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Abstract

Germany has been the front-runner in the introduction of feed-in tariffs. Under the Renewable Energy Sources Act, the so-called Erneuerbare-Energien-Gesetz (EEG), a massive expansion of electricity from renewable energy sources in Germany occurred over the last decade. The increase in non-competitive renewable power generation though went hand in hand with a substantial rise in electricity prices - with consumers paying for the renewable energy subsidies. The high cost burden has provoked an intense public debate on the benefits of renewable energy promotion. In this paper, we assess one popular justification for the feed-in tariff scheme, i.e., the demand-side effect of the EEG induced innovation. The aggregate results do lend support to the proposition that the feed-in tariff scheme under the EEG spur innovation. However, the technology-specific findings cast doubts on the aggregate effect as only yearly additions to subsidies earmarked for biomass technologies contribute significantly to renewable innovation.

JEL Classification: C23, H23, O38

Keywords: renewable energy promotion; feed-in tariffs; renewable innovation

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1. Introduction

Subsidies for electricity production from renewable energy sources have been on the agenda of German energy policies since the early 1990s. A central justification for renewable energy promotion policy is climate protection, i.e., the reduction of anthropogenic greenhouse gas emissions emerging to a large extent from the combustion of fossil fuels. Germany aims at curbing greenhouse gas emissions compared to 1990 levels by 40% by the year 2020, and by 80% to 90% by 2050. A major contribution to emission reduction should thereby stem from the "greening" of the power sector with a target share of renewable electricity production in total electricity consumption of 35% by 2020 and 80% by 2050.

The primary policy instrument for pushing power generation from renewable energy sources in Germany is a feed-in tariff scheme that guarantees purchases of green power at fixed prices over longer periods. Feed-in tariffs (FITs) are differentiated by technology to outweigh technology-specific cost disadvantages compared to conventional power generation based on fossil or nuclear fuels. Between 1991 and 1999, feed-in tariffs were prescribed through the Electricity Feed-in Law, the so-called Stromeinspeisungsgesetz (SEG). The SEG obligated grid operators to purchase green power at a minimum price calculated as a share of the average revenue for electricity in past years.

In 2000, the SEG was replaced by the Renewable Energy Sources Act, the so-called Erneuerbare-Energien-Gesetz (EEG). Compared to the preceding SEG, the EEG increased feed-in-tariffs in particular for solar photovoltaic and included additional technologies such as geothermal energy into the promotion scheme. The EEG guarantees investors above-market fees for renewable energy for 20 years from the point of installation. An EEG surcharge – equal to the difference between feed-in tariffs paid by utilities for renewable energy and the revenue from electricity fed into the grid – is added to the bills of electricity consumers.[1]

[1] Energy-intensive companies pay a reduced EEG surcharge so as to remain competitive.

The subsidies granted under the SEG and EEG triggered a massive growth in renewable electricity production. The share of renewables increased from 3.4% in 1990 to 6.2% in 2000 and to 27.8% in 2014. Within the various renewable energy technologies, wind power currently commands the highest share (34.8%) followed by biomass (30.6%), photovoltaic (21.7%) and hydropower (12.8%) (BMWi 2015). The increase in non-competitive renewable power generation went hand in hand with a substantial rise in electricity prices. Between 2000 and 2014 the effective subsidies under the EEG increased from less than a billion Euro to roughly 24 billion Euro in 2014. As a consequence, the EEG surcharge on households' electric bills reached 6.24 Eurocent/kWh in 2014. The EEG surcharge thus accounts roughly for one fourth of the average household electricity price in Germany.

Given its high cost burden to consumers, the EEG has been particularly criticized due to its ineffectiveness with respect to greenhouse gas emission abatement. As a matter of fact, greenhouse gas emissions for energy-intensive industries (including the power sector) in the EU are capped through an emissions trading system. Subsidies to renewable power production will simply reallocate emissions across these energy-intensive industries while the overall cost of the emission cap will rise due to excessive abatement from expansion of renewable energies and too little abatement from other mitigation opportunities such as fuel switching (Böhringer et al. 2009, 2014; Frondel et al. 2010).

As the argument of climate protection fails, protagonists of renewable energy promotion strive after additional reasons to justify green subsidies. In the context of renewable innovation, theory suggests that the development of renewable energy technologies (RETs) is subject to two main externalities or market failures: environmental externality and knowledge externality due to low appropriability of innovation. Incomplete appropriation of knowledge spillovers to competitors may result in substantial underinvestment in technological innovation by firms relative to the social optimum (Mitchell et al. 2011). Expansion of renewable power capacity and production could generate spillovers that are external to the individual firm thereby justifying subsidies to correct such a market failure. In this vein, the EEG with its long-term take-and-pay provisions is envisaged to encourage research and development (R&D) and to spur technological innovation.

In the present paper we scrutinize the innovation argument for renewable energy promotion. Our analysis investigates the impact of the feed-in-tariff scheme in Germany on technological innovation measured by patent counts in renewables. While the aggregate results based on regressions with a fixed effect negative binomial model point to positive innovation effects, the findings based on technology-specific policy variables cast doubts on the positive innovation hypothesis of the differentiated feed-in tariff scheme under the EEG. Innovation impacts of solar technology subsidies are generally insignificant while in some specifications the coefficients for the policy variables consistently show significant negative innovation impacts particularly for biogas and geothermal technologies. Note however that yearly increases in biomass subsidies which reflect new technologies drives innovation while the coefficients for the remaining technologies remain largely insignificant.

The innovation impacts of promotion policies for renewable energy have been investigated in various empirical studies. Johnstone et al. (2010) examine the effects of environmental policies on technological innovations in renewable energy using a panel dataset across 25 countries and across several sources of renewable energy.[2] They provide evidence that the effectiveness of alternative policy measures depends on the specific energy source.[3] Furthermore, they conclude that broader market-based regulation such as tradable green certificates are more likely to induce innovation in renewable technologies which are close to competitive while technology-specific measures are needed to induce innovation in more

[2] These include wind, solar, ocean, geothermal, biomass, and waste-to-energy.
[3] Price-based instruments such as tax measures and investment subsidies are found to be most effective in encouraging innovation in solar, biomass, and waste-to-energy. Quantity-based policy instruments such as standards or tradable certificates turn out to be most effective in spurring innovation in wind power.

costly energy technologies such as solar power. They find that renewable-specific public R&D spending is a significant determinant of innovation in renewable energy overall, with its effects most noticeable for wind, solar, and geothermal technologies.

