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# Energy prices, technological knowledge and green energy innovation: A dynamic panel analysis of patent counts

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We examine the effect of energy prices and technological knowledge on innovation in green energy technologies. In doing so, we consider both demand-pull effects, which induce innovative activity by increasing the expected value of innovations, and technology-push effects, which drive innovative activity by extending the technological capability of an economy. Our analysis is conducted using patent data from the European Patent Office on a panel of 26 OECD countries over the period 1978-2009. Utilizing a dynamic count data model for panel data, we analyze 11 distinct green energy technologies. Our results indicate that the existing knowledge stock is a significant driver of green energy innovation for all technologies. Furthermore, the results suggest that energy prices have a positive impact on innovation for some but not all technologies and that the effect of energy prices and technological knowledge on green energy innovation becomes more pronounced after the Kyoto protocol agreement in 1997.

Keywords: Green energy technologies, innovation, patents, demand-pull, technology-push, dynamic count data model

JEL classification: C33, O31, Q40, Q42, Q55

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# 1 Introduction

In a growing field of literature, economists have empirically investigated which economic and political factors influence the rate and direction of innovation in green energy technologies. However, researchers still lack evidence on the determinants of green energy innovation, especially when it comes to the determinants of innovation in specific technologies. Understanding these determinants is crucial in order to design the appropriate policies to foster green energy innovation. Should these policies stimulate the demand for green energy technologies by increasing energy prices, or should they enhance technological capability by improving the knowledge base of an economy?

This paper empirically investigates how green energy innovation in different technologies has developed in response to changes in energy prices and technological knowledge. For the purpose of this paper we define green energy technologies as energy efficiency, renewable energy, fuel cell, carbon capture and storage (CCS) and energy storage technologies. We consider both demand-pull effects, which induce innovative activity from the demand side by increasing the expected value of innovations, and technology-push effects, which drive innovative activity from the supply side by extending the technological capability of an economy. We aim to shed light on the ongoing debate as to whether demand-pull or technology-push factors are the main drivers of green energy innovation. We hypothesize that both increasing demand, due to higher energy prices, and increasing technological capability induce green energy innovation.

To test these hypotheses, we analyze a panel on green energy innovation drawing from data on patent applications at the European Patent Office (EPO). We count patent applications in green energy technologies following a structure defined by the International Energy Agency (IEA) and using International Patent Classification (IPC) codes from the green inventory developed at the World Intellectual Property Organization (WIPO). Our dataset covers 11 distinct green energy technologies for 26 OECD countries, spanning over a 32-year period from 1978 to 2009.

This paper is related to the empirical body of literature on the determinants of green energy innovation. In particular, we build on the pioneering work of Popp (2002), who uses aggregate US patent data from 1970 to 1994 to estimate the impact of energy prices and quality-weighted knowledge on innovation in environmentally-friendly technologies. Popp finds that both factors have a significant, positive impact on innovation.

More recently, a similar analysis was carried out by Verdolini and Galeotti (2011). They study the impact of energy prices and knowledge stocks on innovation in energy technologies using panel data on United States Patent and Trademark Office (USPTO) patent applications for 17 countries from 1975 to 2000. Their baseline results confirm the positive effects of both factors on innovation. Although the authors do not differentiate by individual technologies, separate estimations reveal differences between energy-supply and energy-demand technologies. While the effect of energy prices stays significant for supply technologies, it becomes insignificant for demand technologies.

This result is a first indicator that the relative importance of demand-pull and technology-push factors is specific to individual technologies. However, up to now, reliable and detailed technology-specific empirical evidence is still missing. One notable exception is Johnstone et al. (2010), who use a panel framework covering patent counts for 25 OECD countries over a 1978-2003 period to investigate the determinants of technological change in five renewable energy technologies. They find important differences across technologies. However, their study focuses on policy instruments and does not explicitly account for technology-push effects. Our study seeks to fill this void in previous research by accounting for these technology-push effects and by additionally covering a broader base of technologies.

Our work contributes to the existing literature in three respects. First, we investigate the determinants of innovation separately for 11 different green energy technologies. This may help scholars and policy makers understand the divergent effects of energy prices and technological knowledge on green energy innovation across technologies. Second, our analysis uses European patent data to assess the validity of the conclusions reached using US patent data. Third, we apply state-of-the-art count data techniques to control for unobserved heterogeneity, account for the dynamic character of knowledge generation and address endogeneity issues.

The remainder of the paper is organized as follows. Section 2 provides a brief outline of the baseline theory guiding our empirical analysis. Section 3 presents the data. Section 4 describes the econometric methodology employed. Section 5 presents and discusses the results. Section 6 concludes.

## 2 Theoretical background

For green energy technologies, the process of technological change is characterized by two key market failures. First, the harmful consequences of energy production and energy use on the environment constitute a negative externality. In the absence of appropriate price signals, there is no economic incentive to reduce these negative consequences. Since there is no demand for reduction, the demand for reduction-technologies will also be low. Consequently, there is insufficient private incentive to invest in R&D for such technologies. Second, the value accruing from private investments in R&D tends to spill over to other technology producers. These spillovers constitute a positive externality. Since the private investor incurs the full costs of its efforts but cannot capture the full value, there is insufficient private incentive to invest in R&D. As a result the two market failures lead to a double underprovision of green energy technologies by market forces. This double underprovision can be addressed by a combination of environmental and innovation policies (see Jaffe et al., 2005; Newell, 2010).

The underlying concept is policy-induced innovation. This concept is the theoretical basis for the demand-pull and technology-push effects on innovation activities. First proposed by Hicks (1932), it originally states that changes in relative factor prices induce innovation which reduces the need for the factor which has become relatively more expensive. More generally, it posits that both changes in demand and changes in technological capability determine the rate and direction of innovation. Changes in demand include shifts on the macro level that affect the profitability of innovative activity at a given level of technological capability. Analogously, changes in technological capability include scientific and technological advancements that affect the profitability of innovative activity at a given level of demand (see Griliches, 1990; Verdolini and Galeotti, 2011).

Following Verdolini and Galeotti (2011), the relationship between demand, technological capability and innovation can be formalized as

$$I_t = f(D_t, TC_t), \tag{1}$$

where $I$ denotes innovative activity, $D_t$ denotes demand and $TC_t$ denotes technological capability. Demand can be proxied by expected energy prices $p_t^e$, which signal the expected general scarcity of energy in an economy. Increasing energy prices increase the willingness to pay for R&D in technologies that either produce energy at a lower average cost or use energy more efficiently. Technological capability can be proxied by technological knowledge, a concept which is typically measured by innovation activities undertaken in the past. Innovation activities in the past are expected to induce innovation activities today or, as expressed by Baumol (2002), "innovation breeds innovation". Acemoglu et al. (2012) show that this path dependence exists in green technological change. Firms in economies with a history of innovation in green technologies in the past are more likely to innovate in green technologies in the future. Using the end-of-period stock of past patents, $K_{t-1}$, as a measure for innovation activities in the past Equation 1 becomes

$$I_t = g(p_t^e, K_{t-1}), \tag{2}$$

where both factors are expected to have a positive impact on innovation activity.

Following these expectations, governments can foster green energy innovation in two ways: implement policies that increase energy prices and thus increase the private pay-off to successful innovation, i.e. demand-pull, and implement policies that increase the stock of knowledge and thus decrease the private cost of producing innovation, i.e. technology-push. Examples of policies that increase energy prices are emission taxes and emission trading systems. Examples of policies that increase the knowledge stock are government support for the generation and dissemination of basic scientific and technological knowledge, provision of high quality education and training systems, promotion of business networks and technology transfer as well as government-sponsered R&D and tax incentives to invest in private R&D. Researchers have come to a consensus that in order to stimulate innovation in green energy technologies, both types of instruments are necessary (see Nemet, 2009).

## 3 Data

Our analysis is conducted using patent data from the OECD REGPAT database (OECD, 2013). The database combines information on patent activities from two complementary sources: the EPO's Worldwide Patent Statistical Database (PATSTAT) and the OECD patent database. It contains patent applications filed at the EPO based on the priority date, that is, the first filing date of the invention worldwide. Several studies have shown that this date is strongly related to R&D activities and is closest to the date of discovery of an invention (see, e.g., Griliches, 1990; OECD, 2009). Furthermore, in contrast to patent applications filed at national institutions, multinational patent applications such as those filed at the EPO often constitute innovations of high value that are expected to be commercially profitable and thus justify the relatively high application costs (see Johnstone et al., 2010). Hence, utilizing EPO patent applications ensures that applications for low-value inventions are excluded from our analysis.[1]

All patents are classified according to the IPC system, which assigns each patent to a specific area of technology. In particular, the "IPC Green Inventory" provides the IPC codes for patents relating to so-called Environmentally Sound Technologies (EST) (WIPO, 2013*a*,*b*). Combining the IPC codes with the energy technology structure developed at the IEA (IEA, 2011), we count the technology-specific annual green energy patent applications at the EPO between 1978 and 2009 on the country level. The patent applications are assigned by country of origin (based on the country of the inventor) using fractional counts. That is, each patent application is counted as a fraction for the respective country, depending on the inventor's share in the patent.

As a result of the availability of appropriate IPC codes and missing values for some of the utilized variables, our analysis covers 11 green energy technologies and 26 OECD countries. The technologies are: energy efficiency in residential and commercial buildings, appliances and equipment (EEBAE), energy efficiency in transport (EET), other energy efficiency (EEO)[2], solar energy, wind energy, ocean energy, biofuels, geothermal energy, fuel cells, CCS and energy storage.

