Universidad de Navarra

Facultad de Ciencias Económicas y Empresariales

Working Paper nº 11/09

Renewable Energy Innovations in Europe: A Dynamic Panel Data Approach

Nadia Ayari
Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

Szabolcs Blazsek
Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

Pedro Mendi
Facultad de Ciencias Económicas y Empresariales
Universidad de Navarra

Renewable Energy Innovations in Europe: A Dynamic Panel Data Approach
Nadia Ayari, Szabolcs Blazsek and Pedro Mendi

Working Paper No.11/09
October 2009

ABSTRACT

We investigate the determinants of renewable energy R&D intensity and the impact of renewable energy innovations on firm performance, using several dynamic panel data models. We estimate these models using a large dataset of European firms of 19 different countries, with some patenting activity in areas related with renewable energies during the 1987-2007 period. The results that we obtain confirm our a prioris on the determinants of the rapid development of renewable energy R&D intensity during the last decades. Additionally, we find evidence that renewable patent intensity has significant dynamic impact on the stock market value of firms.

Nadia Ayari
Universidad de Navarra
Depto. Economía
Campus Universitario
31080 Pamplona
nayari@alumni.unav.es

Szabolcs Blazsek
Universidad de Navarra
Depto. Economía
Campus Universitario
31080 Pamplona
sblazsek@unav.es

Pedro Mendi
Universidad de Navarra
Depto. Economía
Campus Universitario
31080 Pamplona
pmendi@unav.es

Renewable energy innovations in Europe: A dynamic panel data approach

Nadia Ayari[a], Szabolcs Blazsek[a] and Pedro Mendi[a,*]

[a] *Department of Business Administration, Universidad de Navarra, Pamplona, Spain*

Abstract

We investigate the determinants of renewable energy R&D intensity and the impact of renewable energy innovations on firm performance, using several dynamic panel data models. We estimate these models using a large dataset of European firms of 19 different countries, with some patenting activity in areas related with renewable energies during the 1987-2007 period. The results that we obtain confirm our a prioris on the determinants of the rapid development of renewable energy R&D intensity during the last decades. Additionally, we find evidence that renewable patent intensity has significant dynamic impact on the stock market value of firms.

JEL classification: C15; C31; C32; C33; C41

Keywords: R&D intensity; Stock market value; Patents; Count data; Dynamic panel data

*Corresponding author. Department of Business Administration, Universidad de Navarra, Facultad de Económicas, Ed. Bibliotecas-Este, 31080 Pamplona, Spain. *Telephone:* +34 948425600 (S. Blazsek). *E-mail addresses:* Ayari: nayari@alumni.unav.es, Blazsek: sblazsek@unav.es, Mendi: pmendi@unav.es. The authors thank to Mirko Abbritti, Luis Albériko Gil-Alana, Antonio Moreno and Jerome Vandenbussche for their comments. All errors are our own.

1. Introduction

Ever since the energy crises of the 1970s, many governments started to promote the use of renewable energies as desirable substitutes for traditional fossil fuels. Climate change concerns and fluctuating oil prices are factors behind the increase in the share of renewable energy relative to the world energy consumption. In this setting, the increasing demand for electricity, the strict environmental policies and the potential future gains from access to renewable energy markets have stimulated the private sector's interest in developing more innovations in these alternative energies. However, the most important barrier limiting the expansion of renewable energies is related to the high capital costs needed for their development. At the firm level, several R&D activities have been carried out in order to reduce costs and accelerate the expansion of renewable energy innovations. While private R&D expenses and factors such as fossil fuels price increases or growing energy demand are expected to stimulate renewable energy innovations, how effective these factors are in the generation of new technologies in these specific areas has yet to be proved empirically.

The purpose of this paper is twofold. First, we inquire into the main determinants of the evolution of R&D activities related to renewable energy. Second, we estimate the impact of renewable energy R&D intensity on firm performance using recently developed dynamic panel data techniques. Specifically, we will estimate panel data models that are specific to count data, as well as a panel vector auto-regression model. We analyze a panel of European firms, spanning over a 21-year period between 1987 and 2007, for 19 European countries. We find statistically significant effects of R&D expenditures on patenting activitites, and of patenting on firm performance.

During the 1971-2004 period, the total renewable energy supply experienced an annual growth rate of 2.3 percent. Particularly, wind, solar and geothermal experienced an increase of 48 percent, 28 percent and 7.5 percent during the same time-period, respectively (IEA, 2007). More recent data show that, in 2008, global energy coming from renewable sources increased 75 percent comparing to 2004. Specifically, in the same time-period, solar photovoltaic (PV) capacity and biodiesel production increased six fold, ethanol production and solar heating capacity doubled, while wind capacity increased 250 percent. Germany and Spain overcame the other of European countries in total renewable power, wind power and solar PV capacities as for end-2008 (Renewables: Global Status Report, 2009).

The state of the art in renewable energies varies depending on the specific source of energy. For instance, recently, innovations in solar PV industry have largely exceeded other technological innovations innovations in renewable energy fields. In fact, the International Energy Agency (IEA) classifies renewable energy technologies into three main categories according to the novelty of their development. For instance, it sets First-generation technologies as those that emerged at the end of the nineteenth century such as hydropower, biomass combustion, and geothermal power and heat, some of which are still in widespread use. Second-generation technologies, generally, reflect revolutionary advancements. They include solar heating and cooling, wind power modern forms of bio-energy, and solar PV, whereas the Third-generation category of renewable energy technologies include innovations under development such as in concentrating solar power, ocean energy, geothermal energy, and integrated bio-energy systems.

In order to study the technological innovations, researchers have debated on what was the appropriate measure to use in order to quantify firms' level of innovation. One of the widely used measures are basically inputs of the innovative activity i.e. R&D expenditures, R&D intensity, etc. However, since this type of measures show a relatively weak power to evaluate the real innovation activity of firms, many studies considered that the best proxies for technological innovations are patents.

In this paper, we employ patent data based measures of firms' R&D intensity. During the past two decades, innovations protected by patents have played a key role in business strategies. This fact motivated several studies of the determinants of patents and the impact of patents on innovation and competitive advantage. Patents help sustaining competitive advantages by increasing the production cost of competitors, by signaling a better quality of products and by serving as barriers to entry. Griliches (1990) states that the main advantages of patent data are the followings: (a) by definition patents are closely related to inventive activity; (b) patent documents are objective because they are produced by an independent patent office and their standards change slowly over time; and (c) patent data are widely available in several countries, over long periods of time, and cover almost every field of innovation.