The cross-country study by Walz et al. (2011) focuses on wind power only, but accounts for international spillovers via trade. The study includes additional explanatory variables beyond public R&D spending such as characteristics of green policy legitimacy and stability. The results indicate that a stable and favorable green policy environment encourages patenting in wind power. Furthermore, there are significant trade effects – proxied by the volume of exports in wind power – on innovation. Peters et al. (2012a) for photovoltaic as well as Dechezlepretre and Glachant (2013) for wind power show that domestic and foreign demand-pull policies (e.g., production tax credits) in OECD countries trigger innovation within national borders and also create cross-country innovation spillovers in renewable energies.[4] Both cross-country studies by Walz et al. (2011) and Peters et al. (2012a) find that public R&D expenditures on specific renewable technologies have significant positive impact on innovation in renewable energy. As to Germany, Wangler (2012) identifies a positive correlation between renewable energy promotion and innovation at the aggregate technology level.

However, all the above studies except Wangler (2012) focus on cross-country analysis without considering the innovative effects of specific renewable policies at the individual country level. Additionally, most of the empirical studies so far bundle all demand pull policies together and thus fall short of differentiating the specific innovative effects of the different demand pull policies (e.g., cap-and-trade systems, renewable portfolio standards, feed-in-tariff etc.).

[4] The two studies differ with regard to the marginal effect of domestic and foreign demand (policies) on patented innovation. Dechezlepretre and Glachant (2013) identify factors driving the international diffusion of inventions. They are able to show that local demand for wind power exerts a positive influence on technology inflows.

The remainder of this paper is organized as follows. In section 2, we lay out data sources and describe the econometric model settings underlying our econometric estimations. In section 3, we discuss results. In section 4, we draw policy conclusions.

2. Empirical framework: data and model specifications

Our empirical analysis is based on a panel dataset with annual observations from 1990-2014. The entire dataset integrates both SEG and EEG regulatory policies whereas the period from 2000-2014 focuses on the EEG regulation only. Seven different renewable technologies can be distinguished in our dataset: solar, onshore wind, offshore wind, biomass, biogas, geothermal and hydro. Table A1 and A2 in the appendix show the descriptive statistics and the correlation matrix of all variables used in the regression analysis.

2.1. Measuring innovation activity

Consistent with prior studies on innovations in renewables, we use annual patent counts to proxy innovation in renewable energy technologies. Patent-based indicators are in wide-spread use for assessing the rate of technical change, measuring the competitive positions of firms and evaluating scientific progress as well as knowledge spillovers (Danguy et al. 2014). One concern in using patent counts as an indicator for innovation output is that patents differ significantly in quality (value) and a number of ground-breaking technologies developed by firms are often not patented to safeguard their competitive advantage. Furthermore, the propensity to patent varies across sectors and countries. That notwithstanding, only a few examples of inventions with substantial economic values have not been patented (Dernis and Guellec 2002; Dernis and Kahn 2004). Patent data therefore is usually perceived as an appropriate indicator for innovation output or knowledge production (Schmookler 1966; Griliches 1990; Wakasugi and Koyata 1997).

Our patent data consists of patent applications to the European Patent Office (EPO), which were filed by applicants with residence in Germany. We obtain patent counts for seven groups of renewable technologies based on the Cooperative Patent Classification (CPC) system developed by the EPO and United States Patent and Trademark Office for Environment-Related Technologies (ENV-TECH).[5] We use the priority date of the patent filings since it allows us to abstract any differences in filing strategies. Our focus on patent applications reflects the notion that we are interested in mapping innovation activity rather than successes in the filing process which would be captured in granted patents.

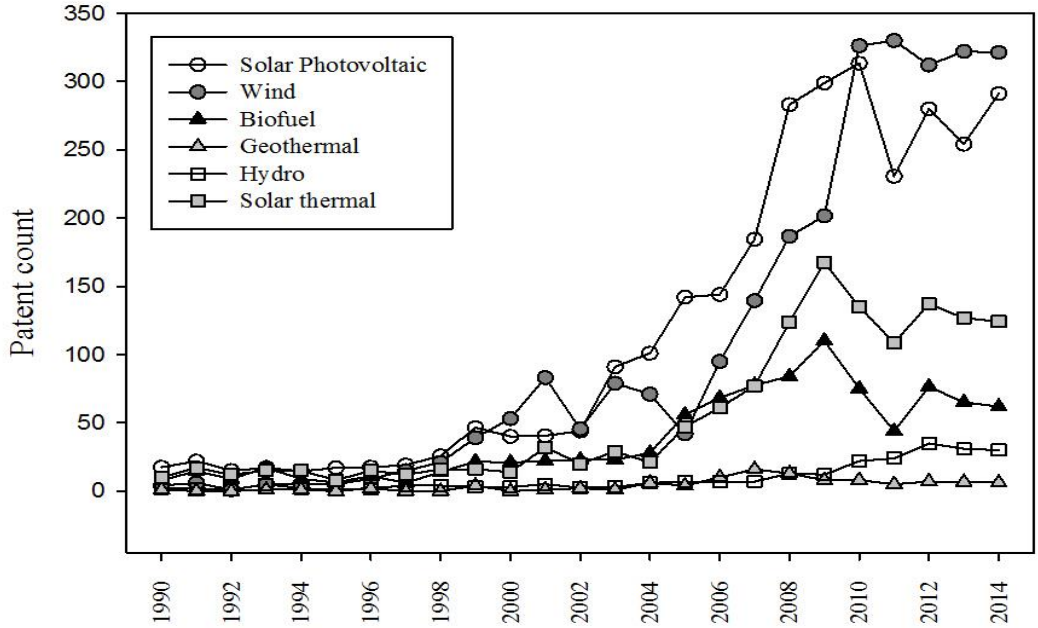

Figure 1: Patent count for renewable energy technologies (RETs)

Figure 1 depicts patent applications in renewable energy filed by applicants with residence in Germany to the EPO from 1990 to 2014. For Solar PV, wind, solar thermal and biofuel, we observe a relatively smooth increase in patenting activities between 1990 and 2004; but there is a sharp increase in patenting from 2005 onwards for these technologies.[6] This trend is however not unique to patent filings by German applicants but the increase in patenting in RETs is also observed in other countries with different support schemes (e.g. USA, Japan,

[5] See http://www.cooperativepatentclassification.org/cpc/scheme/Y/scheme-Y02E.pdf
[6] Solar thermal energy technologies have a different support scheme that is not tied to the EEG FIT scheme.