Table 1 provides an overview on the development of the total number of EPO patent applications in these technologies for the 26 countries. As shown, in the whole sample period, the highest number of green energy patent applications is observed for the United States, followed by Japan and Germany. The lowest number of green energy patent applications belongs to Slovakia. Furthermore, all countries significantly increase their patent activities in green energy technologies over time. Across all countries, we observe an increase in green energy patenting of more than 130% from the 1978-1984 period to the 2005-2009 period. In total, our database contains more than 175,000 green energy patent applications.

As patent activities in green energy technologies may be affected by a country's overall propensity to patent innovations, we include a control variable covering the country-specific total number of annual EPO patent applications. In doing so, we control for variations in the propensity to patent both across countries and across time. Figure 1 shows the trend in green energy and total patenting for the six leading (in terms of green energy) innovative countries in our database. Green energy patent applications are shown on the left axis and total patent applications on the right axis. In all countries, we see a steady and similar growth in green energy and total patent applications.

Figure 2 illustrates the trends in patenting for the 11 technologies. First of all, it can be seen that the number of patent applications differs significantly among the technologies.

[1] The advantages and disadvantages of using patents as a proxy for innovation have been discussed comprehensively in the literature. See, e.g., Griliches (1990), Dernis et al. (2002) and OECD (2009).

[2] Following the IEA energy technology structure, the other energy efficiency group includes waste heat recovery and utilization, heat pumps and measurement of electricity consumption.

Table 1: Number of green energy EPO patent applications by country and time period.

| Country | 1978-1984 | 1985-1989 | 1990-1994 | 1995-1999 | 2000-2004 | 2005-2009 | Total |
|---|---|---|---|---|---|---|---|
| AT | 213 | 226 | 316 | 328 | 543 | 752 | 2,379 |
| AU | 157 | 173 | 204 | 340 | 487 | 413 | 1,774 |
| BE | 171 | 148 | 202 | 378 | 442 | 422 | 1,763 |
| CA | 170 | 259 | 266 | 671 | 966 | 993 | 3,325 |
| CH | 654 | 609 | 563 | 766 | 780 | 896 | 4,269 |
| CZ | 1 | 1 | 5 | 11 | 32 | 70 | 120 |
| DE | 4,544 | 3,829 | 3,555 | 5,303 | 7,421 | 8,394 | 33,046 |
| DK | 69 | 130 | 238 | 448 | 546 | 939 | 2,371 |
| ES | 30 | 32 | 91 | 170 | 278 | 651 | 1,252 |
| FI | 45 | 92 | 185 | 224 | 274 | 348 | 1,168 |
| FR | 1,630 | 1,619 | 1,512 | 1,900 | 2,101 | 2,670 | 11,433 |
| GB | 1,323 | 1,260 | 1,046 | 1,592 | 1,788 | 1,572 | 8,581 |
| GR | 5 | 9 | 26 | 23 | 26 | 51 | 140 |
| HU | 64 | 40 | 27 | 32 | 27 | 42 | 232 |
| IE | 7 | 14 | 6 | 36 | 60 | 121 | 244 |
| IT | 341 | 515 | 471 | 612 | 1,080 | 1,364 | 4,383 |
| JP | 1,647 | 2,628 | 3,195 | 5,934 | 10,043 | 10,082 | 33,528 |
| LU | 10 | 3 | 7 | 18 | 15 | 32 | 84 |
| NL | 615 | 634 | 656 | 1,008 | 1,439 | 1,542 | 5,894 |
| NO | 35 | 45 | 68 | 130 | 206 | 327 | 810 |
| NZ | 9 | 18 | 20 | 48 | 72 | 68 | 236 |
| PT | 1 | 7 | 7 | 9 | 16 | 49 | 88 |
| SE | 415 | 255 | 373 | 481 | 505 | 633 | 2,663 |
| SK | 0 | 0 | 1 | 8 | 19 | 18 | 45 |
| TR | 2 | 2 | 1 | 5 | 14 | 39 | 63 |
| US | 5,849 | 6,628 | 7,362 | 12,324 | 13,341 | 9,824 | 55,328 |
| Total | 18,004 | 19,177 | 20,405 | 32,798 | 42,521 | 42,314 | 175,220 |

Note: The country codes represent Austria (AT), Australia (AU), Belgium (BE), Canada (CA), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), Luxembourg (LU), Netherlands (NL), Norway (NO), New Zealand (NZ), Portugal (PT), Sweden (SE), Slovakia (SK), Turkey (TR), and United States (US).

A huge number of patent applications is related to biofuels, EET and EEO. In contrast, the number of patent applications in ocean energy is rather low. Furthermore, for all technologies, we observe an increase in patent activities over time. However, the growth paths differ substantially. For example, for biofuels and fuel cells, we see a significant increase during the 1990s. After that, patent activities begin to decrease. A completely different picture emerges for wind and solar energy. Here, we observe an above-average growth starting from the mid-1990s, with exceptionally high growth from the mid-2000s. This result emphasizes the increasing prominence of electricity generation from wind and solar energy resources over the last two decades.

Energy storage, CCS and geothermal energy have experienced relatively steady growth but on rather low levels. Apart from different growth paths, there is also a significant difference in the level of patent activity between the categories considered. In particular,

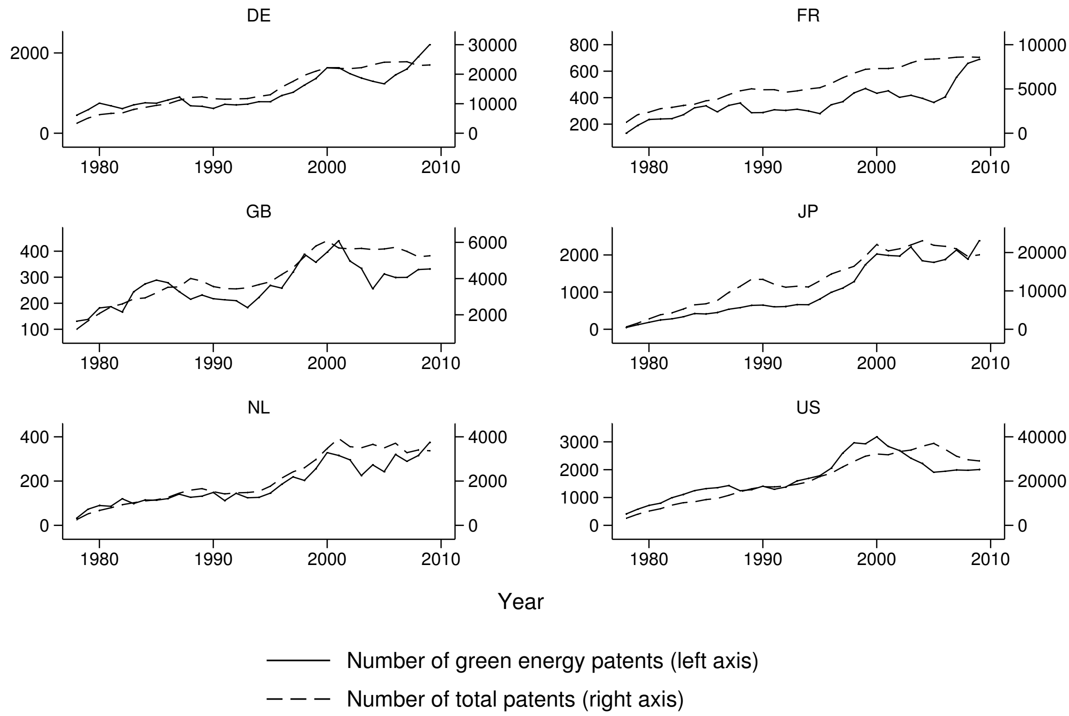


Figure 1: Number of green energy EPO patent applications and number of total EPO patent applications by 6 major innovators, 1978-2009. *Note*: The country codes are the same as in Table 1.

patent activity has grown from about zero to above 1,000 for solar energy and the three energy efficiency technologies, while other technologies grew on rather low levels. An exception is biofuels, which had a high level of patent activity already in 1980.

