013).

tion between power prices and patenting for solar technologies only, but not for other RES, they conclude that policies rather than power prices are driving innovation activity.

Costantini et al. (2015) draw on data from 36 OECD and non-OECD countries between 1990 and 2010 to analyse the factors driving patenting activity in biofuel-related technologies. They find that patenting in biofuel technologies is positively related to public R&D expenditures and to the innovative capacity of a country. Distinguishing between mature and less-mature biofuel technologies, Costantini et al. (2015) further find patenting activity for the former to be mainly related to demand-side policies. In comparison, patenting activity for less-mature technologies is related to both 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 whether FITs are conducive to innovation activities for energy technologies in RES. In comparison, the impact of other demand-side factors has only been explored in case studies, where identification of the effects turned out to be difficult (e.g. Hekkert and Negro 2009). The majority of empirical studies explore the effect of support systems on deployment of RES rather than on innovation activity, e.g. Polzin et al. (2015) or del Río and Peñasco (2014).

Like Johnstone et al. (2010), our empirical analysis focuses on technologies for RES in the power sector and includes R&D expenditures as a standard supply-side policy, and allows for differences in support mechanisms. Similar to Costantini et al. (2015), we also allow for learning effects. In addition, and complementary to the case-study analyses relying on the systems of innovation and policy studies frameworks, our empirical model accounts for the effects of technological legitimacy, target setting and the stability of the regulatory framework on innovation. While information on the support mechanisms is less detailed than in Johnstone et al. (2010) or Costantini et al. (2015), our specification includes a broader set of explanatory and control variables and also allows support mechanisms to interact with the stability of the regulatory framework.

3 The case of wind power

Wind energy plays an important role for decarbonising the electricity sector around the globe. According to GWEC (2014) about 370 GW of wind power had been installed by the end of 2014 globally. Asia leads in terms of cumulative installations, with 142 GW, followed by Europe and North America, with 134

GW and 78 GW respectively. Initially (until about 2006) the development of wind power was driven by European countries, particularly Denmark and, later, Germany and Spain. The markets in Asia have developed very dynamically in recent years, with an annual installed capacity of 26 GW in 2014. In Europe capacity growth has stabilized at about 11 - 13 GW per year; in North America the annually installed capacity has varied between 3 and 15 GW per year during the last three years. About 98% of the globally installed wind capacity is onshore wind. Only about 7 GW of offshore wind capacity had been constructed in 2013. Europe dominates the offshore wind market; only about 480 MW offshore wind was installed in Asia in 2013.

All large markets are strongly policy driven. The types and design of the support mechanisms differ across countries and within countries over time.[3] For example, the US has traditionally implemented federal PTCs for power generated from certain RES (including wind). In addition, several US states have renewable portfolio standards in place. But the yearly expiration and hesitant re-extension of the PTC has led to a stop-and-go investment cycle. In Europe wind energy was initially driven by feed-in tariffs 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. For power generated from RES, Germany replaced its technology-neutral power purchase agreements with a technology-specific FIT in 2000. This FIT specified a fixed remuneration level for 20 years (in addition to the year when the plant starts operating). Since then, FITs have become the dominant support system in most industrialized countries, as well as in many emerging and developing countries including China and India. Across countries design features differ. For example, Spain's FIT, in place from 1997 until it was terminated in 2012 in the aftermath of the financial crisis, fixed the remuneration period for only 5 years. Several countries have switched support systems over time, primarily from FIT and TGC to feed-in premium (FIP) systems. For example, Germany, Italy, the Netherlands and the UK introduced FIPs during recent years in order to increase the compatibility of their support scheme with the overall electricity market. Under a FIP, electricity producers receive a premium on top of the wholesale market price of electricity. To prevent under- and over-compensation, FIPs are typically combined with predetermined price floors and caps or minimum and maximum levels of total remuneration. Alternatively, float-

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

ing FIPs are also commonly used. Here, the total remuneration is fixed (at a "strike price") if a predefined benchmark for market revenues is reached. Thus, FIPs provide similar incentives as FITs. In early 2014, the EU adopted the new "Environmental and Energy State Aid Guidelines for 2014-2020", effectively making FIPs that are based on bidding systems the central support instrument for renewable power in the future. It also bans feed-in tariffs for most situations. Policies that reduce long term revenue risks are considered to be particularly suited to support capital-intensive technologies like wind energy (e.g. Kleßmann et al 2013). Therefore, many EU member states currently consider the introduction of auctions to determine support levels replacing the current administrative procedure. In the key Asian markets, including China and India, tender-based feed-in tariffs are the dominating policy instruments.