Actually, patents, as an output measure, provide relevant information about the nature of the inventions, their application dates, the identity and the home country of the applicant, the detailed description of the invention and even the citation to previous patents related to the current innovation. Moreover, patent data allow for an examination of the different levels of innovative activities across countries and permit to classify patents according to their area of application following the International Patent Classification (IPC) codes developed at the World Intellectual Property Organization. The IPC codes are particularly preferable in the renewable energy innovations to the conventional sectoral classification as they allow distinguishing between the relevant technological classes of a particular section.

Regarding firm performance, innovation activity exists because it has a positive impact on future profits of a company, which motivates owners to promote innovative activity within their firm. Indeed, the R&D intensity of private firms is an important source of wealth in developed countries. Since profits on R&D are usually realized during several years in the future, current accounting-based net profit is a very noisy measure of R&D benefits. Therefore, in the economics literature, several papers have decided to investigate the impact of R&D on stock market price, which avoids the problem of timing differential of R&D expenses and associated future profits by a forward-looking perspective.

The remainder of the paper is organized as follows. Section 2 reviews the literature directly related to the topics addressed in this paper. Section 3 presents and discusses the dataset used in this paper. In Section 4, we present the panel data models to be estimated; a number of technical details have been relegated to the appendix. Section 5 discusses the estimation results, and finally, we present a number of concluding remarks in Section 6.

2. Literature review

In the existing literature a number of empirical analyses have investigated the determinants of renewable energy innovations, mainly due to the difficulty in obtaining this kind of data. The majority of studies provide evidence on factors influencing environmental innovations rather than renewable energy innovations. In the present section we summarize the most important empirical contributions that have been developed in this area.

The panel framework of Johnstone et al. (2008) applied to 25 OECD countries over the 1978-2003 period examine the determinants, particularly environmental policies, of the technological innovations in the area of renewable energy. The authors use patent counts as proxy for innovation activities and find that renewable R&D public spending and public policy are both significant factors influencing patent activity in renewable energy. They also consider that growing electricity consumption is likely to increase incentives to innovate in renewable energy technologies.

Sagar (2000) argues that, unlike in sectors such as pharmaceuticals, where returns to R&D can be very high, in the energy sector R&D mainly serves to lower capital expenditures of energy conversion plans or the substitution of fuel based technologies.

Using German panel data applied to firms in the environmental sectors, Horbach (2008) studies factors that determine environmental technological innovations. He finds that R&D activities encourage environmental innovation. Also, Margolis and Kammen (1999) show that R&D investments are positively correlated with the total number of patents granted in energy sector in the US.

In their study applied to 15 EU-Member States, Ragwitz and Miola (2005) confirm that in R&D intensive renewable energy technologies, such as the photovoltaic sector, R&D spending constitute a major factor influencing the generation of international patents. The authors state that in this kind of technologies the role of research activities is the most relevant driver to the development of innovating activities. However, they find that in sectors such as wind energy, other factors play a more important role in the development of the technological innovations since in this kind of technologies the practical experience will have the dominant impact.

Popp (2002) considers that energy prices have a strong positive impact on patenting activity for various environmentally-friendly technologies. Indeed, he sustains that energy prices tend to generate more environmental regulations, such as taxes and abatement policies that encourage the development of new energy technologies. He also finds that prices of fossil fuels are likely to stimulate the development of these types of research in relatively small period of time (five-year period has been experienced for one-half of the effects of energy price increase on R&D). Moreover, focusing on a particular energy technology, his findings show that energy crisis en 1972 have immediately contributed to big jumps in patenting activity in solar technology.

In a theoretical study applied to use of patents in environmental innovations, Popp (2003) considers that patent counts are a good measure of innovative output of the firm and that they indicate the corporate level of innovative activity. Moreover, Dernis and Guellec (2001) justify the increasing use of patent data in empirical studies on determinants of innovative activities of firms by the extensively recognized relationship between patents and innovative output and also by the interesting information contained in patents. The authors also consider that among the few indicators of technology output patent-based indicators are particularly useful for comparing innovative trends across countries.

Regarding the econometric techniques used in this paper, in a similar way as several past studies, which used patent data to measure the inventive activity of firms, the present paper employs a

Poisson-type patent count model. By patent counts we mean the number of successful patent applications assigned to firms during a given year.[1] Common characteristic of these models is that patent counts are treated as discrete-valued random variables and are analyzed by a *count data model*. In these models it is assumed that: (1) the arrival rate (or *conditional intensity*) of patents has some parametric functional form, and (2) the arrival rate is constant over a period of time. The consequence of the second assumption is that the statistical inference of the model can be done based on the number of patent applications during each period and the exact time of the innovation is irrelevant. Although in recent patent databases the application date of patents is available with daily precision, this information is a noisy measure of the time of innovations. Therefore, following Hausman et al. (1984) most authors aggregate patent data over the year. Thus, the patent counts are assumed to follow a Poisson distribution. Fortunately, Wooldridge (2002) notes that the Poisson distribution has a very nice robustness property: whether or not the Poisson distribution holds, we still get consistent, asymptotically normal estimators of the parameters given that the conditional mean is correctly specified and the regularity conditions hold (see Wooldridge, 1997 and 2002).

Finally, several papers have investigated the impact of R&D activity on the stock market value of firms. Pakes (1985) focuses on the dynamic relationships among the number of successful patent applications of firms, a measure of the firm's investment in inventive activity (its R&D expenditures), and an indicator of its inventive out (the stock market value of the firm). Pakes concludes that the events that lead the market to reevaluate the firm are significantly correlated with unpredictable changes in both the R&D and the patents of the firm. Hall (1993) shows that the stock market overvalues R&D. Nevertheless, Hall et al. (2006) shows that the valuation on R&D has been relatively low during the past decade. On the other hand, a number of studies have shown the correlation of R&D activity with contemporaneous and future market value (see Lev and Sougiannis, 1996 and Lev et al., 2005). Chan et al. (2001) show a positive relationship between R&D intensity as measured by R&D to market value and abnormal future returns. This association of R&D activity and future excess stock returns could be due to delayed reaction by the stock market or inadequate adjustment for risk (Chambers et al., 2002). Moreover, Chan et al. (2001) also show that the future excess returns for R&D intensive firms are driven by lower stock price valuation in the current year due to R&D firm's earnings being depressed. Recently, Lev et al., (2006) show that R&D leaders earn significant future excess returns, while R&D followers only earn average returns. Lev et al. (2006) find that R&D leaders show higher future profitability and lower risk than followers, but the investors' reaction seems to be delayed. They conclude that investors probably do not get information in a timely fashion leading to a delayed reaction. We model R&D intensity and stock market value in dynamic setup and to use a multivariate model to identify R&D leader and follower companies.