As the main focus of our analysis is to investigate the impact of energy prices and technological knowledge on green energy innovation, we include a price index and a knowledge stock in our model. The price index is drawn from the Energy Prices and Taxes Database of the IEA (IEA, 2012*a*). It depicts the country-specific real total energy end-use price (including taxes) for households and industry with the base year 2005. As described in Section 2, expected energy prices signal the expected scarcity of energy in an economy and thus affect the demand for innovation in green energy technologies. Our energy index is used as a proxy for these expected energy prices. Using different energy prices for different technologies would be preferable. However, technology-specific price series often show a high amount of missing values. Furthermore, as we have technology groups covering several sub-technologies, it is not always possible to identify the appropriate price. Overall, as the index used in this study is a composite of industry and household prices for oil products, coal, natural gas and electricity, it is expected to be

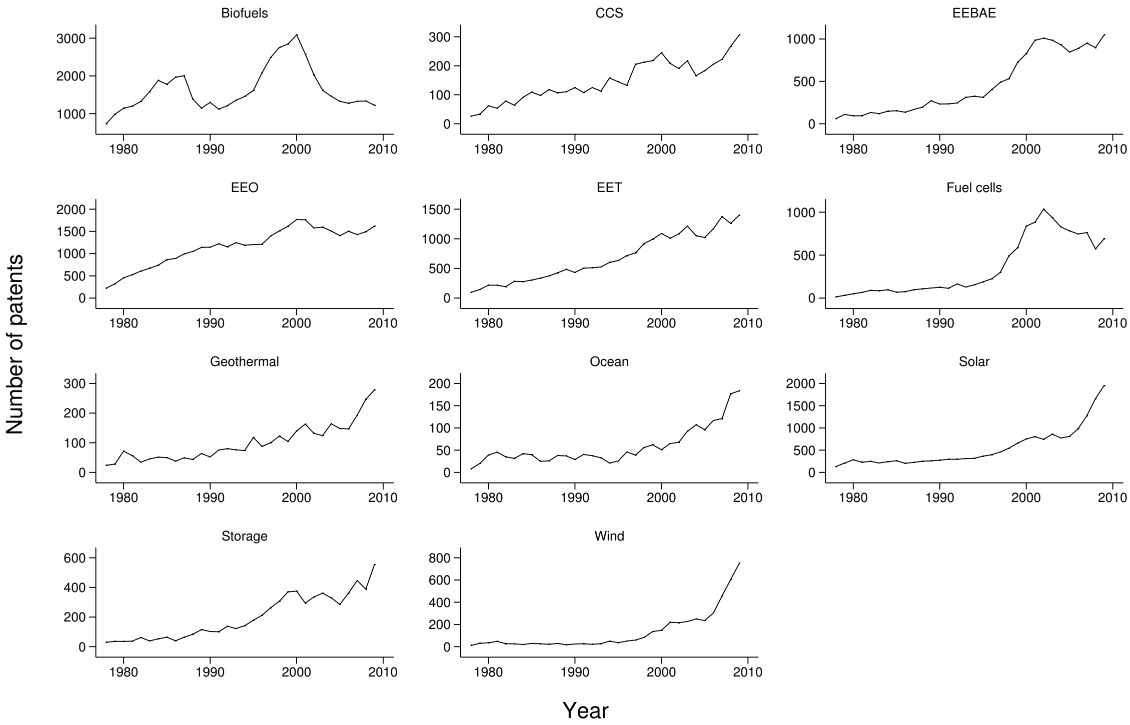


Figure 2: Total number of EPO patent applications of 26 OECD countries by green energy technology, 1978-2009. *Note*: EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

a reliable proxy for the average development of energy prices.[3] Comparable indices have been used in a number of other studies (see, e.g., Popp, 2002; Verdolini and Galeotti, 2011).

Figure 3 displays the average real total energy end-use price index for households and industry among the 26 OECD countries in the database from 1978 to 2009. After a peak in the early 1980s (following the oil crises of the 1970s), a rough decrease in the energy price index is seen until the late 1990s. From then on, the index almost continuously increases. In 2008, it indicates an increase in the total energy end-use price of approximately 15%, relative to the base year 2005. A similar pattern can be observed for the vast majority of the country-specific indices.[4]

The knowledge stock is constructed using the perpetual inventory method following Cockburn and Griliches (1988) and Peri (2005). Basically, the technology-specific knowledge stock is obtained by counting all patents which have accumulated for the respective technology in a country up to a certain year. The technology-specific knowledge avail-

[3] In fact, the development of the individual energy price time series for the years and countries where detailed data are available is very similar to the development of the utilized composite index.

[4] The country-specific price indices are provided in the appendix (Figure A5).

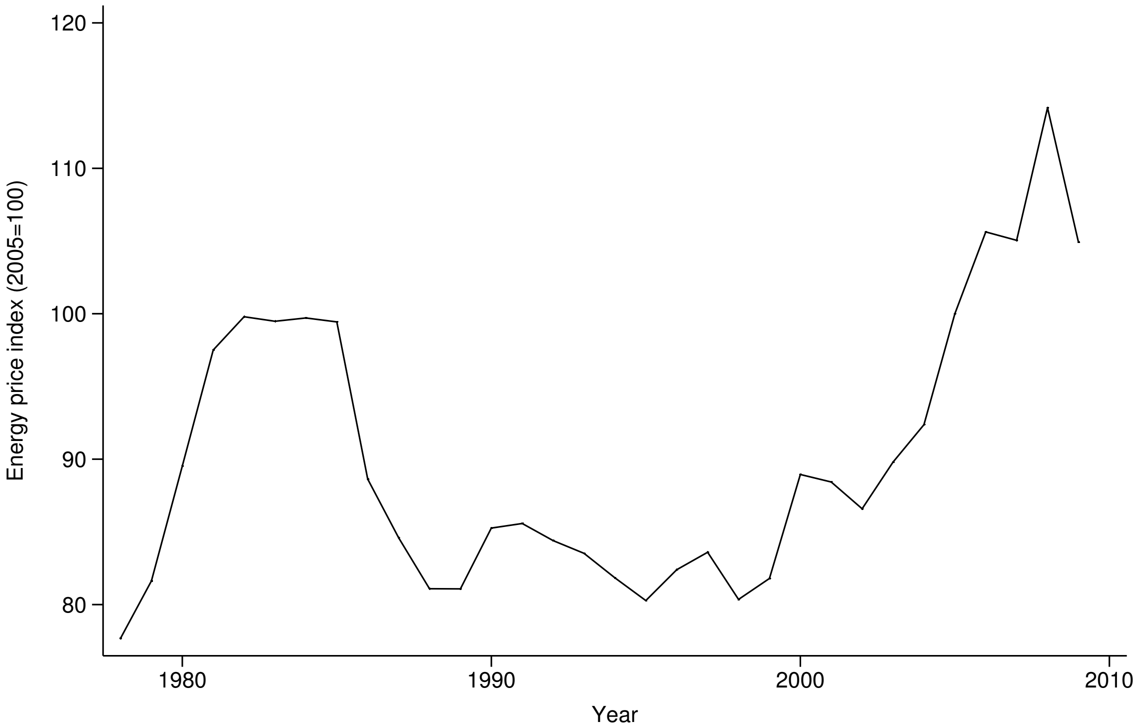


Figure 3: Average real total energy end-use price for households and industry among 26 OECD countries (index: 2005=100), 1978-2009.

able to researchers and inventors in each country and year is then represented by the end-of-period stock, which covers all patents accumulated up to the previous year.

The end-of-period knowledge stock $K_{ijt-1}$ for technology $j = 1, ..., M$ in country $i = 1, ..., N$ and year $t = 1, ..., T$ is calculated as

$$K_{ijt-1} = PAT_{ijt-1} + (1 - \delta) K_{it-2}, \tag{3}$$

where $PAT_{ijt-1}$ is the number of patent applications and $\delta$ is a depreciation rate that accounts for the fact that knowledge becomes obsolete as time goes by. The rate of depreciation is set to 10%, which is consistent with other applications in the patent and R&D literature (see, e.g., Verdolini and Galeotti (2011)). The initial knowledge stock $K_{ijt_0}$ is given by $K_{ijt_0} = PAT_{ijt_0}/(\delta + g)$, where $PAT_{ijt_0}$ is the number of patent applications in 1978, the first year observed. The growth rate $g$ is the pre-1978 growth in knowledge stock, assumed to be 15%, and $\delta$ again represents depreciation of 10%.[5]

In addition to the price, knowledge stock and total patents variables, we also include a variable reflecting publicly funded research, development and demonstration expenditures. The data is drawn from the Energy Technology Research and Development

[5] Note that our empirical analysis is conducted for the time span 1983-2009. Thus, the influence of any inaccuracies that may be inherent in the way in which the initial knowledge stock is calculated is rather small.

Database of the IEA (IEA, 2012*b*) and contains the annual national government expenditures on energy research, development and demonstration disaggregated by technology in million constant US dollars at 2011 prices.

## 4 Model specification

As we measure green energy innovation by patent counts, we use count data techniques in our econometric approach. A standard Poisson regression model for panel data takes the following exponential form:

$$y_{it} = exp(x'_{it}\beta + \eta_i) + u_{it}, \tag{4}$$

where $y_{it}$ is a non-negative integer count variable, $x'_{it}$ is a vector of explanatory variables, $\eta_i$ is a unit-specific fixed effect and $u_{it}$ is a standard error term. The subscripts $i = 1, ..., N$ and $t = 1, ..., T$ denote the observation unit and time, respectively.

It should be noted that the values of our dependent variable, the fractional counts of patent applications, are not necessarily integers. That is, strictly speaking, our dependent variable is not count data. However, as noted by Silva and Tenreyro (2006) and Wooldridge (2002), the dependent variable does not have to be an integer for the Poisson estimator to be consistent. An alternative approach used in a number of empirical studies is the estimation of a log-linear model by ordinary least squares. However, this approach can not handle zero values in the data and hence would be unnecessarily restrictive. For this reason, Silva and Tenreyro (2006) strongly recommend a Poisson specification for a non-negative continuous dependent variable with zero values.

Following this recommendation, our baseline model can be defined as

$$\begin{aligned} PAT_{ijt} = exp(&\beta_P \, ln \, P_{it-1} + \beta_K \, ln \, K_{ijt-1} + \beta_{R\&D} \, ln \, R\&D_{ijt-1} \\ &+ \beta_{TPAT} \, ln \, TPAT_{it-1} + \beta_t \, T_t + \eta_i) + u_{it}, \end{aligned} \tag{5}$$

where $PAT_{ijt}$ is the fractional patent count for technology $j$ in country $i$ and time $t$, $P$ is a price index, $K$ represents the end-of-period knowledge stock as defined in Equation 3, $R\&D$ denotes publicly funded expenditures on research, development and demonstration, $TPAT$ is the fractional patent count of all patent applications, $T$ represents a time trend, $\eta_i$ is a unit-specific fixed effect and $u_{it}$ is a standard error term. The independent variables $P_{it}$, $R\&D_{ijt}$ and $TPAT_{it}$ are lagged by one year in order to mitigate any reverse causality problems.