During the last three decades, wind-energy technology has progressed substantially, resulting in substantial cost reductions. For example, estimating learning curves for wind technologies between 1981 and 2004, Nemet (2009) finds a progress ratio of 89%. Innovation and technological development is mainly driven by technology providers. During the last two decades the capacity of a standard turbine increased by a factor of ten. This cost reduction was driven mainly by economies of scale; development of new technology concepts and materials; and standardisation and automation of manufacturing processes.

4 Methodology

We employ panel econometrics to estimate the impact of policy on patenting activity, relying on a time series (1991 to 2011) 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 mainly motivated by their importance for patenting in wind power technologies during the period considered, as well as data availability. The countries included in our sample account for 75 to 90 percent of total annual 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.

4.1 Dependent variable

We use the number of patents for wind power technology (*patents*) as the dependent variable. Despite several empirical and conceptual caveats (e.g. Griliches, 1990), patents have been widely used as an indicator for innovation in quantitative empirical studies in the environment and innovation domain (e.g. Lanjouw and Mody, 1996; Brunnermeier and Cohen, 2003; Johnstone et al., 2010; Costantini et al., 2015).

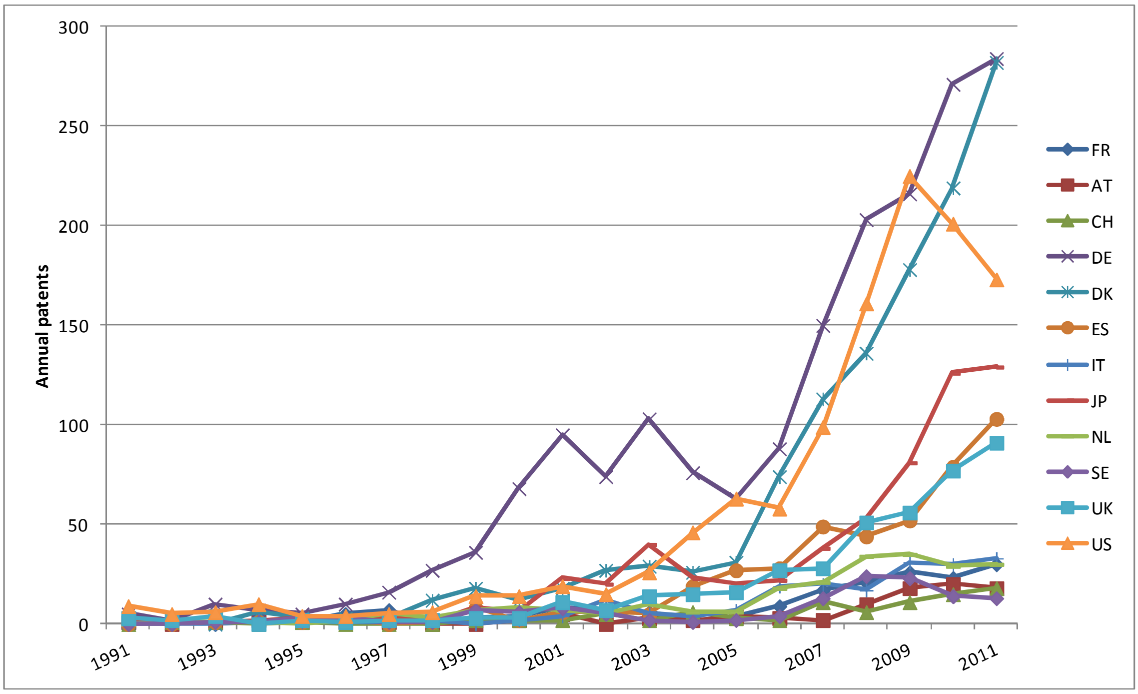
Among renewable energy technologies, wind power technologies are particularly well classified: they form the patent sub-class F03D. This sub-class relates to the main focus of wind power plants such as motors, masts and rotors, but does not cover the electrical power generation or distribution aspects of wind power plants. Likewise, auxiliary technologies which are relevant for off-shore wind energy, such as marine vessels for erecting off-shore turbines or foundations for water towers, are not included. They are parts of other patent subclasses which are more likely to be also triggered by developments outside wind energy development. Furthermore, off-shore wind energy has become prominent only recently and was much less prevalent during the time horizon analysed in this paper.