China, Denmark, France etc.).[7] Patent applications for geothermal and hydro on the other hand, remained relatively stable throughout the observation period.

2.2. Determinants of innovation

Our central policy variables for innovation in RETs include the overall annual cost (million €) for electricity produced from each technology, cost differential/compensation payment and technology-specific feed-in tariff rate (FITs). The annual technology-specific cost differential denotes the sum of the difference between the amount paid to renewable energy producers (feed-in tariffs) and the market value of renewable electricity on the spot market. Given that the subsidy scheme has been the underlying cause of the sharp increase in installed capacities, we focus on these technology-specific subsidy/cost variables in the regression analysis for the EEG period (2000-2014). For the integral analysis of the SEG and EEG regimes captured by the dataset ranging from 1990 to 2014, we use installed capacity as the only policy variable since both policies aimed at increasing the deployment of the technologies. Installed capacity thus measures the market size or diffusion of renewable energy technologies. This helps us to investigate how the promotion of renewables under the two policy environments incentivizes technological innovation.[8] Data on EEG policy variables (overall cost, market value and cost differential) are obtained from the Federal Ministry for Economic Affairs and Energy (BMWi 2014) while installed capacity data stems from the Working Group on Renewable Energies - Statistics (AGEE-Stat 2015).

As illustrated in Table A2 in the appendix, all other explanatory variables except patent intensity correlate positively with patent filings. There is also a positive correlation between overall costs, cost differential, FITs and installed capacity. Note that increasing capacity installations coupled with decreasing spot prices and exemptions for energy-intensive

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[7] See http://stats.oecd.org/index.aspx?queryid=29068#

[8] The EEG adopted much higher feed-in tariffs (above-market price) than the SEG. Contrary to the SEG where annual tariff rates are set as a fraction of the consumers' electricity price paid in the preceding last-but-one year, the EEG fixes tariff rates exogenously over a 20 year horizon.

industries from the EEG surcharge increases the total compensation payment. On the other hand, RETs are noted to follow the so-called “price learning curve” where increases in capacity results in substantial cost reductions per unit of installed capacity. The EEG legislation, thus, seeks to take into account such scale effects with an annual degression rate for all the technology-specific FITs.

Figure 2 displays the technology-specific installed capacities (measured in MW) from 1990 to 2014 in Germany. For the period under consideration, hydro energy remained the most important renewable energy source until 2000 when wind became more prominent than the other renewable energy sources. Installed capacity for hydro, however, remained fairly constant throughout the SEG and EEG periods. Installed capacity for wind on the other hand increased drastically under the EEG from 2000 onwards, while the strong increase of biomass and photovoltaic capacities is observed after 2004.

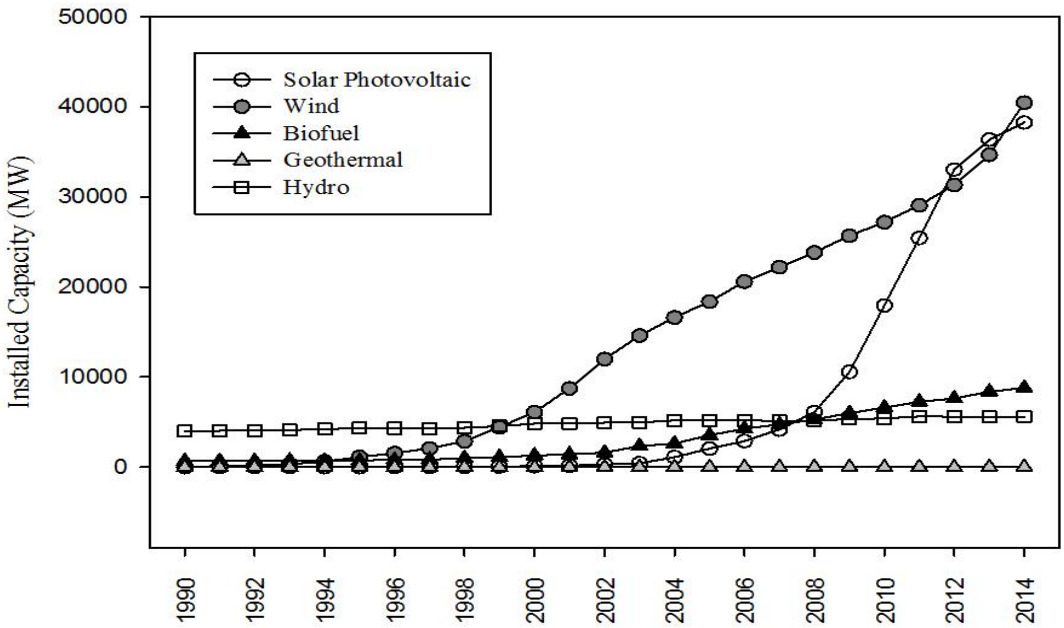

Figure 2: Installed capacity for renewable technologies

As laid out in other cross-country studies (Johnstone et al. 2010; Walz et al. 2011; Peters et al. 2012a), public R&D expenditures might be a significant driver of innovation in renewable technologies. Hence, we include public R&D (measured in million Euro) as a control variable in our estimations. For the parameterization of public R&D we use government expenditures on energy R&D disaggregated by type of renewable technology (IEA 2015).[9] Since data on private R&D energy expenditures are unavailable, we rather include an intensity measure relating total patent filings to the EPO by all applicants with residence in Germany to overall industrial R&D expenditures in Germany as a control variable.[10] Although this intensity variable is not specific to renewables, its inclusion partly captures the patenting potential of industrial R&D expenditures as well as possible spillover effects of private R&D investments from other sectors especially in cases where patents classified under renewables may have alternate uses in other sectors.

We also include Brent spot price of crude oil since the development of crude oil prices may as well determine the extent of innovation in renewable energy technologies. Crude oil price serves as an essential price signal in the energy market, influences input prices for electricity generation and also correlate strongly with electricity prices. Thus, sustained increases in crude oil prices or fluctuations in it supply should increase incentives for innovation in renewable power technologies. The data for Brent crude oil price (in Euro/barrel) is obtained from the EIA´s International Energy Statistics Database (EIA 2015). Note that all explanatory variables are log-transformed.