Another econometric issue that needs to be addressed is the dynamic character of our model. As defined in Section 3, our knowledge stock variable is a function of the lagged dependent variable. This path dependence violates the assumption of strict exogeneity of all regressors required by the traditional fixed effect count data estimator developed by Hausman et al. (1984).

To account for this problem of predetermined (i.e., weakly exogeneous) regressors in dynamic count data models, Blundell et al. (1995, 2002) propose an alternative estimator: the pre-sample mean scaling (PSM) estimator. This estimator relaxes the strict exogeneity assumption by modeling the unit-specific fixed effects via pre-sample information on the dependent variable. Following this approach, the unit-specific fixed effects in Equation 5 are defined as

$$\eta_i = \theta \, P\bar{A}T_{ip}, \tag{6}$$

where $P\bar{A}T_{ip} = (1/TP) \sum_{r=0}^{TP-1} PAT_{i,0-r}$ is the PSM of patent applications by country $i$, $TP$ is the number of pre-sample observations and $\theta$ is an unknown parameter to be estimated.

Another alternative to estimate dynamic count data models with predetermined regressors is the quasi-differenced generalized method of moments (GMM) estimator developed by Chamberlain (1992) and Wooldridge (1997). However, as noted by Blundell et al. (2002), a well-known problem of this estimator is that it can be severely biased. In particular, when the sample is small and the regressors are highly persistent over time, the lagged values of the predetermined regressors can be weak predictors of the future.

Conducting Monte Carlo simulations, Blundell et al. (2002) show that the PSM scaling estimator outperforms the quasi-differenced GMM estimator in almost all settings. Furthermore, while formally shown to be consistent for a large number of pre-sample periods only, it outperforms the quasi-differenced GMM estimator even in the case of only four pre-sample observations. We therefore follow Blundell et al. (1995, 2002) and build our empirical model on the PSM scaling estimator as defined in Equations 5 and 6.

## 5 Results

### 5.1 Baseline results

Our baseline results are presented in Table 2. As the explanatory variables enter the estimations in log form, the estimated coefficients can be interpreted as elasticities. We estimate our model for each technology separately as well as for all technologies together. As shown, the results differ significantly between the technologies, which strongly supports our approach of a technology-specific analysis. The observed differences can be explained by the different application areas, cost structures as well as maturity levels of the technologies. Nevertheless, one common result for all technologies is the positive impact of the knowledge stock on patent applications. The corresponding coefficients are positive and statistically significant at the 1% level in all models. The estimated elasticities between 0.534 and 1.020 suggest that, depending on the technology, a 10% increase in knowledge stock is associated with a 5.3 to 10.2% increase in patent activities. This finding is consistent with previous research (see, e.g., Popp, 2002; Verdolini and Galeotti, 2011) and in line with the technology-push hypothesis stating that innovation is induced by advances in the technological capability of an economy.

A completely different picture emerges for our second focus of interest, the impact of energy prices or demand-pull effects on innovation activities. Here, our results reveal significant differences among the technologies. The coefficient for the energy price is positive and statistically significant for solar, ocean, geothermal energy and CCS only.

Table 2: Estimated coefficients of the PSM Poisson model. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

| | EEBAE | EET | EEO | Solar | Wind | Ocean |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ (log) | $-0.559$ | 0.205 | 0.059 | 1.115*** | $-0.180$ | 0.612* |
| | (0.350) | (0.179) | (0.166) | (0.150) | (0.496) | (0.348) |
| Knowledge stock$_{t-1}$ (log) | 0.930*** | 1.011*** | 0.534*** | 0.640*** | 0.884*** | 0.743*** |
| | (0.095) | (0.067) | (0.079) | (0.080) | (0.069) | (0.128) |
| Public R&D$_{t-1}$ (log) | $-0.002$ | $-0.004$ | $-0.001$ | 0.036 | 0.187*** | 0.072 |
| | (0.011) | (0.011) | (0.008) | (0.051) | (0.042) | (0.063) |
| Total patents$_{t-1}$ (log) | 0.316** | 0.185*** | 0.558*** | 0.497*** | $-0.049$ | $-0.002$ |
| | (0.145) | (0.058) | (0.075) | (0.133) | (0.060) | (0.098) |
| Time trend | $-0.026$** | $-0.036$*** | $-0.039$*** | 0.013** | 0.059*** | 0.030*** |
| | (0.012) | (0.007) | (0.006) | (0.006) | (0.007) | (0.010) |
| Constant | 0.029 | $-2.706$*** | $-2.642$*** | $-1.917$*** | $-1.228$* | $-4.349$ |
| | (2.170) | (0.950) | (0.727) | (1.137) | (2.244) | (1.595) |
| Observations | 518 | 517 | 517 | 534 | 518 | 462 |

| | Biofuels | Geothermal | Fuel cells | CCS | Storage | All |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ (log) | $-0.638$* | 0.370** | 1.730 | 0.563*** | 0.026 | 0.086 |
| | (0.380) | (0.145) | (1.847) | (0.215) | (0.250) | (0.165) |
| Knowledge stock$_{t-1}$ (log) | 0.749*** | 0.793*** | 0.948*** | 1.020*** | 0.732*** | 1.013*** |
| | (0.130) | (0.117) | (0.207) | (0.068) | (0.081) | (0.032) |
| Public R&D$_{t-1}$ (log) | 0.100*** | 0.050 | 0.024 | $-0.057$** | 0.048 | 0.017* |
| | (0.024) | (0.043) | (0.068) | (0.023) | (0.035) | (0.010) |
| Total patents$_{t-1}$ (log) | 0.371*** | 0.215*** | 0.017 | $-0.015$ | 0.510*** | 0.138*** |
| | (0.107) | (0.069) | (0.212) | (0.047) | (0.137) | (0.022) |
| Time trend | $-0.058$*** | 0.006 | $-0.218$** | $-0.024$*** | $-0.018$* | $-0.036$*** |
| | (0.007) | (0.009) | (0.088) | (0.005) | (0.010) | (0.006) |
| Constant | 1.232 | $-4.351$*** | $-3.011$ | $-3.436$*** | $-4.062$*** | $-1.856$** |
| | (1.673) | (0.735) | (5.785) | (1.052) | (1.523) | (0.848) |
| Observations | 523 | 503 | 114 | 485 | 519 | 5210 |

Notes: All models control for unit-specific fixed effects by using PSM information on the first 5 years available (1978-1982). Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

The strongest impact is observed for solar energy, indicating a price elasticity higher than 1. This finding is in accordance with Johnstone et al. (2010), who also find a significant positive effect of the energy price on patent activities in solar energy. Furthermore, also in common with Johnstone et al. (2010), we do not find any effect of the energy price on patent activities in wind energy. For the other two technologies, however, our results differ from those of Johnstone et al.. While Johnstone et al. (2010) do not find any effect of the energy price on patent activities in geothermal or ocean energy, our results indicate a positive effect. However, the estimated coefficient for ocean energy is only significant at the 10% level.

Interestingly enough, for biofuels, we observe a statistically significant negative coefficient for the energy price; however, again only at the 10% level. Finally, for the three energy efficiency technologies, we do not find any significant impact of the energy price on patent activities.

Referring to public R&D expenditures, the estimated coefficients indicate either no or just a minor impact of public R&D expenditures on patent activities. A statistically significant impact of public R&D expenditures is shown for wind energy, biofuels and CCS only. Among these, the highest elasticity can be observed for wind energy. The estimated elasticity of 0.187 suggests that a 10% increase in public R&D expenditures results in an approximate 1.9% increase in patent activities. This result is consistent with Klaassen et al. (2005), who find that public R&D plays a key role in inducing cost-reducing wind energy innovations in Europe. In contrast, the estimated negative elasticity of public R&D expenditures for CCS indicates a decrease in patent activities when public R&D expenditures increase. As noted by Popp (2002), such a result may be driven by a crowding-out effect of public R&D expenditures on private R&D expenditures.[6]

The estimation results for our control variable total patents are generally as expected. For 7 of the 11 technologies, we find a statistically significant and positive coefficient, suggesting that for the majority of green energy technologies, patent activities are affected by the overall propensity to patent. This is also confirmed by the highly statistically significant and positive coefficient for total patents in the model including all technologies. Only for wind energy, ocean energy, fuel cells and CCS do overall patent activities seem to have no impact on the technology-specific patent activities.

In order to account for the development of green energy innovation activities over time, we also add a time trend to our estimations. Here, we observe a statistically significant negative time trend for 7, a statistically significant positive time trend for 3 and a statistically insignificant time trend for 1 of the 11 technologies. A negative time trend suggests diminishing returns to R&D activities or, in other words, more difficulties in developing new innovations. As new innovations are more difficult for relatively mature

[6] As noted before, we lag the R&D variable by one year in order to mitigate any reverse causality problems. This approach also accounts for the fact that R&D efforts do not immediately lead to innovative output (Hall et al., 1986). In order to test the sensitivity of the R&D results to other lag structures, we re-estimate the baseline model from Table 2 with public R&D expenditures lagged two, three and four years. Overall, the results are robust to these alternative specifications.

technologies, the different signs of the time coefficients point to different maturity levels of the technologies.