The patent data refers to patent applications and country assignment based on the country in which the inventor lives rather than the location of the headquarter of the company filing the patent. Thus, the data is more likely to indicate the country in which the new knowledge has been acquired. Patent data is collected relying on the transnational patent approach described by Frietsch and Schmoch (2010).[4] 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. However, in order to avoid double counting, we only count the direct EPO applications

4 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 favor 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, the triadic approach would not allow analyzing patent applications before 2001, since until then the USPTO only published data for patents granted, i.e. not for all patents applied. 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, relying on the triadic patent approach does not appear appropriate in the context of this paper.

without precursor PCT application. Thus, all patent families with at least a PCT application or an EPO application are taken into account. After testing and comparing different approaches, 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 grasping the relations between different countries reliably. The available data was retrieved from the Questel database (www.questel.com) and covers the period from 1991 to 2011. For this time period, 6527 patents were identified. The data indicate a strong increase in total patenting of wind power technologies between 1991 and 2011 (see Figure 1 and also Annex Table A1). Until 1998 patenting activity was relatively low. It then started to increase in a few countries, namely in the US, Denmark, and Germany. After 2005, patenting activity climbed strongly in these countries, as well as in Japan, the UK, and Spain. In sum, patenting activity increased in all twelve countries since the early 1990s, but the levels and the development of *patents* differs across countries.

Figure 1: Annual transnational patents in wind power technology for 12 OECD countries



4.2 Explanatory variables

Reflecting supply-side policy, we include public R&D expenditures for wind power including onshore and offshore technologies and wind energy systems and other technologies (*r&d*) (see Table 2). As is typically the case, private R&D expenditures for wind power technologies could not be included for lack of data.[5]

To capture demand-side policy effects, we include a dummy variable, FIT, which takes on the value of one if a FIT was in place in a specific year.[6] Similarly, we include the dummy variable NOFIT, which is equal to one if other-than-FIT support mechanisms were implemented. FIT and NOFIT only capture differences in the types of support mechanisms, but not in the support levels.[7] We further include the export volume of wind power technologies (*export)* which is meant to roughly capture the impact of export demand (e.g. via foreign support mechanisms) on domestic patent activity. Similar to Costantini et al. (2015), learning effects are captured by the cumulative capacity of wind power installed in a particular country (*windcap*). Since the effects of the capacity installed in a particular year are likely to fade over time, we follow the empirical literature on the depreciation rate of knowledge stock and apply an annual decay rate to the capital stock. We use a rate of 10 percent, which is in the range of rates typically employed for the depreciation of the knowledge stock. Similar to Costantini et al. (2015), we include the number of total patents (net of patents for RES) per capita (*patents_all_pc)* to proxy a country's innovative capacity.

Empirically, legitimacy of technology has been analyzed via case studies by looking at rise of growth of interest groups, extent of lobbying activities, and debate in parliament and 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 legitimacy of technology we include the share of votes for green parties at national level during the most recent election

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5 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.

6 *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 US.

7 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 support schemes.

(*greenvote)*[8]. To be considered a green party, it had to be a member of the Global Green, the European Green Party or the parliamentary group of the Greens in the European Parliament.