2.3. Model specification

Due to the count data characteristics of our dependent variable (patents), we use a fixed effect negative binomial model to estimate the relationship between patent filings and possible determinants of innovation (Maddala 1983; Hausman et al. 1984; Cameron and Trivedi 1998). The presence of overdispersion in the patent data warrants the use of a negative binomial model which has also been found to be generally more efficient (Lawless 1987; Blundell et al.

[9] The IEA database comprises all programs that focus on sourcing energy, transporting energy, using energy and enhancing energy efficiency.
[10] Industrial R&D expenditure (in million Euro) is obtained from OECD (2015): http://stats.oecd.org

1995). The fixed effect also applies to the distribution of the dispersion parameter such that the dispersion remains the same within a group or technology.

The relationship between patent counts for renewable technologies and our policy variables is modeled as follows:

$$Patent_{i,t} = \exp\left[\beta_1 Policy_{i,t} + \beta_{2-4} Z_{i,t} + \alpha_i\right] + \xi_{i,t} \tag{1}$$

where i = 1,..,7 indexes the seven different renewable technologies (solar, on/offshore wind, biomass, biogas, geothermal and hydro) and t = 1990, .., 2014 indexes the observation year. Z_t represents all other control variables, in our case: public R&D funding, patent intensity of private R&D and crude oil price. We include a linear time trend to control for aggregate time trends in patenting dynamics that are common across technologies. Given the differences among technologies, α_i captures technology fixed effects which control time-invariant technology-specific unobservable effects – allowing us to explore the within variation of the data. All other residual variation is captured in the error term $(\xi_{i,t})$.

To ascertain the contribution of technology-specific policies on innovation in RETs, we define a model variant as specified in Equation (2) where the individual policy variables are segregated into technology-specific variables.

$$Patent_{i,t} = \exp\left[\beta_1 Policy_{i,t} + \beta_2 \alpha_i Policy_{i,t}^{tech} + \beta_{3-5} Z_{i,t} + \alpha_i\right] + \xi_{i,t} \tag{2}$$

where $\alpha_i Policy_{i,t}^{tech}$ represent technology-specific variables. This model specification permits us to determine the innovation effects of technology-specific policy variables i.e., annual overall cost, cost differential, FITs and installed capacity.

For the complete dataset (i.e., the data ranging from 1990 to 2014), we set up a further variant of our regression model for testing the effect of the different feed-in tariff schemes under the SEG and the EEG.

$$Patent_{i,t} = \exp\left[\beta_1 CAP_{i,t} + \beta_2 D^{EEG} CAP_{i,t} + \beta_{3-5} Z_{i,t} + \alpha_i\right] + \xi_{i,t} \qquad (3)$$

In Equation (3) we generate EEG dummy (D^{EEG}) taking the value 1 for the EEG period (2000-2014) and zero for the SEG period (1990-1999). The regime dummy is interacted with the installed capacity variable (CAP) which serves as the only policy variable for the longer dataset. This allows us to estimate the impact of the switch from the SEG to the EEG regulatory regime.

3. Empirical results

In Table 1 and 2, we report results for the regression models that use the longer dataset thereby covering both the SEG and the EEG regimes. We test the effect of the growing market size or increasing diffusion of renewable technologies promoted using feed-in tariffs under both the SEG and EEG as specified in Equation (1) and (2). As mentioned before, there are substantial differences in the feed-in regulations between SEG and EEG. Under the SEG, the feed-in tariff rates in a particular year are specified as a fixed share of the average electricity price that final consumers paid two years ago. The EEG on the other hand grants fixed tariffs over 20 years. The tariff rates under the EEG are much more differentiated by specific technologies with a particularly high rate for solar photovoltaic. Both subsidy schemes are geared towards increasing the diffusion of renewable technologies; hence, we use installed capacity as our market size or diffusion variable across the two promotion systems.

Column 1 of Table 1 displays the estimates from Equation (1) without the differentiation of technology-specific installed capacity while the remaining columns report the estimates for Equation (2) where we include technology-specific policy variables.[11] The estimated coefficient for installed capacity in column 1 (CAP-All) is positive and statistically significant at the 5% level. This implies that the increasing diffusion of renewable energy technologies

[11] Note that the column headings (e.g., Solar, Windl etc.) in these cases refer to the technology-specific policy variable under consideration. Results remain qualitatively similar if year dummies (time fixed effect) are included in all models.

which is triggered by the SEG and EEG policies drives technological innovation. However, the results in column 2-8 reveal heterogeneous impacts of technology-specific policies on patent applications. The coefficients for onshore wind (WindL), offshore wind (WindS) and hydro installed capacities are positive and significant while that of biomass is also positive but insignificant at all conventional significance levels. Thus, the increasing market size for wind and hydro technologies appears to stimulate patenting activities in renewable technologies. In contrast, the estimated coefficients for the increasing market sizes for solar, biogas and geothermal are all negative. But only biogas installed capacity exerts significant negative innovation effects.

The results in Table 2 confirm the positive and significant coefficient of installed capacity in Table 1. The dummy variable which reflects the EEG policy regime in model 1 is insignificant. Model 2 and 3, however, differentiate installed capacity by the EEG regulatory regime, but the estimated coefficient for installed capacity under the EEG is again insignificant in both models. Thus at the aggregate level, the switch to the EEG regime seems not to have significant positive impact on patenting activities.

Among the core control variables, the results for patent intensity and crude oil price are very robust with statistically significant coefficients across all models. Consistent with the results in Tables 1 and 2, persistent increases in crude oil price and high patent applications per unit of overall industrial R&D expenditures appear to be important determinants of patenting activities in RETs. However, we cannot detect significant positive effect of public R&D funding on patent applications. Hence, the positive innovation hypothesis for public R&D funding in RETs is not supported by the regressions results.