## 5.2 Robustness tests

In order to test the sensitivity of our baseline results, we conduct a number of robustness tests. First, we repeat the estimations in Table 2 with different dynamic specifications for the energy price. More specifically, we re-estimate our baseline model with the energy price lagged two years, three years and with a moving average of past energy prices over five years. The estimated coefficients for the alternative energy prices as well as for the one-year lagged energy price used in our baseline model are depicted in Table 3.

Table 3: Different dynamic specifications for the energy price. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

| | EEBAE | EET | EEO | Solar | Wind | Ocean |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ (log) | −0.559 | 0.205 | 0.059 | 1.115*** | −0.180 | 0.612* |
| | (0.350) | (0.179) | (0.166) | (0.150) | (0.496) | (0.348) |
| Energy price$_{t-2}$ (log) | −0.481 | 0.340** | 0.085 | 1.198*** | −0.015 | 0.577 |
| | (0.346) | (0.148) | (0.144) | (0.165) | (0.526) | (0.365) |
| Energy price$_{t-3}$ (log) | −0.366 | 0.353** | 0.138 | 1.209*** | 0.007 | 0.610*** |
| | (0.311) | (0.164) | (0.130) | (0.182) | (0.535) | (0.227) |
| Energy price$_{MA}$ (log) | −0.411 | 0.344* | 0.119 | 1.275*** | 0.006 | 0.526* |
| | (0.363) | (0.182) | (0.154) | (0.169) | (0.617) | (0.295) |
| | **Biofuels** | **Geothermal** | **Fuel cells** | **CCS** | **Storage** | **All** |
| Energy price$_{t-1}$ (log) | −0.638* | 0.370** | 1.730 | 0.563*** | 0.026 | 0.086 |
| | (0.380) | (0.145) | (1.847) | (0.215) | (0.250) | (0.165) |
| Energy price$_{t-2}$ (log) | −0.552 | 0.382*** | 0.600 | 0.703*** | 0.148 | 0.159 |
| | (0.368) | (0.128) | (1.186) | (0.127) | (0.224) | (0.146) |
| Energy price$_{t-3}$ (log) | −0.528* | 0.322** | 1.413 | 0.818*** | 0.253 | 0.211* |
| | (0.307) | (0.145) | (0.991) | (0.105) | (0.231) | (0.118) |
| Energy price$_{MA}$ (log) | −0.714* | 0.375** | 3.369** | 0.805*** | 0.216 | 0.179 |
| | (0.405) | (0.152) | (0.145) | (0.145) | (0.259) | (0.144) |

Notes: Estimations are based on the same specification as in Table 2. To conserve space only the coefficients for the different energy prices are presented. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. Energy price$_{MA}$: Moving average of the energy prices of the previous five years. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

Overall, the estimated coefficients are very similar for all specifications. Only for EET, ocean energy and fuel cells do we see some notable changes in statistical significance or magnitude. With an increasing time lag between energy prices and patent activities, the price coefficients for EET become statistically significant. Thus, it seems that energy prices from two or more years prior have a positive impact on patent activities in transport energy efficiency. A similar effect can be observed for fuel cells, with the moving average of past energy prices being statistically significant at the 1% level. For ocean energy, however, the results remain ambiguous. While the highly statistically significant coefficient for the three-year lagged price indicates a positive price effect, the other price coefficients are either insignificant or only significant at the 10% level.

The second robustness test we conduct is the utilization of different depreciation rates in the calculation of the end-of-period knowledge stock. Table 4 reports the estimated knowledge stock coefficients for depreciation rates of 5%, 10% (as used in the baseline model depicted in Table 2), 15% and 20%. For all specifications, the coefficients are positive and highly statistically significant at the 1% level. Furthermore, the magnitude of the coefficients is very similar within each technology. Thus, our baseline result saying that the knowledge stock is a significant driver of patent activities in all technologies is robust to different assumptions on the depreciation rate.

Another robustness test is conducted by limiting our sample to the time span 1998-2009. The reasoning for this is twofold: First, we observe a significant growth in green energy patent applications within the latter periods of our sample. Hence, our results may be influenced, in particular, by developments in these periods. Second, a shorter sample period implies a longer pre-sample period that can be used to calculate the PSM information. By choosing the cut-off year 1998, we increase the number of pre-sample periods from 5 to 20 years.

Furthermore, 1998 is the first year after the Kyoto protocol was signed. The Kyoto protocol was the first international agreement among the world's industrialized countries that aimed to reduce air-polluting greenhouse gas emissions via a legally-binding commitment. Even though the protocol did not come into force until 2005, it can be interpreted as a first indicator towards a more green energy-oriented policy. This change of future policy expectations may have affected the development of green energy innovation in the years following (see Johnstone et al., 2010).[7]

Table 5 reports the results of our short-term model with the estimation time span 1998-2009. Still, for all technologies, the knowledge stock seems to be a major driver of green energy innovation. Moreover, for most technologies, the magnitude of the corresponding coefficient is much higher than in our baseline estimations. The most pronounced impact is shown for fuel cells, with an estimated elasticity of 1.378. This value indicates that a 10% increase in knowledge stock is associated with an approximately 14% increase in patent activities.

For the energy price, a more diversified picture is shown. In fact, we observe a number of significant changes compared to the results of our baseline model depicted in Table 3. While the formerly statistically significant price coefficients for ocean energy, biofuels

[7] The signature of the Kyoto protocol may not be the only factor that changed the development of green energy innovation in these years. Other political and economic reasons might be, for instance, the rise of China and India or the liberalization of the European energy markets. Nevertheless, since the Kyoto protocol marks a substantial break in international environmental policy, the Kyoto-argumentation seems to be the most plausibel one in this context.

Table 4: Different depreciation rates for the knowledge stock. Estimation time span: 1983-2009. Dependent variable: Number of patent applications at the EPO.

| | EEBAE | EET | EEO | Solar | Wind | Ocean |
|---|---|---|---|---|---|---|
| Knowledge stock$_{t-1}$, | 0.952*** | 1.055*** | 0.522*** | 0.641*** | 0.941*** | 0.741*** |
| $\delta = 0.05$ (log) | (0.107) | (0.079) | (0.083) | (0.091) | (0.071) | (0.156) |
| Knowledge stock$_{t-1}$, | 0.930*** | 1.011*** | 0.534*** | 0.640*** | 0.884*** | 0.743*** |
| $\delta = 0.10$ (log) | (0.095) | (0.067) | (0.079) | (0.080) | (0.069) | (0.128) |
| Knowledge stock$_{t-1}$, | 0.915*** | 0.980*** | 0.547*** | 0.638*** | 0.844*** | 0.718*** |
| $\delta = 0.15$ (log) | (0.086) | (0.060) | (0.075) | (0.070) | (0.070) | (0.113) |
| Knowledge stock$_{t-1}$, | 0.904*** | 0.958*** | 0.560*** | 0.635*** | 0.814*** | 0.684*** |
| $\delta = 0.20$ (log) | (0.079) | (0.055) | (0.072) | (0.063) | (0.071) | (0.105) |
| | Biofuels | Geothermal | Fuel cells | CCS | Storage | All |
| Knowledge stock$_{t-1}$, | 0.804*** | 0.836*** | 0.948*** | 1.063*** | 0.738*** | 1.069*** |
| $\delta = 0.05$ (log) | (0.138) | (0.133) | (0.229) | (0.087) | (0.094) | (0.039) |
| Knowledge stock$_{t-1}$, | 0.749*** | 0.793*** | 0.948*** | 1.020*** | 0.732*** | 1.013*** |
| $\delta = 0.10$ (log) | (0.130) | (0.117) | (0.207) | (0.068) | (0.081) | (0.032) |
| Knowledge stock$_{t-1}$, | 0.723*** | 0.746*** | 0.949*** | 0.977** | 0.720*** | 0.980*** |
| $\delta = 0.15$ (log) | (0.124) | (0.107) | (0.191) | (0.063) | (0.072) | (0.028) |
| Knowledge stock$_{t-1}$, | 0.716*** | 0.702*** | 0.950*** | 0.938*** | 0.704*** | 0.960*** |
| $\delta = 0.20$ (log) | (0.118) | (0.101) | (0.179) | (0.065) | (0.067) | (0.025) |

Notes: Estimations are based on the same specification as in Table 2. To conserve space only the coefficients for the different knowledge stocks are reported. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

and CCS are now insignificant, the respective coefficients for EET and energy storage become significant. Furthermore, the magnitude of the still positive and statistically significant price coefficients for solar and geothermal energy is much higher than before.

Referring to the other variables, public R&D, total patents and the time trend the results of the short-term model are in general in line to those obtained from the baseline model. Still, public R&D expenditures seem to have only a minor impact on patent activities. However, compared to our baseline model indicating a statistically significant and positive impact of public R&D on patent activities for wind energy and biofuels only, we now observe a statistically significant and positive impact of public R&D for two more technologies, namely EEBAE and energy storage. Furthermore, in spite of some changes in significance, the estimated coefficients for total patents and the time trend again suggest a positive impact of the overall propensity to patent and diminishing returns to R&D activities over time on green energy patent activities for most technologies.