To further capture factors of innovation identified in the policy analysis literature, we construct two variables (see also Annex Table A2). First, *target* takes the value of one of if a national target is in place for electricity generated from wind power or from renewable energies in general. For example, of the countries considered in our sample, Germany was the first 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 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 had introduced renewable portfolio standards 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.

Second, and 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 programs 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.[9] Denmark started to foster RES in the

8 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 intrusion or visual impact on the landscape. On the benefit side, wind power may boost local employment.

9 A detailed description of the country-specific assessment and the sources used is beyond the scope but is available from the authors upon request.

mid-1970s, passed the Electricity Supply Act in 1976 (still in place), implemented 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 strengthened by the wind energy co-operative tax incentive of 1997 and the offshore wind agreement in 1998, among others. But, in the wake of liberalization of the energy markets in the late 1990s and a change in government in 2001, the regulatory framework became unstable. 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 force), and a long term energy strategy. Since there was discretion on the side of the authors, when constructing *stability*, we did not include *stability* in the baseline specification of the econometric model.

4.3 Control variables

We include the price of electricity (*powerprice)* to control for financial incentives to innovate. Since we use the price of end-users, *powerprice* may also capture the effect of support mechanisms for RES (policy-induced innovation). In particular, the remuneration for RES is often directly linked to the electricity price via a bonus which is paid to power generators of RES on top of the power price. Similarly, end users' electricity prices may also include energy and environmental taxes or the price of greenhouse gas certificates (e.g. for EU allowances in the EU Emissions trading systems since 2005). In this sense *powerprice* also reflects the stringency of environmental regulation.

Finally, we include the number of patents in technologies for RES (net of patents for wind power technologies) to control for changes in the propensity to patent in RES over time and across countries.[10] 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 (in-

10 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*).

cluding hydrothermal and hot, dry rock resources), and hydroelectricity (including large and small hydroelectricity).

Table 1 provides an overview of the variables, references to the data sources and expected signs in the econometric analysis. The descriptive statistics appear in Table 2.

Table 1: Definition of variables

	Definition	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).	+	IEA RDD online data service: http://www.iea.org/statistics/RDDonlinedataservice/
FIT	Dummy, value of 1 if a FIT or FIP is implemented.	+	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.		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).	+	UN-COMTRADE for HS classification number 850231 “Electric generating sets and rotary converters - Wind-powered”.
windcap	Accumulated installed wind power capacity (GW = 1,000 MW); decay rate of 10% p.a. is applied.	+	Global Wind Energy Council Global Statistics.
patents_all_pc	Number of international patents (net of *patents* and *patents_reg*) per million inhabitants.	+	Patent families with at least a PCT application or an EPO application; EPO and WIPO data, retrieved with Questel.

	Definition	Expected sign	Data sources
greenvote	Share of votes of Green party (in %).	+	For EU member states, outcomes of the most recent European Parliament elections were used. For other countries and for EU MS prior to their joining the EU, data were taken from the elections of national parliaments.
Control variables			
powerprice	Electricity price for households ($ 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.

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

4.4 Econometric model

To analyse the factors driving innovation activity in wind power technologies we employ a similar panel econometrics model as Johnstone et al. (2010) or Costantini et al. (2015):

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

where *i* = 1,...,12 indexes the cross-sectional units (countries) and *t* = 1991,..., 2011 indexes time; α_i represents an unobserved country-specific effect (unobserved heterogeneity), and $\varepsilon_{i,t}$ is the usual idiosyncratic error term. 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.[11] Since *patents_regl* is supposed to control for general trends in the propensity to patent for renewables, it is not lagged. Lagging explanatory variables is also expected reduce potential endogeneity problems related to the policy variables.

As is common in patent analysis (Hausman et al., 1984; Hall et al., 1986; Johnstone et al., 2010; Costantini et al. 2015), we use a negative binomial specification to reflect the count nature of the dependent variable (the number of patents). Unlike a Poisson model, which is also frequently applied in patent analyses, the negative binomial model does not assume that the conditional mean is equal to the conditional variance (equidispersion).[12] Inappropriate use of the Poisson model means that standard errors and p-values are too low, thus overstating the significance of the parameters.