Table 1: Estimates of the innovation effects of renewable policies (SEG & EEG)

	CAP_All	Solar CAP	WindL CAP	WindS CAP	Biomass CAP	Biogas CAP	Geothermal CAP	Hydro CAP
Tech Capacity#		-0.0235	0.2279	0.0692	0.0203	-0.3821	-0.1637	2.6861
		[0.0347]	[0.0867]**	[0.0345]*	[0.1745]	[0.0734]**	[0.1086]	[1.3989]+
Installed Capacity	0.0666	0.0729	0.0609	0.0095	0.0685	0.0508	0.0620	0.0889
	[0.0296]*	[0.0300]*	[0.0298]*	[0.0400]	[0.0339]*	[0.0270]+	[0.0290]*	[0.0310]**
Public R&D	0.0024	-0.0295	0.0413	-0.0622	-0.0019	0.1891	0.0076	0.0366
	[0.0948]	[0.1055]	[0.0958]	[0.0979]	[0.1014]	[0.0992]+	[0.0944]	[0.0963]
Patent Intensity	0.8688	0.8052	0.7133	0.7674	0.8711	1.0647	0.8412	0.8993
	[0.2782]**	[0.2934]**	[0.2798]*	[0.2762]**	[0.2787]**	[0.2636]**	[0.2776]**	[0.2645]**
Crude Oil Price	0.5997	0.6052	0.5605	0.6388	0.5994	0.6452	0.5947	0.5969
	[0.1607]**	[0.1609]**	[0.1577]**	[0.1623]**	[0.1606]**	[0.1535]**	[0.1603]**	[0.1588]**
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-582.77	-582.55	-579.57	-580.83	-582.77	-571.47	-581.65	-580.95
No. of Observations	175	175	175	175	175	175	175	175
No. of Technologies	7	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech Capacity denotes technology-specific installed capacities (as indicated by the headings of column 2-7)

Table 2: Estimates of the innovation effects of EEG feed-in tariff scheme

	(1)	(2)	(3)
Capacity	0.0646	0.0893	
	[0.0299]*	[0.0354]*	
Dummy^{EEG}	-0.0997		
	[0.1918]		
Capacity*Dummy^{EEG}		-0.0291	0.0087
		[0.0256]	[0.0218]
Public R&D	-0.0100	-0.0087	-0.0375
	[0.0975]	[0.0946]	[0.0967]
Patent Intensity	0.9386	0.9446	0.6203
	[0.3098]**	[0.2903]**	[0.2613]*
Crude Oil Price	0.6456	0.6722	0.5498
	[0.1838]**	[0.1730]**	[0.1693]**
Tech Fixed Effects	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes
Log Likelihood	-582.64	-582.14	-585.26
No. of Observations	175	175	175
No. of Technologies	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.

Table 3 reports the estimated coefficients of the innovation effects of the feed-in tariff scheme exclusively under the EEG framework (2000-2014). As indicated before, three main policy variables namely: overall cost, cost differential and feed-in tariffs (eurocent/kWh) all differentiated by technologies are used to proxy the EEG policy regime. In addition to these variables, we also include the market value of renewable electricity and installed capacity to respectively, enable us to compare their innovation impacts with the main policy variables and the results of Table 1 where we use installed capacity as the policy variable for the longer dataset. Focusing on these variables, the significant coefficient on the overall cost variable indicates its positive impact on innovation. It is worth noting that the estimated coefficient for the market value of renewable electricity excluding the compensation payment is also positive and significant at the 1% level.

The positive innovative effect of the market value for renewable electricity is therefore suggestive of the indirect effect of EEG-FITs. The promotion of non-competitive renewable power generation has resulted in a substantial rise in electricity prices due to increasing EEG surcharge paid by consumers and used as a subsidy to defray the cost difference between the fixed FITs and spot prices of electricity. Thus, the effect of the market value on patenting activities may partly be related to the impact of the EEG surcharge on electricity prices.

The cost differential alone, however, has an insignificant effect on patent applications, albeit having a positive coefficient. That is, in spite of the high cost of the EEG scheme the subsidy or additional payment to renewable electricity producers does not incentivize patent applications. The finding that the cost differential has insignificant effect while the market value exerts significant innovation effect is suggestive of the fact that the significant results of the overall cost is driven by the portion of the total cost which stems from the market value of renewable electricity.

The coefficients for both the differentiated feed-in tariff and the installed capacity variables are however, positive and statistically significant at the 5% level. All in all, the estimates are suggestive of the positive effect of the feed-in tariff scheme under the EEG on patent filings in renewable technologies, albeit the insignificant innovative effects of the top-up payment (subsidy). This outcome is not surprising given that the feed-in tariff scheme ensures above-market payments for a 20-year time horizon and also creates a well-protected market that enhances innovation efforts.

Furthermore, the coefficient for domestic public R&D funding is only significant in one out of the five models, notwithstanding being positive in all cases. Consequently, the results do not generally support the notion that domestic public R&D expenditure on renewable energy technologies triggers patenting activities. Given the high level of uncertainty, appropriability problems as well as financing difficulties that characterizes private R&D investments in high cost technologies, we would have expected public R&D funding to significantly influence renewable innovation. Possibly, the role of public R&D funding is more evident at the very early stages of technological development when there is less private investment due to uncertainties.

Given the heterogeneous effects of similar policies or market stimulus, e.g., FITs or subsidies on patent filings in different RETs, we expand our analysis by investigating the innovation impacts of technology-specific EEG policy variables (see Equation 2). The results of this analysis are presented in Table 4-8. We first consider the innovation effects of the market value of electricity for each of the technologies in Table 4.

The estimated coefficients indicate that the respective market value of electricity for the individual technologies i.e., solar, onshore wind, offshore wind, biomass and hydro are all positive but statistically insignificant. The coefficients for biogas and geothermal technologies on the other hand are negative but only significant at the 5% level in the case of biogas. In effect, even though the aggregate results in Table 3 suggest significant innovation effects, the technology-specific variables suggest otherwise with significant negative effects in the case of biogas. In the absence of the EEG policy variables, the coefficient for public R&D surprisingly remains positive and significant in models.

In Table 5 where we consider the overall cost of the EEG per each technology, the estimates again show mixed effects. The coefficients for solar, onshore wind and hydro are all positive but only significant at the 10% level in the case of onshore wind. The estimates for the remaining technologies are negative but statistically insignificant. In terms of cost differential (Table 6), we find insignificant innovation effects in the case of onshore and offshore wind, biomass and hydro. Moreover, the estimated coefficients for biogas and geothermal subsidies are both negative and significant at the 5% and 10% levels, respectively. Thus, the production-based subsidies for these technologies rather stifle innovation.

Table 3: Estimates of the innovation effects of the EEG policy (2000-2014)

	Market Value	Overall Cost	Differential	FITs	Capacity
Policy variable[#]	0.1872	0.1137	0.0620	0.1395	0.0768
	[0.0322]**	[0.0353]**	[0.0461]	[0.0570]*	[0.0372]*
Public R&D	0.2416	0.1392	0.0365	0.0222	0.1256
	[0.1134]*	[0.1307]	[0.1465]	[0.1535]	[0.1384]
Patent Intensity	1.5614	1.4802	1.3794	0.9699	1.4161
	[0.3437]**	[0.4161]**	[0.5024]**	[0.4681]*	[0.5159]**
Crude Oil Price	0.3523	0.4691	0.6060	0.5335	0.5389
	[0.1809]+	[0.2092]*	[0.2385]*	[0.2211]*	[0.2219]*
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-381.49	-387.07	-384.42	-387.56	-388.37
No. of Observations	105.0	105	105	105	105
No. of Technologies	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
The heading of the columns represents the policy variable.