Table 5: Estimated coefficients of the PSM Poisson model. Estimation time span: 1998-2009. Dependent variable: Number of patent applications at the EPO.

| | EEBAE | EET | EEO | Solar | Wind | Ocean |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ | 0.376 | 0.766* | 0.163 | 1.735*** | 0.721 | −1.158 |
| (log) | (0.750) | (0.429) | (0.389) | (0.480) | (0.592) | (0.795) |
| Knowledge stock$_{t-1}$ | 1.362*** | 1.260*** | 0.816*** | 1.005*** | 0.955*** | 1.015*** |
| (log) | (0.092) | (0.111) | (0.200) | (0.085) | (0.071) | (0.154) |
| Public R&D$_{t-1}$ | 0.054*** | 0.008 | −0.020** | −0.010 | 0.194*** | 0.069 |
| (log) | (0.016) | (0.008) | (0.010) | (0.040) | (0.053) | (0.072) |
| Total patents$_{t-1}$ | −0.067 | 0.040 | 0.496*** | 0.485*** | −0.132** | −0.048 |
| (log) | (0.198) | (0.074) | (0.154) | (0.127) | (0.054) | (0.095) |
| Time trend | −0.134*** | −0.084*** | −0.054*** | −0.053** | −0.016 | 0.072** |
| | (0.029) | (0.022) | (0.018) | (0.022) | (0.020) | (0.036) |
| Constant | 0.467 | −3.104 | −2.102 | −9.407*** | −2.805 | 2.564 |
| | (3.638) | (1.906) | (1.744) | (2.109) | (2.502) | (3.183) |
| Observations | 241 | 240 | 241 | 248 | 243 | 225 |

| | Biofuels | Geothermal | Fuel cells | CCS | Storage | All |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ | 0.251 | 1.536*** | 1.398 | 0.093 | 1.080*** | 0.529** |
| (log) | (0.158) | (0.239) | (1.907) | (0.499) | (0.317) | (0.234) |
| Knowledge stock$_{t-1}$ | 0.824*** | 0.817*** | 1.378*** | 0.916*** | 0.369** | 1.235*** |
| (log) | (0.269) | (0.184) | (0.139) | (0.189) | (0.165) | (0.083) |
| Public R&D$_{t-1}$ | 0.129** | 0.066 | 0.029 | −0.033 | 0.089*** | 0.012 |
| (log) | (0.059) | (0.040) | (0.050) | (0.023) | (0.029) | (0.012) |
| Total patents$_{t-1}$ | 0.277*** | 0.277*** | 0.281* | −0.104** | 0.011 | 0.139*** |
| (log) | (0.073) | (0.101) | (0.160) | (0.046) | (0.097) | (0.026) |
| Time trend | −0.154*** | −0.037 | −0.218** | −0.014 | −0.035** | −0.096*** |
| | (0.022) | (0.024) | (0.087) | (0.023) | (0.014) | (0.015) |
| Constant | 0.648 | −8.598*** | −2.850 | −0.728 | −5.727*** | −1.649 |
| | (0.709) | (1.355) | (6.244) | (2.114) | (1.761) | (1.208) |
| Observations | 247 | 229 | 114 | 236 | 242 | 2506 |

Notes: All models control for unit-specific fixed effects by using PSM information on the first 20 years available (1978-1997). Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

Our last robustness test deals with the observed differences between the estimated price coefficients in our short-term and our baseline models (see Tables 2 and 5). In order to obtain a more comprehensive picture and to check whether these differences are only related to the usage of a one-year lagged energy price specification, we re-estimate our short-term model with different dynamic specifications for the energy price (as done before for the baseline model, see Table 3). The results are shown in Table 6.

Table 6: Different dynamic specifications for the energy price. Estimation time span: 1998-2009. Dependent variable: Number of patent applications at the EPO.

| | EEBAE | EET | EEO | Solar | Wind | Ocean |
|---|---|---|---|---|---|---|
| Energy price$_{t-1}$ (log) | 0.376 | 0.766* | 0.163 | 1.735*** | 0.721 | −1.158 |
| | (0.750) | (0.429) | (0.389) | (0.480) | (0.592) | (0.791) |
| Energy price$_{t-2}$ (log) | 0.379 | 1.125*** | 0.151 | 1.728*** | 1.002* | −1.273 |
| | (0.690) | (0.266) | (0.339) | (0.458) | (0.553) | (0.916) |
| Energy price$_{t-3}$ (log) | 0.597 | 1.095*** | 0.331 | 1.662*** | 0.891* | −0.742 |
| | (0.493) | (0.319) | (0.292) | (0.468) | (0.486) | (0.661) |
| Energy price$_{MA}$ (log) | 0.766 | 1.155*** | 0.342 | 1.879*** | 1.227** | −1.394 |
| | (0.554) | (0.333) | (0.328) | (0.429) | (0.607) | (0.916) |
| | **Biofuels** | **Geothermal** | **Fuel cells** | **CCS** | **Storage** | **All** |
| Energy price$_{t-1}$ (log) | 0.251 | 1.536*** | 1.398 | 0.093 | 1.080*** | 0.529** |
| | (0.158) | (0.239) | (1.907) | (0.499) | (0.317) | (0.234) |
| Energy price$_{t-2}$ (log) | 0.320** | 1.479*** | −0.366 | 0.624* | 1.166*** | 0.650*** |
| | (0.133) | (0.238) | (1.057) | (0.334) | (0.277) | (0.196) |
| Energy price$_{t-3}$ (log) | 0.832*** | 1.457*** | 0.453 | 1.094*** | 1.151*** | 0.848*** |
| | (0.190) | (0.252) | (0.958) | (0.283) | (0.326) | (0.169) |
| Energy price$_{MA}$ (log) | 0.979*** | 1.757*** | 1.858 | 0.941** | 1.181*** | 0.886*** |
| | (0.361) | (0.297) | (1.562) | (0.420) | (0.353) | (0.194) |

Notes: Estimations are based on the same specification as in Table 5. To conserve space only the coefficients for the different knowledge stocks are reported. The complete tables are available from the authors upon request. Robust standard errors clustered by country (Model EEBAE - Storage) and by country-technology (Model All) are in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

First of all, it can be seen that all estimated price coefficients in the model including all technologies are positive and statistically significant at the 1% level. In our baseline model, we observe a positive impact of the energy price on patent activities in green energy technologies only for the three-year lagged price and just at a 10% level of significance. This finding, together with the other observed differences in the estimates of our baseline and short-term models, point to the fact that, at least for some green energy technologies, the development of patent activities changed significantly in the post-Kyoto period. With the number of green energy patents rapidly increasing within this period, our results for the knowledge stock and for the energy price suggest that both technology-push effects and demand-pull effects gain a more pronounced impact on patent activities in this period.

Nevertheless, while this observation holds for all technologies in the case of technology-push effects, demand-pull effects seem to affect only some technologies. With at least three of the four energy price specifications tested being statistically significant, the results in Table 6 clearly indicate a positive impact of the energy price on patent activities in 7 of the 11 technologies, namely EET, solar energy, wind energy, biofuels, geothermal energy, CCS and energy storage. In our baseline model, this is only the case for 4 technologies: EET, solar energy, geothermal energy and CCS.

Referring to the magnitude of the estimated price coefficients, some other interesting results are obtained from our short-term model estimations. For EET, solar and geothermal energy, the magnitude of the price coefficients is much higher in the short-term model than in the baseline model. Moreover, for solar and geothermal energy, the price coefficients are much higher than the knowledge stock coefficients, indicating that the energy price for these technologies is the main driver of patent activities in the post-Kyoto period.

A similar result can be observed for energy storage. While the estimated price coefficients are insignificant for all energy price specifications tested in our baseline model, they are highly statistically significant and positive in our short-term model. Moreover, the magnitude of the price coefficients is much higher than the magnitude of the knowledge stock coefficient.

Overall, these results point to a change in expectations after the Kyoto protocol was signed. In particular, they suggest that market participants expected green energy-oriented policies to be pushed forward and energy prices to persistently increase in the future. Such a development creates more profitable market conditions for green energy technologies and hence raises patent activities in this area.

## 6 Conclusions

In this paper, we analyzed the effect of energy prices and technological knowledge on innovation in green energy technologies. We based our analysis on green energy patent counts from 26 OECD countries and 11 technologies over the period 1978-2009. Our contribution to the induced innovation literature is threefold. We investigated demand and supply determinants of green energy innovation separately for different technologies. We used European patent data to consolidate previous results reached on US patent data. Finally, we estimated a dynamic count data model for panel data using the PSM scaling estimator proposed by Blundell et al. (1995, 2002). This approach allowed us to account for path dependencies in knowledge production, endogeneity issues and unobserved heterogeneity.

Our analysis yields several interesting findings. First of all, our results indicate that the main determinant of innovation in green energy technologies is the availability of technological knowledge. This confirms the technology-push hypothesis, stating that innovation is induced by advances in the technological capability of an economy. It also confirms previous results suggesting that inventors build on existing knowledge and "see further by standing on the shoulders of giants". Moreover, concerning the demand-pull hypothesis suggesting energy prices as a major driver of green energy innovation, our results reveal significant differences across technologies. We find that increasing energy prices induce innovation in some but not all green energy technologies. This result supports our approach of a technology-specific analysis. However, even more important is that we uncovered significant differences comparing the pre- and post-Kyoto period. More precisely, our results indicate that the effect of both energy prices and technological knowledge on green energy innovation is stronger after the Kyoto protocol agreement. This suggests that the general awareness for clean energy generation increased. Finally, evidence is presented that government R&D plays either no or just a minor role in inducing green energy innovation.