3. The data

We provide a general discussion of the data set employed, which comes from different sources. First, we describe the characteristics of our patent data, then data on firm characteristics, and finally macroe-

[1] See Hausman et al. (1984), Pakes (1985), Lanjouw et al. (1998) or Trajtenberg (2002).

conomic data.

Patent data. Our sample of patents in renewable energy includes 15 EU countries: (1) Austria, (2) Belgium, (3) Denmark, (4) Finland, (5) France, (6) Germany, (7) Greece, (8) Ireland, (9) Italy, (10) Luxembourg, (11) Netherlands, (12) Portugal, (13) Spain, (14) Sweden, (15) United Kingdom and four EFTA : (1) Iceland, (2) Liechtenstein, (3) Norway and (4) Switzerland. The patent data set used in this paper is the PATSTAT database, acquired from the European Patent Office (EPO) for the period 1960-2007. We have collected a sample of 141,276 patent applications over the period 1960-2007 for the 19 countries in the sample. For each patent, we have obtained the following information: (1) patent ID number, (2) application date, (3) publication date, (4) IPC code, (5) assignee name (firm name), (6) number of citations received from future patents and (7) country name.

Patents are classified into seven main renewable energy categories: (1) biomass, (2) geothermal, (3) hydro, (4) solar, (5) waste, (6) wave/tide and (7) wind. In order to identify these patents, we used the specific International Patent Classification (IPC) codes related to renewable energy patents in these areas as proposed by Johnstone et al. (2008, see Table 4). The IPC codes referring to Hydro Energy were collected from the World Intellectual Property Organization (WIPO) web page. We show the evolution of different types of renewable R&D during 1960-2007 in Tables 1A, 1B and Figures 4, 5. We can observe the next ranking of renewable energy types according to patent counts over 1960-2007: (1) waste, (2) wind, (3) solar, (4) biomass, (5) geothermal, (6) hydro and (7) wave/tide.

We aggregated the patent information over each year for each firm to get a panel data set. This way we created the following two variables: (1) number of patent applications, (2) sum of the number of patent applications and the number of citations received from future patents.[2] The rapid growth of these variables over 1960-2007 can be observed on Figures 1-5.

The patent data set contains the application date and issue (publication) date for each patent. As proposed by Hall et al. (2001) we use the application date in order to determine the time of an innovation because inventors have incentive to apply for patent as soon as possible after completing the innovation. The patent database contains patents published until the end of the observation period. This means that the data set excludes patents, which were submitted to the EPO before that date but were not published before the end of our sample. It order to investigate the impact of the sample truncation, we analyze the distribution of the application-grant-lag (i.e., time elapsed between the publication date and the application date of a patent) in our sample (see Figure 6). We can see on the graph that the last five years of the sample (i.e. 2003-2007) are affected by the truncation bias. Therefore, in the empirical part we need to control for these years due to missing data. The observations for the 1960-2002 period are not affected, thus, we observe all patents of the corresponding period.

Regarding the quality of knowledge embodied in each patent, we compute a measure of patent quality based on the number of citations received for each patent. We measure the quality of knowledge represented by a patent by computing the number of citations the patent receives from future patents (see also Hall et al., 2001). Nevertheless, the number of citations a patent receives from future patents is subject to sample truncation bias because the sample excludes future patents, which may potentially

[2]These two variables we use alternatively as patent counts in our empirical application.

cite the observed patents. This is a limitation of this patent quality measure. However, it may be advantageous to employ citations weighted patent counts than to use simple patent counts because the information on the number of citations received allow for distinction among patents quality. This motivates us to compute two alternative measures of patent counts: (1) number of patent applications and (2) number of patent applications plus number of citations received from future patents.

Firm data. The accounting, R&D expenditure and market value data of firms have been gathered from the Compustat Global database, a broad database containing financial statements and market data of more than 6,200 companies from European countries. Industry classification is made using the modified SIC codes of Hall and Mairesse (1996) that is (1) paper and printing, (2) chemicals, (3) rubber and plastics, (4) wood and misc., (5) primary metals, (6) fabricated metals, (7) machinery, (8) electrical machinery, (9) autos, (10) aircrafts and other trans., (11) textiles and leather, (12) pharmaceuticals, (13) food, (14) computers and inst., (15) oil, (16) nonmanufacturing.

More specifically, we use the following firm specific variables: (1) R&D expenditure, (2) R&D expenses of competitors in the industry, (3) R&D expenses of other industries, (3) number of employees, (4) country name, (5) Standard Industry Classification (SIC) code, (6) return on assets (ROA) and (7) stock return. We use the ROA and stock return variables as alternative measures of firm performance. We account for R&D spillovers effects by computing the total R&D expenditure of competitors' in the same industry and also the total R&D expenses of other industries for each company and each year. As the R&D spillover process is dynamic, in our application we shall consider several lags of these R&D variables. Data coverage in the Compustat database ranges from 1987 to 2007.

Macroeconomic data. We also include macroeconomic data collected from EcoWin Energy database in order to control for the economic factors related to traditional and renewable energy that could influence the patenting activity of firms in renewable energy area.

These data refer to (1) oil price (USD), (2) electricity production (TWh), (3) hydro electricity consumption (TWh), (4) nuclear energy consumption (TWh) and (5) primary energy consumption (tonnes of oil equivalents, toe) in each country of our sample. In our application, the oil price quoted in USD is changed to EUR price using exchange rate data obtained from Reutres. The data period of these variables is 1960-2007. We present the evolution of oil price in USD during 1960-2007 on Figure 2. We show the total electricity production (TWh) of the EU and Europe during 1990-2007 on Figure 7. Finally, the total hydroelectricity (TWh), nuclear energy (TWh) and primary energy (toe) consumption of the EU during 1965-2007 is presented on Figure 8.

After matching the three databases, our final data set consists of a panel of 154 firms from 14 European countries that applied patents in the EPO over the period 1987-2007. The final panel used in our calculations includes 8,404 patent applications in the renewable energy field and 18,233 patent applications plus number of citations received to account for renewable energy patent quality. Notice that the number of patents and firms included in the matched panel data set is significantly lower than these numbers in the separate PATSTAT and Compustat databases. This is a limitation of our data set used in the estimation procedure. However, we think that we used the two most complete data sets available for European renewable patents and EU-EFTA company specific information and great care has been taken in constructing our final panel data set to exploit the available information efficiently.[3]

4. The model

As it was stated in the introduction, the purpose of this paper is to inquire into the determinants of R&D intensity, as well as to estimate the impact on performance of firms' innovative activities. This section describes the econometric procedures that will be used to carry out these estimations, specifically panel count data models that will be used to identify firms' renewable energy R&D intensity, and other panel data specifications required in order to measure the impact of innovative activity in renewable energy on various measures of firm performance. The purpose of this section is to present the econometric specifications. Technical details on the likelihood functions and on how inference is carried out are relegated to the Appendix section.