Table 4: Estimates of the innovation effects of the market value of renewable electricity

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
Tech-specific[#]	0.0446	0.2446	0.0049	0.0066	-0.0950	-0.1025	0.1567
	[0.0415]	[0.1748]	[0.0464]	[0.0621]	[0.0472]*	[0.2673]	[0.4867]
Market Value	0.1775	0.1887	0.1858	0.1870	0.2360	0.1845	0.1885
	[0.0325]**	[0.0318]**	[0.0349]**	[0.0321]**	[0.0387]**	[0.0333]**	[0.0323]**
Public R&D	0.3099	0.2528	0.2399	0.2376	0.3122	0.2333	0.2475
	[0.1264]*	[0.1130]*	[0.1147]*	[0.1192]*	[0.1120]**	[0.1161]*	[0.1145]*
Patent Intensity	1.6476	1.4858	1.5664	1.5590	1.7765	1.5633	1.5515
	[0.3435]**	[0.3465]**	[0.3472]**	[0.3438]**	[0.3382]**	[0.3446]**	[0.3446]**
Crude Oil Price	0.3312	0.3333	0.3560	0.3509	0.3546	0.3571	0.3497
	[0.1750]+	[0.1790]+	[0.1847]+	[0.1809]+	[0.1720]*	[0.1823]+	[0.1807]+
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-380.96	-380.50	-381.49	-381.49	-379.65	-381.42	-381.44
No. of Observations	105	105	105	105	105	105	105
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the market value of technology-specific electricity (as indicated by the column headings).

Table 5: Estimates of the innovation effects of tech-specific EEG policy variables: Overall Cost

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
Tech-specific[#]	0.0800	0.4571	-0.0025	-0.0534	-0.0553	-0.1849	0.2285
	[0.0504]	[0.2437]+	[0.0435]	[0.0734]	[0.0541]	[0.1255]	[0.9031]
Overall Cost	0.1174	0.1288	0.1156	0.1099	0.1380	0.1054	0.1142
	[0.0331]**	[0.0333]**	[0.0477]*	[0.0380]**	[0.0426]**	[0.0379]**	[0.0351]**
Public R&D	0.2635	0.1774	0.1412	0.1708	0.1633	0.1088	0.1400
	[0.1464]+	[0.1318]	[0.1354]	[0.1391]	[0.1325]	[0.1321]	[0.1307]
Patent Intensity	1.6341	1.4036	1.4763	1.4827	1.6514	1.4536	1.4786
	[0.3935]**	[0.4051]**	[0.4207]**	[0.4248]**	[0.4392]**	[0.4237]**	[0.4168]**
Crude Oil Price	0.4006	0.4307	0.4655	0.4778	0.4842	0.4844	0.4732
	[0.2042]*	[0.2052]*	[0.2182]*	[0.2110]*	[0.2068]*	[0.2107]*	[0.2099]*
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-385.87	-385.29	-387.07	-386.80	-386.62	-386.04	-387.04
No. of Observations	105	105	105	105	105	105	105
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the technology-specific overall cost of electricity (as indicated by the column headings).

Table 6: Estimates of the innovation effects of tech-specific EEG policy variables: Cost differential

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
Tech-specific#	0.0610	0.1583	0.0642	-0.1257	-0.1137	-0.2536	0.1976
	[0.0558]	[0.2064]	[0.0493]	[0.0915]	[0.0494]*	[0.1359]+	[0.2141]
Cost Differential	0.0624	0.0708	0.0039	0.0272	0.1075	0.0428	0.0468
	[0.0439]	[0.0437]	[0.0791]	[0.0585]	[0.0463]*	[0.0536]	[0.0530]
Public R&D	0.1157	0.0404	0.0101	0.1792	0.0522	0.0225	0.0099
	[0.1589]	[0.1432]	[0.1579]	[0.1810]	[0.1347]	[0.1546]	[0.1528]
Patent Intensity	1.5658	1.4268	1.2938	1.1009	1.7410	1.2426	1.3561
	[0.4789]**	[0.4733]**	[0.6579]*	[0.6471]+	[0.4848]**	[0.5819]*	[0.5307]*
Crude Oil Price	0.5821	0.6112	0.6685	0.5356	0.7392	0.5937	0.6177
	[0.2371]*	[0.2366]**	[0.2571]**	[0.2371]*	[0.2550]**	[0.2397]*	[0.2423]*
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-383.83	-384.11	-383.55	-383.53	-382.48	-382.76	-383.99
No. of Observations	105	105	105	105	105	105	105
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the cost differential (overall cost – market value) of technology-specific electricity (as indicated by the column headings).

Table 7: Estimates of the innovation effects of tech-specific EEG policy variables: Feed-in tariff

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
Tech-specific#	0.5361	1.7228	0.1364	-0.7672	-0.2704	-0.0123	4.2077
	[0.6034]	[2.1120]	[0.1141]	[0.4485]+	[0.1436]+	[0.1691]	[0.9208]**
FITs#	0.0952	0.1489	0.0295	0.1082	0.1565	0.1406	0.1727
	[0.0761]	[0.0578]*	[0.1072]	[0.0575]+	[0.0586]**	[0.0587]*	[0.0602]**
Public R&D	-0.0110	0.0044	0.0369	0.1624	0.0366	0.0204	0.0170
	[0.1622]	[0.1525]	[0.1509]	[0.1702]	[0.1542]	[0.1554]	[0.1457]
Patent Intensity	0.7298	1.0351	1.1057	0.9140	1.0803	0.9699	1.3962
	[0.4964]	[0.4766]*	[0.4930]*	[0.4506]*	[0.4803]*	[0.4677]*	[0.4648]**
Crude Oil Price	0.4814	0.5446	0.5811	0.5189	0.5801	0.5348	0.5663
	[0.2210]*	[0.2212]*	[0.2256]*	[0.2167]*	[0.2228]**	[0.2218]*	[0.2144]**
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-387.22	-387.23	-386.91	-386.16	-386.04	-387.56	-377.59
No. of Observations	105	105	105	105	105	105	105
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the technology-specific feed-in tariffs (as indicated by the column headings).