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 equation (1)) are roughly constant over the period in question. We allow for random effects and fixed effects panel models. In a random effects model (RE model), the dispersion parameter, which captures the extent to which the variance exceeds the mean, varies randomly across countries such that the inverse of the dispersion follows a Beta distribution (e.g. Hilbe, 2011). In the fixed effects model (FE model), the dispersion can take on any value. However, to estimate the parameters the fixed effects estimator only uses variation within countries (i.e. deviation of variables from country means). If unobserved effects are not correlated with observed explanatory variables, then the RE model (i.e. treating unobserved effects as random) yields more efficient parameter estimates than the FE model that treats these effects as country specific. Parameter estimation in a RE model exploits the variation of variables within countries as well as variation between countries. But, if unobserved effects are correlated with observed ex-

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11 Following, among others, Hall et al. (1986) and Costantini et al. (2015). In Johnstone et al. (2010) the explanatory variables entered without lags, implying that patenting activities respond instantaneously to market and policy signals. We report the results of alternative lag structures in the section on robustness checks.

12 The conditional probability function of the negative binomial models includes an additional term reflecting unobserved heterogeneity, which is assumed to follow a gamma distribution.

planatory variables, then the RE model yields inconsistent estimates. The FE model yields consistent estimates in both cases.

In our estimations of equation (1), except for the dummy variables, *greenvote* and the count variables, all variables are transformed into the natural logarithm.13 Thus, the coefficients for these variables may be interpreted as elasticities while the coefficients for the dummy variables and for *patentsall* may be interpreted as semi-elasticities.

5 Results

STATA 13 was used to estimate the models. Table 3 displays the findings for the negative binomial fixed and random effects models.14 In general, the findings hardly differ between the FE model 1 and the RE model 2 in terms of significance levels and parameter values (for statistically significant parameters). As is often the case in practice, the fitted models failed to meet the asymptotic assumptions of a Hausman test. To be on the safe side, we use the FE model as the benchmark model and also for the interpretation of the findings.[15]

The empirical findings in Table 3 support most of our predictions. More specifically, the coefficients associated *with r&d, windcap, patents_all_pc, greenvote, target*, and *patents_reg* exhibit the expected positive sign and are statistically significant at least at the 5% level. Unlike our predictions, though, *export* is not found to be statistically significant. This finding may be explained by the dominant role of domestic markets in almost all countries. Before 2000, only Denmark exhibited significant exports in the order of magnitude of three-digit level of million $ dollars per year, amounting to roughly 90 % of world exports. Germany was a distant second with a two-digit level of million $, or roughly 5 % of world trade share.

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13 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 if these observations were dropped.

14 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.

15 This also allows for a better comparison of the findings with Johnstone et al. (2010), who estimate a *FE model* only. Based on a Hausman test, Costantini et al. (2015) find the *FE model* to be more appropriate than the *RE model*.

In particular, and similar to Johnstone et al. (2010), *FIT* exhibits a negative sign, but is not statistically significant in our baseline specification. This finding is consistent with Johnstone et al. (2010), but for a more updated sample, which reflects the dynamic developments in wind power patenting in the past decade in numerous countries, and for different model specifications, which include a richer set of explanatory and control variables. In addition, the dummy employed to reflect the impact of FITs does not adequately capture design features which are relevant for patenting activities such as the duration or the level of support (the stringency), or digression in FIT rates. As in Johnstone et al. (2010), the coefficient for *powerprice* is positive and not statistically significant. Thus, at a general level, our results for the supply-side and demand-side factors of patenting in wind power technologies are qualitatively similar to those of Costantini et al. (2015) for biofuels.