4.1 Patent count data models

Our dataset consists on a panel of $i = 1, \dots, N$ firms over the $t = 1, \dots, T$ period. Depending on the specification, n_{it} denotes either the number of patent applications or the sum of the number of patent applications and number of citations received from future patents of the i-th firm at the t-th year.[4] Denote a set of exogenous explanatory variables associated to the i-th firm at period t by Z_{it}. The Z_{it} may include: (1) firm specific variables, (2) energy specific variables, (3) dummy variables controlling time, country and industry effects.[5]

Suppose that the conditional distribution of n_{it} given all previous observable information $\mathcal{F}_{it} = \sigma[(n_{i1}, Z_{i1}), \dots, (n_{it-1}, Z_{it-1}), Z_{it}]$ available at time t is $n_{it}|\mathcal{F}_{it} \sim Poisson(\lambda_{it})$. In what follows, we shall parameterize the λ_{it} intensity parameter of this distribution.

We are going to consider count panel data models that may or may not include an unobservable heterogeneity term. We will also consider models that introudce an $AR(1)$ component. First, we shall specify the Basic Poisson model that excludes unobserved heterogeneity. In these models, we control for heterogeneity of individuals by including firm and country specific constant variables into the specification for example industry and country dummies. Next, we also consider models with *fixed effects* specifications for the unobservable heterogeneity term ω_i (see in the Appendix). In the models that do not include the unobserved heterogeneity component, we replace ω_i by a constant parameter denoted ω.

Basic Poisson model. In the basic Poisson model, we specify the $\lambda_{it} > 0$ parameter of the patent count distribution as follows:

$$\ln \lambda_{it} = \omega + \theta Z_{it} \tag{1}$$

[3] An extension of the present work could be the application of a more complete firm specific data set, which would result a more complete panel after matching firm data with the PATSTAT database.

[4] We have two alternative choices for the endogenous variable in the patent count data model. We shall estimate two alternative specifications for each count data model. (See the Data and the Empirical application section.)

[5] We shall be more precise regarding the Z_{it} term in the empirical applications section.

In this and all the following specifications all parameters are real numbers because we specify the logarithm of the intensity parameter.

Basic Poisson-AR(1) model. In the AR(1) specification, we also include a first-order term of $\ln \lambda_{it}$ as follows:

$$\ln \lambda_{it} = \omega + \beta \ln \lambda_{it-1} + \theta Z_{it} \tag{2}$$

where $\ln \lambda_{i0} = \kappa$ is a parameter controlling for the initial conditions and $|\beta| < 1$ is the AR(1) coefficient.[6]

Fixed effects Poisson model. In the Poisson model with fixed effects, we specify the λ_{it} parameter of the patent count distribution by replacing ω by the unobservable heterogeneity term:

$$\ln \lambda_{it} = \omega_i + \theta Z_{it} \tag{3}$$

Fixed effects-AR(1) Poisson model. In this specification, we also include an AR(1) term of $\ln \lambda_{it}$:

$$\ln \lambda_{it} = \omega_i + \beta \ln \lambda_{it-1} + \theta Z_{it} \tag{4}$$

where $\ln \lambda_{i0} = \kappa$ is a parameter controlling for the initial conditions and $|\beta| < 1$ is the AR(1) coefficient.

4.2 Firm performance panel data models

In this set of regressions, we use the same panel of $i = 1, \dots, N$ firms over the $t = 1, \dots, T$ period. We use the R&D intensity estimates obtained in the count data model to characterize R&D activity. Denote the log R&D intensity of the i-th firm at the t-th year by $\log \lambda_{it}$. Let y_{it} denote the performance of the i-th firm in period t.[7] In the following part of this subsection, we present two alternative panel data models that evaluate the impact of R&D activity on firm performance. These panel data models account for unobserved heterogeneity among firms that we denote by ω_i in the equations.

Basic panel data regression. In this model, we parameterize firm performance y_{it} as follows:

$$y_{it} = \omega_i + \zeta \log \lambda_{it} + \epsilon_{it} \tag{5}$$

where ω_i is a company specific *fixed effect*, ζ measure the contemporaneous impact of log patent activity on firm performance and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ is the error term. In this model, we assume that $\log \lambda_{it}$ is an exogenous variable.

Panel vectorautoregression (PVAR). In the previous panel data regression, we assumed the exogeneity of $\log \lambda_{it}$ and we only measured the contemporaneous impact of R&D on firm performance.

[6] We control for initial conditions because we are in a short-panel setup in this paper. An alternative formulation of the AR(1) Poisson models of this paper would be the dynamic Poisson specification proposed by Wooldridge (2005): $\ln \lambda_{it} = \omega + \kappa n_{i1} + \beta n_{it-1} + \theta Z_{it}$. We estimated this specification as well and found similar results to our specification. Therefore, in the empirical application section we only report the results corresponding to our specification in equations (2) and (4).

[7] We shall be more specific regarding the firm performance variable in our empirical application section.

However, patent intensity is endogenous as firm performance impacts R&D activity and the relationship between R&D and firm performance is dynamic over several years. Therefore, we also estimate a panel data model where both variables are endogenous in the dynamic PVAR setup suggested by Binder et al. (2005).

Define a 2×1 vector of endogenous variables for the i-th firm at period t by $X_{it} = (y_{it}, \ln \lambda_{it})'$. Then, formulate the PVAR(1) model as follows:

$$X_{it} = \omega_i + \delta_t + \zeta(X_{it-1} - \delta_{t-1}) + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon). \tag{6}$$

where $\omega_i = (\omega_{1i}, \omega_{2i})'$ is a 2×1 vector of firm specific *random effects* with covariance matrix Ω_ω and $\delta_t = (\delta_{1t}, \delta_{2t})'$ is a 2×1 vector of time effects. The ζ is a 2×2 matrix capturing the lagged impact of the first lag of firm performance and log patent intensity on current firm performance and R&D activity. We control for the initial conditions $\tilde{X}_{i0}$ by introducing the Ω_0 covariance matrix of $\tilde{X}_{i0}$ because in this paper we are in a short-panel setup. Moreover, $\epsilon_{it} \sim N(0, \Omega_\epsilon)$ is a vector of error terms where Ω_ϵ is a 2×2 covariance matrix of the error terms capturing the contemporaneous interaction of R&D and stock returns. Elements of the ϵ_{it} vector of error terms may be contemporaneously correlated with each other (through Ω_ϵ) but are uncorrelated with their own lagged values and uncorrelated with all the right-hand side variables of the regression equation.