Table 8: Estimates of the innovation effects of tech-specific EEG policy variables: Installed Capacity

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
Tech-specific[#]	0.0422	0.5390	0.0424	0.0241	-0.3909	-0.1715	11.6424
	[0.0533]	[0.2937]+	[0.0726]	[0.3089]	[0.1327]**	[0.1214]	[2.1931]**
Installed Capacity	0.0777	0.0954	0.0243	0.0796	0.0444	0.0703	0.1161
	[0.0365]*	[0.0353]**	[0.0993]	[0.0515]	[0.0398]	[0.0383]+	[0.0335]**
Public R&D	0.1877	0.1413	0.0779	0.1202	0.2633	0.1085	0.1715
	[0.1575]	[0.1371]	[0.1608]	[0.1539]	[0.1442]+	[0.1387]	[0.1345]
Patent Intensity	1.5531	1.3872	1.2704	1.4327	1.3616	1.3534	1.5854
	[0.5211]**	[0.4864]**	[0.6137]*	[0.5530]**	[0.5588]*	[0.5271]*	[0.4216]**
Crude Oil Price	0.5198	0.5402	0.5632	0.5410	0.5564	0.5457	0.5849
	[0.2208]*	[0.2160]*	[0.2290]*	[0.2228]*	[0.2200]*	[0.2222]*	[0.2075]**
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-388.06	-386.62	-388.18	-388.36	-384.01	-387.41	-376.47
No. of Observations	105	105	105	105	105	105	105
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the technology-specific installed capacities (as indicated by the column headings).

The estimates in Table 7 also reflect both negative and positive technology-specific feed-in tariff effects. The results indicate that even the high feed-in tariff rates assigned to solar photovoltaic under the EEG have insignificant effects on innovative output as measured by patent filings. Likewise, the coefficients for onshore and offshore wind and geothermal FITs are also insignificant while the feed-in tariffs for hydro technologies appear to spur renewable patent applications. The estimates for biomass and biogas on the other hand show significant negative effects on patent applications. For installed capacity exclusively under the EEG regime (see Table 8), the coefficients for onshore wind and hydro capacities are again positive and hence exert significant influence on renewable patents. In contrast, capacity increases for biogas suppresses innovation in renewable technologies.

Note, however, that a huge part of the annual cost of the feed-in tariff scheme (overall cost and cost differential) is largely determined by pre-existing installed capacities that has less room for innovation. As such, incremental or annual changes in the cost/subsidy variables may most likely reflect new technologies. Table A3 and A4 in the appendix display the results of using the changes in the overall cost and cost differential as our policy variables. The estimates show that the year-to-year increases in the cost of the feed-in tariff scheme for biomass significantly drive patenting activities while the effects of subsidies for the other technologies remain insignificant.

We also conduct similar analysis by combining onshore and offshore wind technologies together considering the fact that these two technologies are fundamentally the same based on the Cooperative Patent Classification (CPC) system.[12] But again, the results remain qualitatively consistent with the results obtained by differentiating onshore and offshore wind technologies.

[12] The only difference is in terms of the Cooperative Patent Classification for onshore and offshore towers. The estimation results for this analysis is not presented but would be made available if needed.

One economic explanation for the missing and in some cases negative impacts of the EEG may be related to the limited incentives for developing more radical technological innovations. While the EEG encourages expansion of renewable production capacities alongside with cost degression through learning-by-doing or scale economies, it does not necessarily foster incentives for radical innovation or advanced technologies that are captured in patent statistics.[13] Since the EEG remuneration is calculated based on the average cost of the respective technology, it is thus more attractive for renewable electricity producers to install already established technologies in the market rather than taking the risk to deploy uncertain breakthrough new technologies.

For a potential innovator on the other hand, the revenue from an (ex-post) cost-effective new technology might be less or just the same as the revenue generated through pre-existing established technologies; consequently, it does not pay to embark on risky technological innovations. The EEG thus primarily acts as a production subsidy for electricity with strong short-run incentives for exploitative rather than explorative investment by firms. The EEG-induced market growth with its high profit margins induces firms with relatively mature technologies to shift resources from intensive, risky explorative research activities towards exploitative activities (in terms of increased production). The increase in exploitative behavior of firms can also raise market entry barriers for less mature technologies, while at the same time facilitating lock-in effects in favor of established renewable energy technologies (Peters et al., 2012b).[14]

For the control variables, patenting intensity of R&D investment by business enterprises and crude oil prices again appear to be important drivers of technological change in renewable technologies under the EEG regime. The estimated coefficients for the intensity variable show

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[13] Note that (efficiency) improvements of existing technologies would in general not be captured in patent statistics.

[14] The incentives towards exploitative market expansion can create a risk of reduced competitiveness if firms no longer pursue vigorous R&D investments (as may be evidenced along the example of the German solar industry over the last years).

significant innovation effect across all models. This suggests that renewable energy technologies not only benefits from direct industrial R&D investments but R&D investments and accumulation of knowledge in other technological fields also seem to spur innovation in renewable energy technologies. Similarly, the estimated coefficient for crude oil price is widely significant across models. Since fossil fuel i.e., crude oil remains an important input in electricity production, the positive innovative effect of crude prices is suggestive of how the development in the global energy market spurs technological improvements in renewables.

4. Conclusions

Over the last decades policies to promote renewable energy have become increasingly popular in OECD countries. Policy makers embrace support schemes for renewable energy as a panacea to address the problem of climate change and spur innovation. A prime example is Germany with its feed-in tariffs for electricity produced from renewable energy sources. The feed-in tariffs were established under the Electricity Feed-in Law (Stromeinspeisungsgesetz - SEG) in 1991, followed by the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz - EEG) since 2000. The main pillars of the feed-in regulation is the grid operator’s obligation to renewable energy sources (as opposed to electricity from conventional sources), and the payment of fixed tariffs. An unrestricted take-and-pay clause for fixed and high feed-in tariffs led to a drastic expansion of renewable power production over the last decade. The cost of the feed-in tariff scheme amount to over 24 billion Euro in 2014 with the reallocation charge paid by electricity consumers rising to more than 6 cents/kWh in 2014, i.e., roughly a fourth of the average household’s consumer price.