Relying on the point estimates of the *FE model* suggests that an increase in public R&D for wind technologies by one percent is associated with, on average, about 2.5 more patents in the following year (0.0925*27.16[16]). Similarly, increasing the installed wind capacity by one percent changes the mean number of patents in wind technologies by about 3.6 in the following year. According to our findings, an increase in the share of green voters by one percentage point changes the mean number of patents by 5.8 percent (exp(0.0561)-1), i.e. by 1.6 patents. Finally, the existence of a wind energy target increases the mean number of patents by about 61 percent, i.e. by about 17 patents, compared to countries with no target.

Model (3) presents the findings when we add *stability* to the set of explanatory variables. As expected, the coefficient of *stability* is positive and significant ($p<0.01$). Adding *stability* to the model lowers the coefficient of *windcap*, in particular, while the other coefficients are hardly affected.

Finally, we allow *stability* to interact with *FIT and NOFIT*. In this case, there are two effects. First, the negative main effect of FIT becomes statistically significant (as in Johnstone 2010). Second, the findings for the interaction term (*FIT x stability*) suggest that feed-in-tariffs (compared to other or no support mecha-

16 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.

nisms) are positively and statistically significantly related to patenting in wind technologies if they are implemented within a stable regulatory framework. Thus, FITs alone do not provide sufficient incentives for innovation, and 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 of the Dutch FIT support system. In comparison, the coefficient of *NOFIT x stability* is also positive but not statistically significant at conventional levels. In terms of model fit, we note that the values of the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) decrease, as we first include *stability* (model 3) and then in addition also the interaction terms (model 4). Hence, adding these variables means a better fit of the data, even when accounting for differences in the number of explanatory variables.

Table 3: Results for negative binomial fixed and random effects models (standard errors in parentheses)

	Model (1) FE	**Model (2) RE**	**Model (3) FE**	**Model (4) FE**
r&d (t-1)	0.0925 **	0.110 **	0.135 ***	0.137 ***
	(0.0448)	(0.0446)	(0.0427)	(0.0400)
FIT (t-1)	-0.195	-0.222	-0.186	-0.708 ***
	(0.171)	(0.167)	(0.157)	(0.183)
NOFIT (t-1)	0.0293	0.00183	-0.137	-0.0521
	(0.194)	(0.184)	(0.192)	(0.243)
export(t-1)	0.00211	0.0139	0.00371	0.0107
	(0.0219)	(0.0221)	(0.0214)	(0.0205)
windcap(t-1)	0.133 ***	0.153 ***	0.0885 **	0.107 ***
	(0.0356)	(0.0364)	(0.0346)	(0.0330)
patents_all_pc (t-1)	0.674 ***	0.514 ***	0.507 ***	0.493 ***
	(0.151)	(0.136)	(0.157)	(0.158)
greenvote (t-1)	0.0561 **	0.0393 *	0.0670 ***	0.0554 ***
	(0.0281)	(0.0278)	(0.0247)	(0.0205)
target (t-1)	0.613 ***	0.653 ***	0.563 ***	0.694 ***
	(0.137)	(0.137)	(0.129)	(0.128)
stability (t-1)			0.714 ***	0.0296
			(0.116)	(0.200)
FIT x stability (t-1)				0.889 ***
				(0.171)

	Model (1) FE		Model (2) RE		Model (3) FE		Model (4) FE	
NOFIT x stability (t-1)							0.362	
							(0.293)	
powerprice (t-1)	0.406		0.371		0.342		0.469	*
	(0.308)		(0.280)		(0.287)		(0.264)	
patents_reg (t)	0.00203	***	0.00202	***	0.00187	***	0.00164	***
	(0.000227)		(0.000212)		(0.000220)		(0.000211)	
constant	3.937	*	2.818		2.557		2.260	
	(2.317)		(2.021)		(2.209)		(2.192)	
Log likelihood	-708.4		-791.0		-688.9		-673.0	
χ^2	637.84	***	658.89	***	770.73	***	947.61	***
AIC	1439		1608		1402		1374	
BIC	1477		1653		1444		1423	
Sample size	238		238		238		238	

* indicates individual significance in two-tailed t-test at p = 10 %;