5. Empirical results

In this section, we discuss the empirical results obtained by the estimation of the panel data models described in Section 4. First, we begin by reporting our count data model results on the determinants of the R&D intensity of renewable energy patents. Then, we report the estimation results of several panel data models that measure the effects of renewable R&D activity on firm performance.

5.1 Patent intensity

Tables 4A and 4B display estimated coefficients in the following specifications: (1) Basic Poisson, (2) Basic Poisson-AR(1), (3) Fixed effect Poisson and (4) Fixed effects-AR(1) Poisson models. In all cases, the dependent variable of the count data model is the patent applications count. In addition, we present the estimation results of these four models when the dependent variable considered is the sum of patent application and citations received counts in Tables 5A and 5B. In order to present more clearly the country, industry and time effects estimates of Tables 4B and 5B, we also present the parameters values on Figures 9, 10 and 11. The results obtained are robust across the different models and across the two dependent variables: (1) patent applications counts and (2) patent applications counts plus citations received counts.

Regarding the R&D expenses variable, we evidence that lagged values of R&D expenditure have significant negative impact on patent applications counts. We find that contemporaneous R&D has positive impact on applications counts in case of the *fixed effects* Poisson models, while it has non-significant effect for the Basic Poisson specifications (see Table 4A). When applications counts plus citations counts are considered as endogenous in the count data model, we find similar results. For the *fixed effects* specifications, we find significant positive contemporaneous effects while for the Basic Poisson model the estimates are positive but not always significant. Lagged R&D has typically negative impact on applications plus citations counts (see Table 5A). The positive contemporaneous impact of R&D expenses can be explained by the fact that renewable energy R&D should be protected by patents before the competitors imitate them. The significant negative parameters of past own R&D expenses mean that firms do not benefit from previous investments in renewable R&D, therefore, they are motivated to patent them as soon as possible. Indeed, as has been argued by Sagar (2000), firms in energy sectors do not necessary benefit from the performed R&D activities to enhance their innovations since these activities serve mainly to reduce capital cost expenditures necessary to the development of these kind of innovations.[8]

The contemporaneous and lagged intra-industry and inter-industry R&D expenses variables affect negatively both dependent variables. An exception can be noticed for the third lag of competitors' R&D expenses as it is shown to affect positively own patent applications and citations received intensity. Therefore, it is less likely that firms performing renewable energy R&D benefit from knowledge spillovers from competitors and even less likely that R&D spillover occurs among firms from different sectors. Firms in the currently forming renewable energy sector compete by innovations and they are motivated to protect their R&D investments using patents. Therefore, the negative impact of other firms' R&D on own patent activity can be explained by the fact that competitors and firms from other industries capture certain techonological fields by means of their patent publications.

The size of the firm, measured by the number of its employees, has a positive and significant impact in all the estimated models, suggesting that larger firms have more propensities to generate renewable energy patents. Larger firms tend to have a broader array of research projects, whcih are carried out simultaneously, and this is more likely to generate patents.

Regarding the macroeconomic variables used in the count data models, it can be noticed that oil price in EUR has significant positive impact on patent counts when we consider contemporaneous and fourth and fifth lagged variables.[9] The oil price variable has the expected lagged positive impact on the number of patents applied in renewable energy, suggesting that the increase in the oil price is an important motivation behind the expansion of renewable energy innovations and that actual fossil fuel prices are affecting the future innovations aimed at reducing the dependence on these limited sources of energy. (See also Figure 2.)

The electricity production variable has a significant and positive effect in the four models estimated, when we consider the applications counts dependent variable. Alternatively, when we use the patent applications and citations counts variable, electricity production shows an unexpected negative impact on patent counts. However, the parameters estimates in this second case are not very significant. (See also Figure 7.)

We evidence that nuclear energy consumption affects negatively the renewable energy innovations in all the estimated models. This is mainly due to the fact that nuclear energy can be seen as an

[8]For example in solar energy sector where the cost of developing performing photocells is particularly high.

[9]We exchange oil prices to EUR as our sample includes companies from the EU and EFTA that account their costs in EUR.

alternative of renewable energy. The governments of several countries support nuclear energy as well as renewable energy (see for instance The Economist, 2009b on renewable energy versus nuclear power in the United Kingdom, or The Economist, 2009a, on the future perspectives of nuclear energy in the US and EU). The Economist (2009a) cites the example of Sweden, where some politicians think that nuclear energy can be a real alternative of renewable energy sources. We find similar negative impact of hydro electricity consumption on renewable patent counts which is intuitive because hydro electricity is an alternative of other renewable energy sources like solar or wind energy represented in our patent count variables.

Furthermore, it can be observed that when primary energy consumption is high in a country, this affects positively the patenting activity of firms. This indicates that in countries where fossil fuel consumption and therefore carbon dioxide (CO_2) emissions are high, firms are more likely to develop more innovations in renewable energy which enhances the patenting activity in these areas. This finding is motivated by the existing and regulated European market for CO_2 quotes on which firms may buy or sell these quotes internationally. Thus, when a firm emits a large amount of greenhouse gases then it has to spend money on buying additional quotes of CO_2. Therefore, a country in which firms in general need to buy additional quotes of greenhouse gases is motivated in developing the renewable electricity production capacities. (The nuclear energy, hydro electricity and primary energy total consumption of the EU is presented on Figure 8.)

We observe that the initial condition and lagged dependent variable coefficients used in our autoregressive models are significant. The autorregressive process is also found to be stationary. This is seen in the β coefficient, which is smaller than one in absolute value.

We find that country effects have almost the same influence on the two dependent variables considered. We evidence the following ranking of countries in renewable energy patent activity of a company: (1) Norway, (2) Switzerland, (3) Sweden, (4) Denmark, (5) Austria, (6) Finland, (7) France, (8) Spain, (9) Belgium, (10) Netherlands, (11) Luxembourg, (12) Italy, (13) United Kingdom and (14) Germany. Thus, we find that companies from smaller – usually Scandinavian – countries dominate the renewable energy R&D intensity of Europe. (See Tables 4B, 5B and Figure 9.) However, notice that when we consider the overall number of renewable energy patents applications per country then obviously we find that the largest European countries, i.e. (1) Germany, (2) United Kingdom and (3) France produce the most renewable patents (see Tables 1A, 1B, 2 and Figure 3).