The drastic cost increase of the EEG over the last years has triggered substantial criticism. Climate protection as a wide-spread argument for renewable energy promotion has no bite in the German case: Greenhouse gas emissions of the power sector together with other energy-intensive industries are capped through an EU-wide emissions trading system. Explicit subsidies to renewable power production in Germany will thus simply reallocate emissions across energy-intensive industries in the EU. At the same time, feed-in tariffs increase the economy-wide cost of emission abatement thereby constituting an inefficient means of EU climate policy.

Another popular justification for feed-in tariffs is innovation externalities. In this paper we have scrutinized the innovation argument based on empirical data of the German feed-in regulation over the last two decades. Overall, the estimates show that the deployment of wind technologies under the SEG and EEG spurs radical innovation in renewable energy technologies as measured by patent filings. Particularly under the EEG regime, our regression results also lend support to the proposition that the above-market price feed-in tariff scheme lead to higher innovative output at the aggregate level. Notwithstanding the aggregate innovative effect, only the increases/changes in biomass technology subsidies have significant positive effects on renewable patent applications. Given the drastic cost of the German EEG and less empirical evidence on positive and significant innovation impacts of the technology-specific subsidies, we caution against the appraisal of the German feed-in tariff system on innovation grounds.

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Appendix

Table A1: Descriptive statistics of variables

Variable	N	Mean	Std. Dev.	Min.	Max.	Unit
Renewable patents	175	55.27	91.42	0	330	Counts
Market value	105	387.81	609.25	0	2652	Million Euro
Overall cost	105	1395.92	2318.05	0	10715	Million Euro
Cost differential	105	982	1834.90	-4	9148	Million Euro
Feed-in tariff (FITs)	105	14.64	14.42	0	53	Eurocent/kWh
Installed capacity	175	4139.79	8032.70	0	38236	MW
Public R&D	175	20.06	20.58	0	88.87	Million Euro
Private R&D	175	67002.28	18019.24	23680.90	104920.70	Million Euro
Total patents	175	18711.45	4473.32	11146.98	23670.99	Counts
Patent intensity	175	0.51	0.08	0.34	0.62	Counts/Million Euro
Crude oil Price	175	37.45	24.50	11.41	86.85	Euro/Barrel

Note: N denotes No. of observations

Table A2: Correlation matrix among variables

	RET patents	Market value	Overall cost	Cost diff.	FITs	Installed capacity	Public R&D	Private R&D	Total patent	Patent intensity	Crude price
RET patents	1.000										
Market value	0.457	1.000									
Overall cost	0.513	0.782	1.000								
Cost differential	0.485	0.631	0.977	1.000							
FITs	0.329	0.037	0.299	0.361	1.000						
Installed capacity	0.606	0.791	0.793	0.720	0.117	1.000					
Public R&D	0.737	0.372	0.661	0.699	0.666	0.504	1.000				
Private R&D	0.413	0.361	0.473	0.466	0.137	0.368	0.487	1.000			
Total patents	-0.143	-0.105	-0.225	-0.255	-0.024	-0.171	-0.274	-0.469	1.000		
Patent intensity	-0.410	-0.354	-0.446	-0.440	-0.131	-0.345	-0.486	-0.513	0.688	1.000	
Crude oil Price	0.416	0.357	0.440	0.428	0.147	0.340	0.472	0.903	-0.386	-0.593	1.000

No. of observations= 105

Table A3: Estimates of the innovation effects of changes in tech-specific overall EEG cost

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
ΔTech-specific[#]	-0.1549	0.0532	0.0653	1.1265	-0.1087	-0.1930	0.1209
	[0.3525]	[0.5952]	[0.1473]	[0.3800]**	[0.1291]	[0.3526]	[0.3565]
ΔOverall cost	0.1380	0.1295	0.0985	0.1122	0.1720	0.1349	0.1268
	[0.0606]*	[0.0582]*	[0.0915]	[0.0599]+	[0.0764]*	[0.0583]*	[0.0588]*
Public R&D	0.2472	0.2163	0.1875	0.3410	0.1656	0.2070	0.2158
	[0.1683]	[0.1531]	[0.1661]	[0.1517]*	[0.1635]	[0.1529]	[0.1526]
Patent Intensity	0.9745	0.9270	0.9803	0.9853	0.9759	0.9350	0.8901
	[0.5161]+	[0.5041]+	[0.5156]+	[0.4687]*	[0.4971]*	[0.4866]+	[0.4959]+
Crude Oil Price	0.6143	0.6103	0.6414	0.5183	0.6407	0.6166	0.5999
	[0.2313]**	[0.2313]**	[0.2435]**	[0.2226]*	[0.2340]**	[0.2312]**	[0.2318]**
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-365.47	-365.56	-365.47	-361.86	-365.20	-365.41	-365.51
No. of Observations	98	98	98	98	98	98	98
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the technology-specific overall cost (as indicated by the column headings).

Table A4: Estimates of the innovation effects of changes in tech-specific cost differential

	Solar	WindL	WindS	Biomass	Biogas	Geothermal	Hydro
ΔTech-specific[#]	-0.0997	0.1944	0.1046	0.9943	-0.1981	-0.2993	0.0013
	[0.3510]	[0.2231]	[0.1523]	[0.4492]*	[0.1489]	[0.3476]	[0.1362]
ΔCost differential	0.1328	0.1162	0.0858	0.1124	0.1768	0.1363	0.1280
	[0.0578]*	[0.0579]*	[0.0846]	[0.0554]*	[0.0667]**	[0.0554]*	[0.0629]*
Public R&D	0.1620	0.1298	0.1115	0.2222	0.0544	0.1248	0.1421
	[0.1684]	[0.1546]	[0.1646]	[0.1525]	[0.1715]	[0.1549]	[0.1562]
Patent Intensity	0.8673	0.8341	0.9464	0.8010	0.8709	0.8611	0.8287
	[0.5097]+	[0.4853]+	[0.5319]+	[0.4517]+	[0.4925]+	[0.4833]+	[0.4842]+
Crude Oil Price	0.6409	0.6355	0.7076	0.5668	0.6800	0.6532	0.6374
	[0.2358]**	[0.2364]**	[0.2602]**	[0.2288]*	[0.2405]**	[0.2361]**	[0.2359]**
Tech Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-356.79	-356.46	-356.57	-354.54	-355.88	-356.44	-356.83
No. of Observations	98	98	98	98	98	98	98
No. of Technologies	7	7	7	7	7	7	7

Note: Standard errors in parentheses. +, * and ** denote 10%, 5% and 1% significance levels.
Tech-specific represents the technology-specific cost differential (as indicated by the column headings).

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