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

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

Robustness tests

To verify the robustness of the results presented in Table 3, we tested a series of alternative specifications. First, we also estimated equation (1) using the Poisson specification. As was the case for the negative binomial models (model (1) and model (2)), the Poisson *FE model* results were quite similar to those of the Poisson *RE model*. In general, the findings from estimating models (1) to (4) using the Poission model were quite consistent with the findings for the negative binomial models. Unlike in the negative binomial models though, the coefficient FIT was positive and statistically significant in model (1) (at p<0.1). Likewise, the coefficient associated with NOFIT was negative and statistically significant at p<0.01 in models (1), (2) and (3). Most notably, the coefficient associated with e*xport* was positive and statistically significant at p<0.01 in model (1), (2) and (3) and at p<0.05 in model (4). In this sense, the results of the Poisson model are somewhat more in line with our predictions than the results of the negative binomial model. However, a standard likelihood-ratio test, provided evidence in favour of the negative binomial model against the Poisson model (χ^2 (1) = 550.91, p = 0.00).

Second, the fixed effects estimator for negative binomial models, as developed by Hausman et al. (1984) and implemented in STATA, has been criticized for its lack of controlling for all stable covariates when maximizing the conditional likelihood (Allison and Waterman 2002, Greene, 2005). As suggested by Allison and Waterman (2002), we also estimated the unconditional FE negative binomial model by including dummy variables for all countries, essentially relying on the familiar "dummy variable method" to estimate a fixed effects model. The results were very similar to those presented in Table (3). Qualitatively, noticeable differences were found for FIT, which was not statistically significant in any of the models; for *powerprice*, which was found to be positively and statistically significantly related to patenting in all models; and for *exports*, which was positively and statistically significant in model (1) but not in any of the other models. 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.[17]

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, while the findings for the other variables were quite similar to those reported in Table 3. Similarly, lagging all explanatory variables by one more year than specified in equation (1) yielded quite similar results as those presented in Table (3). However, the coefficient associated with *r&d* and *greenvote* were no longer statistically significant.

Finally, we used the stock of past patents in wind technologies rather than total patents per capita to reflect a country's innovation capacity.[18] 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 with a rate of 10 percent. For this alternative specification, we found the knowledge stock to be positively related to patenting (p<0.01 for models (1), (2) and (3); p<0.1 for models (4)). The findings for the other variables for models (1) to (4) were virtually the same as those presented in Table 3, yet the BIC and AIC values were

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17 All results not shown to safe space are available from the authors.

18 To capture capacity, Costantini et al. (2015) also consider the stock of past patents of their dependent variable, yet also prefer a specification with total patents per capita based on the Bayesian information criteria (BIC).

somewhat higher, thus supporting the use of total patents per capita rather than the stock of past patents in wind technologies.

6 Conclusions

Our econometric analysis of international patents in wind power technologies using a panel of twelve OECD countries over the last two decades supported the predictions that innovation is related to standard supply-side and demand-side policies, and also to broader factors shaping innovation which were derived from the systems of innovation and the policy analysis literature. These findings were robust to alternative model specifications and distributional assumptions.

More specifically, and similar to the scant empirical literature on innovation in RES technologies, we found patenting activity to be positively correlated with specific public R&D spending and with learning-by-doing (as proxied by the stock of wind power capacity). Unlike predicted though, export demand did not exhibit a statistically significant effect on patenting activity 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 contrast to some case study analyses, yet consistent with the previous econometric work, the presence of FIT was not associated with stronger patenting activity for the standard model specification. Arguably, the data employed on instruments in our analysis was not able to capture this important aspect. In particular, as Bergek and Berggren (2014) point out, an instrument's impact also depends on the level of stringency and other design features such as duration of support or digression of support levels over time.

Notably though, extending the extant literature to more explicitly and more comprehensively account for insights from the systems of innovation and policy analysis literatures, our study complements the results from case studies and allows for additional insights. In particular, we found patenting activities in wind power to be positively related to a country's innovation capacity (either measured as patents per capita or as stock of past patents in wind technologies), to legitimacy of technology (as proxied by the share of Green party votes), and to the presence of production or capacity targets for wind power or electricity from RES in general.