From our results several policy implications can be drawn. First, the strong evidence for the technology-push hypothesis suggests that policies should enhance technological capability to foster green energy innovation. That is, policies should support the generation and dissemination of fundamental scientific and technological knowledge, promote investments in complementary infrastructure and enable economies to exploit their existing knowledge base. Above that, depending on the technology, increasing energy prices and subsidizing energy R&D can encourage innovation and thus increase the economy's stock of knowledge. Second, concerning demand-pull, it seems that energy prices are not equally suitable to induce innovation in different technologies. For example, it could be beneficial to increase energy prices for solar energy, but apparently not for EEBAE. Accordingly, policy makers aiming to increase energy prices should be aware of these differences. All together, it may be concluded that distinct technologies have distinct innovation characteristics and thus different sets of policies are required to encourage green energy innovation.

Further research could extend our analysis in two main aspects. On the one hand, the observed differences across technologies seem to be worth examining in more detail. On the other hand, a closer analysis of the post-Kyoto period could lead to a deeper understanding of how this agreement has changed innovators future policy expectations.

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# Appendix

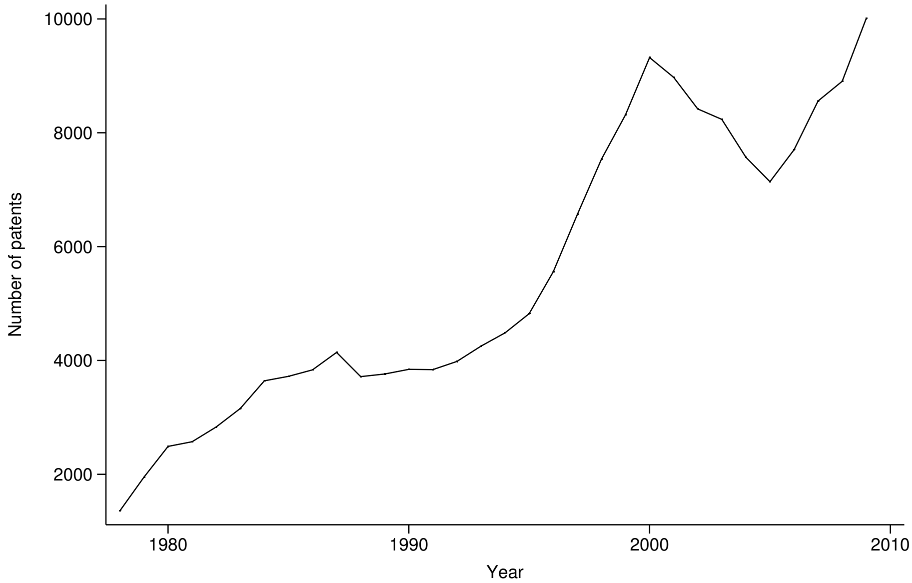


Figure A1: Total number of green energy EPO patent applications of 26 OECD countries, 1978-2009.

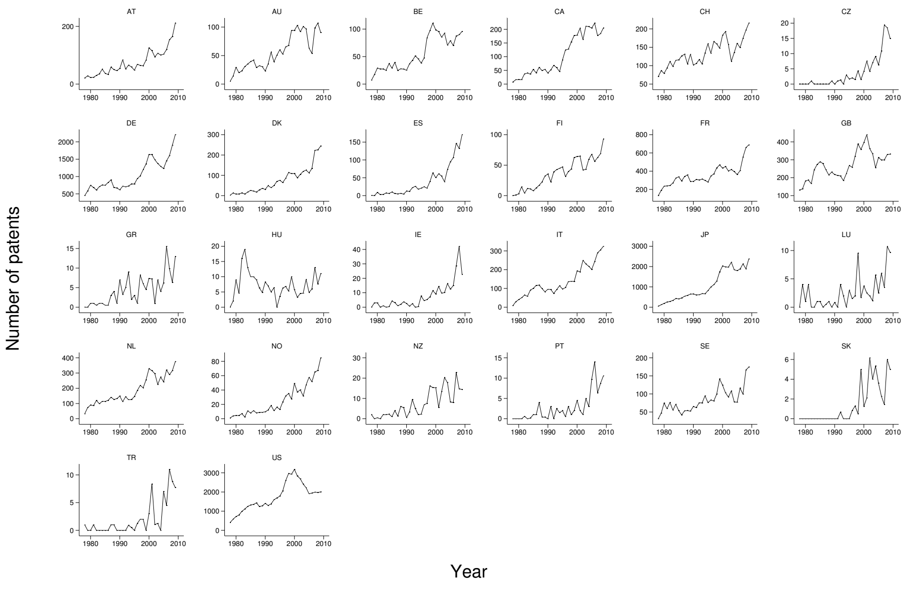


Figure A2: Number of green energy EPO patent applications by country, 1978-2009. *Note*: The country codes are the same as in Table 1.

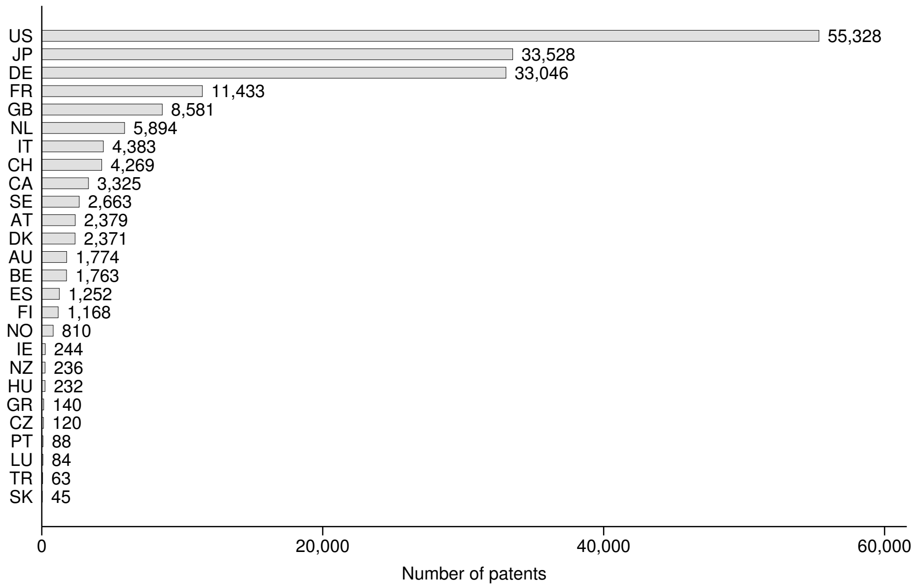


Figure A3: Total number of green energy EPO patent applications over 1978-2009 by country. *Note*: The country codes are the same as in Table 1.

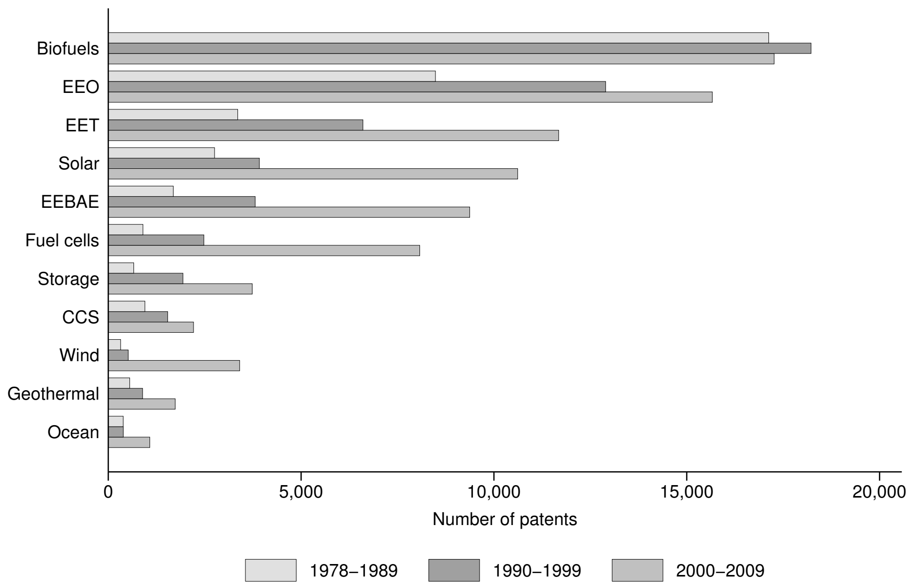


Figure A4: Total number of EPO patent applications of 26 OECD countries over three time periods by green energy technology. *Note*: EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

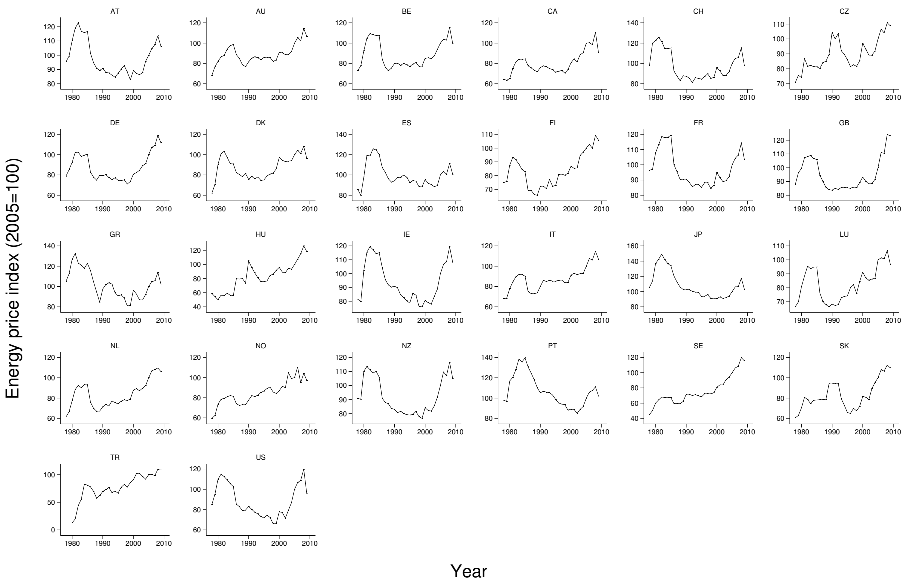


Figure A5: Real total energy end-use price for households and industry by country (index: 2005=100), 1978-2009. *Note*: The country codes are the same as in Table 1.