As far as industry effects are concerned, our results are similar among the two alternative dependent variables specifications. We observe significant differences amoung industries, with some positive and some other negative coefficients on industry dummies, most of them being statistically significant. The ranking of industries with respect to industry effects is the following: (1) paper and printing, (2) primary metals, (3) aircrafts, (4) machinery, (5) chemicals, (6) autos, (7) food, (8) oil, (9) textiles, (10) rubber and plastics, (11) electrical machinery, (12) non-manufacturing, (13) computers, (14) pharmaceuticals, (15) fabricated metals and (16) wood.

During the last years, the number of patents applied in renewable energy has increased progressively. Figures 1-5 show an exponentially increasing trend of the number of renewable energy patents in Europe over the 1960-2007 period. However, on these figures it can be seen that during the last 5 years of our sample period the number of observed patents decreases significantly. This can be explained by looking at Figure 6 where the empirical distribution of the application-grant lag is presented. On this figure we can see that more than 95 percent of the patents have been published during the 1960-2002 time period. As in our sample we only observe published patents, therefore, the last years of our sample excludes patents that have been submitted to EPO but they have not been published before the end of 2007. These missing data motivate us to apply time effects for the last five years of our sample in the count data models. Estimates of the time effects can be seen in Tables 4B, 5B and Figure 11. As predicted by this eyeball examination of the graphs, time dummies for 2004-07 are negative and statistically significant.

5.2 Firm performance

We report our estimation results for the basic panel data regression and the PVAR(1) models in Tables 6A and 6B, respectively. In the first row of these tables, the firm performance measure employed is presented. We estimate the models for two alternative measures of firm performance: (1) ROA and (2) stock return. In the second row of Tables 6A and 6B, we show the count data model used to derive the $\log \lambda_{it}$ values for the firm performance panel data model. For all count data models of this table, we use the patent applications count dependent variable, i.e. not the patent applications counts plus citations received counts variable. We justify this choice by the fact that the count of citations received from future patents are not available for investors as it is a future information. Moreover, we apply the $\log \lambda_{it}$ estimates obtained by the AR(1) Poisson specifications as they are more general than the static Poisson models.

For the Basic panel data regression model, we present the impact of $\log \lambda_{it}$ on ROA and stock return. We find significant positive coefficients for the ROA performance measure. However, for the stock return we do not obtain significant parameters (see Table 6A).

Next, we present the probably more realistic, PVAR(1) model estimates in Table 6B. We evidence significant positive lagged impact of log renewable energy patent intensity on contemporaneous firm performance, $\zeta_{12} > 0$ for both measures (i.e., ROA and stock return) for the *fixed effects* specification. When we consider both the basic Poisson model and the *fixed effects* Poisson model, we find significant positive impact of lagged firm performance on contemporaneous $\log \lambda_{it}$ that is $\zeta_{21} > 0$. Moreover, we also present the estimates of the covariance of contemporaneous log patent intensity and firm performance, $\Omega_{\epsilon_{21}}$. We find significant positive interaction for all models and variables presented, i.e. $\Omega_{\epsilon_{21}} > 0$. Finally, we find significant correlation between the random effects variables, while the interaction between the initial conditions is non-significant.

6. Conclusions

In this paper, we have addressed the question of firms' renewable energy innovations of in 19 European countries using patent data for the 1987-2007 period. We are particularly interested in two issues: The factors influencing the development of firms' renewable energy innovations, and the impact of firms' renewable energy R&D intensity on their performance. These research objectives are investigated by using two types of models. To answer the first question, we specified four alternative count data specifications designed for dynamic panel data. Then, to study the second objective, we used a recent panel vectorautoregression framework.

Our results show that contemporaneous R&D expenses have positive impact on renewable innovation activity. However, we find that renewable energy innovators do not benefit from either competitors' or other industries' R&D expenses. Our results also support the hypotheses that increasing oil prices, especially of their fourth and fifth lags, motivate the development of renewable energy patents. We also find that alternatives of renewable energy R&D such as nuclear energy tend to compete with patents in renewable energy. Moreover, hydro energy which is a specific form of renewable energy also is found to be a competitor of renewable energy patent intensity. Furthermore, primary energy consumption affects positively the patenting activity of firms. This indicates that in countries where CO_2 emissions are high, firms develop more patents in renewable energy. Finally, the dynamic count data models of the paper also evidence that firms' past renewable R&D intensity has a significant positive impact on their contemporaneous performance. These findings exhibit important implications that may be interesting for both researchers and policy makers.

This study provided interesting evidence on the renewable energy patenting activity of firms in several European countries. Although corporate data available on firms in this sector are limited for researchers, the present study can be considered as a first step on the analyses of renewable innovative activity.

Appendix A. Log-likelihood functions and statistical inference

In this appendix, we discuss some details of the statistical inference procedure for the models presented in Section 4. All models presented before are estimated by maximum likelihood method. First, we show the log-likelihood function of the Poisson count data model without unobserved heterogeneity. Second, we present the log-likelihood of the Possion count data models with *fixed effects*. Finally, we review the maximum likelihood estimation of the PVAR model.

A1. Basic Poisson model

All count data models presented in the previous section are estimated by maximum likelihood method. The log likelihood of the basic Poisson model is given by (Gouriéroux, 1984, Chapter XI):

$$\ln \mathcal{L} = \sum_{t=1}^{T} \sum_{i=1}^{N} n_{it} \ln \lambda_{it} - \ln(n_{it}!) - \lambda_{it}. \tag{A1}$$

The estimates of ω, β and θ are obtained by maximizing this log-likelihood function with respect to the parameters.