We further observed that a more stable policy environment is favourable for patenting wind technologies. Interestingly, by allowing the FIT and NOFIT support mechanisms to interact with the stability of the regulatory framework, we discovered a positive and statistically significant correlation of this interaction term for FITs. Thus, the support mechanisms are conducive to patenting (only) when the regulatory environment is stable. While this analysis was rather exploratory and the indicator employed is likely a rather crude proxy for policy stability, future analyses could also explore in greater detail the impact of the policy mix on innovation activities in renewable power technologies. For example, future work could include more explicit indicators reflecting market regulation (e.g. conditions for access to the grid for electricity from renewables) or the availability and quality of the grid infrastructure. Such indicators may also capture the implications of permitting and planning procedures (duration, costs), zoning laws, and environmental legislation (restrictions on land use). The latter is particularly relevant not only for wind power technologies but also for other renewable technologies such as free-standing solar plants or hydropower. Future empirical work may also model the dynamic nature of innovation systems and their differential impact on innovation, thus capturing leader-follower relations across countries (e.g. Bento and Fontes 2015).

Electricity prices were also positively related to patenting in wind power, in particular when lagged by two rather than one year. Thus, it may take firms longer than implied in the extant literature to respond to power prices and to 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. Likewise, there may also be positive spill-over effects from innovation activities across renewable technologies.

To end with, our general findings on the role of policies for innovation activities 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 technology providers for renewable energy supply technologies. 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.

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ANNEX A

Annex Table A1: Descriptive statistics of dependent variable (number of patents) by country for 1991 to 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

Annex Table A2: Values for the policy variables targets (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

Annex Table A3: Results for Poisson fixed and random effects models (standard errors in parentheses)

	Model (1) FE		Model (2) RE		Model (3) FE		Model (4) FE	
r&d (t-1)	0.210	***	0.208	***	0.192	***	0.166	***
	(0.0208)		(0.0207)		(0.0208)		(0.0212)	
FIT (t-1)	0.124	*	0.117		0.0743		-0.637	***
	(0.0750)		(0.0750)		(0.0755)		(0.104)	
NOFIT (t-1)	-0.320	***	-0.310	***	-0.441	***	-0.439	***
	(0.0865)		(0.0863)		(0.0912)		(0.152)	
export(t-1)	0.0478	***	0.0485	***	0.0378	***	0.0260	**
	(0.0112)		(0.0112)		(0.0113)		(0.0113)	
windcap(t-1)	0.199	***	0.209	***	0.131	***	0.158	***
	(0.0239)		(0.0239)		(0.0240)		(0.0237)	
patents_all_pc (t-1)	1.604	***	1.520	***	1.210	***	0.990	***
	(0.108)		(0.109)		(0.114)		(0.115)	
greenvote (t-1)	0.150	***	0.150	***	0.126	***	0.0988	***
	(0.00915)		(0.00913)		(0.00938)		(0.00943)	
target (t-1)	0.531	***	0.537	***	0.528	***	0.588	***
	(0.0623)		(0.0623)		(0.0626)		(0.064)	
stability (t-1)					0.670	***	-0.047	
					(0.0600)		(0.104)	
FIT x stability (t-1)							1.012	***
							(0.107)	
NOFIT x stability (t-1)							0.508	***
							(0.168)	
powerprice (t-1)	-0.00912		0.0275		0.220		0.359	**
	(0.142)		(0.141)		(0.141)		(0.141)	
patents_reg (t)	0.00113	***	0.00111	***	0.00122	***	0.00123	***
	(9.92e-05)		(9.90e-05)		(0.000100)		(0.000102)	
Log likelihood	-945.0		-1037.0		-878.3		-826.9	

	Model (1) FE		Model (2) RE		Model (3) FE		Model (4) FE	
χ^2	4423.88	***	4420.49	***	4452.08	***	4447.23	***
AIC	1910		2098		1779		1680	
BIC	1945		2140		1817		1725	
Sample size	238		238		238		238	

* indicates individual significance in two-tailed t-test at p = 10 %;

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

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

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