Table A1: Number of EPO patent applications by country and green energy technology.

| Country | Biofuels | CCS | Fuel cells | Geothermal | Ocean | EEO | EEBAE | Solar | Storage | EET | Wind | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 318 | 33 | 55 | 64 | 46 | 434 | 307 | 263 | 69 | 722 | 66 | 2,379 |
| AU | 666 | 43 | 69 | 37 | 53 | 286 | 82 | 263 | 47 | 186 | 43 | 1,774 |
| BE | 907 | 22 | 35 | 28 | 17 | 248 | 151 | 167 | 20 | 115 | 52 | 1,763 |
| CA | 1,114 | 110 | 404 | 34 | 42 | 616 | 174 | 179 | 168 | 414 | 70 | 3,325 |
| CH | 1,021 | 58 | 182 | 210 | 55 | 1,074 | 365 | 438 | 109 | 687 | 68 | 4,269 |
| CZ | 25 | 2 | 2 | 5 | 6 | 30 | 10 | 9 | 5 | 25 | 1 | 120 |
| DE | 7,589 | 699 | 1,965 | 878 | 269 | 7,352 | 3,094 | 3,657 | 987 | 5,360 | 1,197 | 33,046 |
| DK | 806 | 39 | 122 | 24 | 43 | 295 | 127 | 200 | 50 | 91 | 574 | 2,371 |
| ES | 257 | 12 | 30 | 26 | 36 | 149 | 93 | 266 | 30 | 175 | 178 | 1,252 |
| FI | 281 | 18 | 36 | 49 | 27 | 403 | 97 | 73 | 43 | 101 | 39 | 1,168 |
| FR | 3,414 | 429 | 425 | 130 | 173 | 2,763 | 641 | 992 | 348 | 1,963 | 156 | 11,433 |
| GB | 3,244 | 304 | 369 | 116 | 197 | 1,883 | 671 | 619 | 166 | 796 | 216 | 8,581 |
| GR | 31 | 0 | 5 | 4 | 14 | 17 | 13 | 20 | 2 | 24 | 10 | 140 |
| HU | 94 | 2 | 2 | 13 | 4 | 40 | 13 | 26 | 11 | 21 | 5 | 232 |
| IE | 50 | 2 | 1 | 1 | 42 | 41 | 41 | 30 | 7 | 11 | 18 | 244 |
| IT | 921 | 52 | 196 | 90 | 80 | 917 | 403 | 467 | 93 | 1,035 | 128 | 4,383 |
| JP | 5,590 | 482 | 3,955 | 547 | 122 | 6,144 | 4,617 | 4,442 | 2,151 | 5,128 | 350 | 33,528 |
| LU | 8 | 1 | 7 | 1 | 1 | 21 | 16 | 12 | 4 | 7 | 6 | 84 |
| NL | 2,086 | 183 | 148 | 73 | 49 | 1,515 | 717 | 435 | 119 | 394 | 175 | 5,894 |
| NO | 139 | 126 | 23 | 27 | 83 | 161 | 32 | 90 | 10 | 46 | 73 | 810 |
| NZ | 96 | 4 | 7 | 5 | 2 | 37 | 9 | 15 | 14 | 43 | 2 | 236 |
| PT | 14 | 3 | 3 | 0 | 9 | 9 | 4 | 25 | 1 | 10 | 10 | 88 |
| SE | 481 | 67 | 54 | 104 | 70 | 703 | 211 | 236 | 144 | 489 | 104 | 2,663 |
| SK | 13 | 0 | 0 | 1 | 5 | 6 | 3 | 6 | 0 | 9 | 2 | 45 |
| TR | 8 | 0 | 5 | 1 | 1 | 9 | 11 | 13 | 2 | 8 | 5 | 63 |
| US | 23,438 | 2,009 | 3,353 | 713 | 405 | 11,889 | 2,965 | 4,348 | 1,729 | 3,781 | 697 | 55,328 |
| Total | 52,614 | 4,701 | 11,455 | 3,181 | 1,853 | 37,044 | 14,867 | 17,290 | 6,330 | 21,640 | 4,245 | 175,220 |

Note: The country codes are the same as in Table 1. EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

Table A2: Number of EPO patent applications by green energy technology and time period.

| Technology | 1978-1984 | 1985-1989 | 1990-1994 | 1995-1999 | 2000-2004 | 2005-2009 | Total |
|---|---|---|---|---|---|---|---|
| Biofuels | 8,848 | 8,277 | 6,442 | 11,780 | 10,778 | 6,488 | 52,614 |
| CCS | 408 | 542 | 628 | 912 | 1,026 | 1,184 | 4,701 |
| Fuel cells | 434 | 465 | 687 | 1,792 | 4,522 | 3,555 | 11,455 |
| Geothermal | 312 | 244 | 357 | 532 | 723 | 1,013 | 3,181 |
| Ocean | 221 | 166 | 161 | 229 | 383 | 694 | 1,853 |
| EEO | 3,546 | 4,938 | 5,957 | 6,940 | 8,213 | 7,450 | 37,044 |
| EEBAE | 760 | 925 | 1,348 | 2,461 | 4,741 | 4,632 | 14,867 |
| Solar | 1,554 | 1,202 | 1,492 | 2,425 | 3,932 | 6,684 | 17,290 |
| Storage | 293 | 367 | 606 | 1,331 | 1,696 | 2,037 | 6,330 |
| EET | 1,430 | 1,926 | 2,576 | 4,027 | 5,450 | 6,229 | 21,640 |
| Wind | 197 | 123 | 149 | 367 | 1,059 | 2,348 | 4,245 |
| Total | 18,004 | 19,177 | 20,405 | 32,798 | 42,521 | 42,314 | 175,220 |

Note: EEBAE: Energy efficiency in residential and commercial buildings, appliances and equipment; EET: Energy efficiency in transport; EEO: Other energy efficiency; CCS: Carbon capture and storage.

Table A3: Total number of total EPO patent applications and total number of green energy EPO patent applications over 1978-2009 by country.

| Country | Number of total patents | Relative share in sum of total patents | Number of green energy patents | Relative share in sum of green energy patents | Ratio of green energy patents to total patents |
|---|---|---|---|---|---|
| AT | 27,813 | 1.19% | 2,378 | 1.36% | 8.55% |
| AU | 19,492 | 0.83% | 1,773 | 1.01% | 9.10% |
| BE | 27,320 | 1.17% | 1,763 | 1.01% | 6.45% |
| CA | 35,753 | 1.53% | 3,324 | 1.90% | 9.30% |
| CH | 65,331 | 2.79% | 4,268 | 2.44% | 6.53% |
| CZ | 1,588 | 0.07% | 120 | 0.07% | 7.57% |
| DE | 475,912 | 20.35% | 33,045 | 18.86% | 6.94% |
| DK | 18,896 | 0.81% | 2,370 | 1.35% | 12.55% |
| ES | 17,496 | 0.75% | 1,251 | 0.71% | 7.15% |
| FI | 23,121 | 0.99% | 1,167 | 0.67% | 5.05% |
| FR | 175,655 | 7.51% | 11,433 | 6.53% | 6.51% |
| GB | 131,161 | 5.61% | 8,580 | 4.90% | 6.54% |
| GR | 1,363 | 0.06% | 139 | 0.08% | 10.26% |
| HU | 3,239 | 0.14% | 231 | 0.13% | 7.16% |
| IE | 4,258 | 0.18% | 244 | 0.14% | 5.74% |
| IT | 86,489 | 3.70% | 4,383 | 2.50% | 5.07% |
| JP | 419,708 | 17.95% | 33,527 | 19.13% | 7.99% |
| LU | 1,596 | 0.07% | 84 | 0.05% | 5.29% |
| NL | 67,132 | 2.87% | 5,894 | 3.36% | 8.78% |
| NO | 8,065 | 0.34% | 810 | 0.46% | 10.05% |
| NZ | 2,925 | 0.13% | 235 | 0.13% | 8.05% |
| PT | 1,050 | 0.04% | 87 | 0.05% | 8.37% |
| SE | 48,335 | 2.07% | 2,663 | 1.52% | 5.51% |
| SK | 347 | 0.01% | 45 | 0.03% | 13.08% |
| TR | 1,927 | 0.08% | 63 | 0.04% | 3.29% |
| US | 672,831 | 28.77% | 55,328 | 31.58% | 8.22% |
| Total | 2,338,817 | 100.00% | 175,220 | 100.00% | 7.49% |

Note: The country codes are the same as in Table 1.