A2. Poisson model with fixed effects

As we have seen in the previous section, the Poisson model with fixed effects has the following form:

$$\lambda_{it} = \exp(\omega_i + \theta Z_{it}). \tag{A2}$$

Substituting this equation into (A1) we obtain the log-likelihood of the fixed effects model:

$$\ln \mathcal{L} = \sum_{t=1}^{T} \sum_{i=1}^{N} n_{it}(\omega_i + \theta Z_{it}) - \ln(n_{it}!) - \exp(\omega_i + \theta Z_{it}). \tag{A3}$$

Solving the first-order condition $\partial \ln \mathcal{L} / \partial \omega_i = 0$ for ω_i we get:

$$\exp(\omega_i) = \frac{\sum_{t=1}^{T} n_{it}}{\sum_{t=1}^{T} \exp(\theta Z_{it})}. \tag{A4}$$

Substituting this equation into (A3) and introducing the notation $p_{it} = \exp(\theta Z_{it}) / \sum_{s=1}^{T} \exp(\theta Z_{it})$ we get the log likelihood of the Poisson model with fixed effects:

$$\ln \mathcal{L} = \sum_{t=1}^{T} \sum_{i=1}^{N} n_{it} \ln \left[p_{it} \sum_{s=1}^{T} n_{is} \right] - \ln(n_{it}!) - p_{it} \sum_{s=1}^{T} n_{is}. \tag{A5}$$

The estimates of β and θ are obtained by maximizing this log-likelihood function with respect to the parameters.

Hausman et al. (1984) and Greene (2001) point out that this likelihood is conditional on the sum of the number of patents in the sample, $\sum_{s=1}^{T} n_{is}$. An alternative approach would be to estimate directly the ω_i parameters by (A3). This would not require conditioning on $\sum_{s=1}^{T} n_{is}$, but for our data set this is computationally not feasible because the number of parameters would be higher than the number of individuals in the sample.

A3. The PVAR model

In this section, we present the statistical method used to estimate the PVAR(1) model presented in Section 4.2. We use the maximum likelihood method suggested by Binder et al. (2005). First, recall the PVAR model to be estimated:

$$X_{it} = \omega_i + \delta_t + \zeta(X_{it-1} - \delta_{t-1}) + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega_\epsilon). \tag{A6}$$

Definitions of parameters in this equation have been presented in Section 4.2. We impose the next assumption about *random effects* to reduce the number of parameters in the numerical maximization procedure of the log-likelihood function.

Assumption 1 (Random effects). The random effect ω_i is uncorrelated with the error term ϵ_{it} and uncorrelated with the initial condition of the observable variables X_{i0}, i.e. $Cov(\omega_i, \epsilon_{it}) = 0_2$ and $\Omega_{0\omega} = Cov(X_{i0}, \omega_i) = 0_2$ are 2×2 matrices of zeros.

In order to ensure the positive semi-definiteness and symmetry of the variance-covariance matrices of error terms Ω_ϵ, initial conditions Ω_0 and random effects Ω_ω, we characterize these matrices by their corresponding lower triangular Cholesky matrices: $\sqrt{\Omega_\epsilon}$, $\sqrt{\Omega_0}$ and $\sqrt{\Omega_\omega}$. In addition, to identify the covariance parameters in these matrices we need to impose the next assumption:

Assumption 2 (Diagonals of covariance matrices). The diagonals of the Ω_ϵ, Ω_0 and Ω_ω matrices are restricted to ones:

$$\sqrt{\Omega_\epsilon} = \begin{pmatrix} 1 & 0 \\ \Omega_{\epsilon_{21}} & 1 \end{pmatrix} \quad \sqrt{\Omega_0} = \begin{pmatrix} 1 & 0 \\ \Omega_{0_{21}} & 1 \end{pmatrix} \quad \sqrt{\Omega_\omega} = \begin{pmatrix} 1 & 0 \\ \Omega_{\omega_{21}} & 1 \end{pmatrix} \tag{A7}$$

where the parameters of the Cholesky matrices are real numbers. To interpret the contemporaneous interaction among the endogenous variables, we need to compute the covariance matrix as $\Omega_\epsilon = \sqrt{\Omega_\epsilon}\sqrt{\Omega_\epsilon}'$.[10]

The inference of the PVAR model is done in two stages. In the first stage, we estimate the time effects as a cross-sectional average of the endogenous variables:

$$\hat{\delta}_t = \frac{1}{N}\sum_{i=1}^{N} X_{it} \tag{A8}$$

[10] We employ the same strategy for the parameterization of the covariance matrices of random effects Ω_ω and initial conditions Ω_0 in order to get the desired properties of these matrices. Thus, in the numerical maximization procedure of the likelihood function we do not need to impose any restriction on the parameters. The identification strategy used in this paper is similar to Blanchard and Quah (1989) and Gil-Alana and Moreno (2009).

Then, in the second stage we substitute the obtained time effects estimates into the following *random effects* maximum likelihood function and maximize it with respect to the parameters ζ, Ω_ϵ, Ω_0 and Ω_ω:

$$\ln \mathcal{L} = -NT\ln(2\pi) - \frac{N}{2}\ln|\Sigma_\eta| - \frac{N}{2}\mathrm{tr}(\Sigma_X^{-1}S_X) \tag{A9}$$

where

$$\Sigma_\eta = \begin{pmatrix} \Omega_0 & \iota_T' \otimes \Omega_{0\omega}' \\ \iota_T \otimes \Omega_{0\omega} & I_T \otimes \Omega_\epsilon + \iota_T\iota_T' \otimes \Omega_\omega \end{pmatrix} \tag{A10}$$

with ι_T being a $T \times 1$ vector of ones, I_T being a $T \times T$ identity matrix and

$$S_X = \tfrac{1}{N}\textstyle\sum_{i=1}^N \mathcal{X}_i\mathcal{X}_i', \tag{A11}$$

where $\mathcal{X}_i = [(X_{i1} - \hat{\delta}_1)', \ldots, (X_{iT} - \hat{\delta}_T)']'$ is a $2T \times 1$ vector. Finally, Σ_X^{-1} matrix of $2T \times 2T$ is defined as

$$\Sigma_X^{-1} = R^{-1}\Sigma_\eta R'^{-1} \quad \text{with} \quad R = \begin{pmatrix} I_2 & 0_2 & \ldots & \ldots & 0_2 \\ -\zeta & I_2 & \ddots & \ddots & \vdots \\ 0_2 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0_2 \\ 0_2 & \ldots & 0_2 & -\zeta & I_2 \end{pmatrix} \tag{A12}$$

References

Binder, M., C. Hsiao, M. H. Pesaran, 2005, Estimation and inference in short panel vector autoregressions with unit roots and cointegration. Econometric Theory, 21, 795-837.

Blanchard, O. J., D. Quah, 1989, The dynamic effects of aggregate demand and supply disturbances. American Economic Review, 79, 655-673.

Chambers, D., R. Jennings, R. B. Thompson, 2002, Excess returns to R&D-intensive firms. Review of Accounting Studies, 7, 133-158.

Chan, L., J. Lakonishok, T. Sougiannis, 2001, The stock market valuation of research and development expenditures. Journal of Finance, 56, 2431-2457.

Dernis, H., D. Guellec, 2001, Using patent counts for cross-country comparisons of technology output. STI Review, 27, OECD, 129-146.

Gil-Alana, L. A., A. Moreno, 2009, Technology shocks and hours worked: A fractional integration perspective. Macroeconomic Dynamics, forthcoming.

Gouriéroux, C., 1984, Econometrie des Variables Qualitatives, Economica, Paris.

Greene, W., 2001, Estimating Econometric Models with Fixed Effects, Working Paper, Stern School of Business, New York University.

Griliches, Z., 1990, Patent statistics as economic indicators: A survey. Journal of Economic Literature, 28, 1661-1707.

Hall, B., 1993, The stock market's valuation of research and development investment during the 1980s. American Economic Review, 83, 259-264.

Hall, B., J. Mairesse, 1996, Estimating the productivity of research and development in French and United States manufacturing firms, in B. van Ark, K. Wagner (eds.), International Productivity Differences, Measurement and Explanations, Amsterdam: Elsevier Science, 1996, NBER Working Paper No. 5501.

Hall, B., A. B. Jaffe, M. Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, NBER Working Paper 8498.

Hall, B., D. Czarnitzki, R. Oriani, 2006, The market value of knowledge assets in U.S. and European firms, forthcoming in D. Bosworth and E. Webster (eds.), The Management Of Intellectual Property.

Hausman, J., B. Hall, Z. Griliches, 1984, Econometric models for count data with an application to the patents-R&D relationship. Econometrica, 52, 4, 909-938.

Horbach, J., 2008, Determinants of environmental innovation – new evidence from German panel data sources. Research Policy, 37, 163-173.

IEA, 2007, Renewables in global energy supply, an IEA fact sheet.

Jaffe, A. B., 1986, Technological opportunity and spillovers of R&D: Evidence from firms patents, profits, and market value. The American Economic Review, 76, 5, 984-1001.

Johnstone, N., I, Hascic, D. Popp, 2008, Renewable energy policies and technological innovation: Evidence based on patent counts, NBER working paper No. 13760.

Lanjouw, J. O., A. Pakes, J. Putnam, 1998, How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data. The Journal of Industrial Economics, 46, 4, 405-432.

Lev, B., T. Sougiannis, 1996, The capitalization, amortization and value-relevance of R&D. Journal of Accounting and Economics, 21, 107-138.

Lev, B., B. Sarath, T. Sougiannis, 2005, R&D-related reporting biases and their consequences. Contemporary Accounting Research, 22(4), 977-1026.

Lev, B., S. Radhakrishnan, M. Ciftci, 2006, The stock market valuation of R&D leaders, SSRN Working Paper Series.

Margolis, R.M., D.M. Kammen, 1999, Evidence of under-investment in energy R&D in the United States and the impact of federal policy. Energy Policy, 27, 575-584.

Pakes, A., 1985, On patents, R&D, and the stock market rate of return. Journal of Political Economy, 93, 2, 390-409.

Popp, D., 2002, Induced innovation and energy prices. American Economic Review, 92, 1, 160-180.

Popp, D., 2003, Lessons from patents: Using patents to measure technological change in environmental models, NBER Working Paper No. 9978.

Ragwitz, M., A. Miola, 2005, Evidence from R&D spending for renewable energy sources in the EU. Renewable Energy, 30, 1635-1647.

Renewables: Global status report: 2009 Update, 2009, Renewable Energy Policy Network for the 21^{th} Century (REN21).

Sagar, A.D., 2000, Evidence of under-investment in energy R&D in the United States and the impact of federal policy: A comment on Margolis and Kammen. Energy Policy, 28, 651-654.

The Economist, 2009a, Nuclear power: The critical issue of safety, March 21-27, 65-66.

The Economist, 2009b, Renewable energy: Greenstanding, April 4-10, 29-30.

Trajtenberg, M., 2002, A Penny for your Quotes: Patent Citations and the Value of Innovations, in Patents, citations, and innovations: a window on the knowledge economy edited by Jaffe, A. B., M. Trajtenberg, MIT Press.

Wooldridge, J. M., 1997, Quasi-Likelihood Methods for Count Data, in I. Pesaran, M. Hashem (eds.), Handbook of Applied Econometrics, BlackWell, 1997, Chapter 8.

Wooldridge, J., 2002, Econometric Analysis of Cross Section and Panel Data, Cambridge, MIT Press.

Wooldridge, J., 2005, Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity. Journal of Applied Econometrics, 20, 39-54.

Table 1A: Total number of patent applications by renewable energy category of 15 EU and 4 EFTA countries over 1960-2007

	Biomass	Geothermal	Hydro	Solar	Waste	Wave/Tide	Wind	TOTAL
Austria	174	386	294	657	890	87	614	3,102
Belgium	116	40	25	308	328	23	504	1,344
Switzerland	228	550	590	1,103	1,812	20	668	4,971
Germany	6,275	2,899	1,004	11,635	26,766	528	18,684	67,791
Denmark	122	126	67	156	1,229	25	4,493	6,218
Spain	95	90	218	938	479	221	2,732	4,773
Finland	258	134	122	505	1,566	37	789	3,411
France	1,705	749	667	2,688	3,151	244	4,210	13,414
UK	4,591	320	424	1,081	4,739	222	3,738	15,115
Greece	5	2	1	41	82	0	212	343
Ireland	38	0	14	53	21	4	87	217
Island	0	0	0	4	0	0	48	52
Italy	588	182	97	960	1,597	73	1,307	4,804
Liechtenstein	1	48	25	49	123	8	26	280
Luxembourg	14	10	32	97	84	0	30	267
Netherlands	763	125	131	693	2,927	132	1,723	6,494
Norway	73	94	372	251	464	265	1,154	2,673
Portugal	0	4	3	71	16	13	292	399
Sweden	332	781	350	610	1,068	153	2,314	5,608
TOTAL	15,378	6,540	4,436	21,900	47,342	2,055	43,625	141,276

Table 1B: Total number of patent applications plus number of citations received by renewable energy category of 15 EU and 4 EFTA countries over 1960-2007

	Biomass	Geothermal	Hydro	Solar	Waste	Wave/Tide	Wind	TOTAL
Austria	296	554	400	909	1,286	131	1,077	4,653
Belgium	220	48	40	609	542	26	1,122	2,607
Switzerland	335	787	874	2,718	4,376	73	1,434	10,597
Germany	12,162	7,081	1,548	26,647	69,743	1,183	42,084	160,448
Denmark	185	178	71	272	2,351	25	9,109	12,191
Spain	113	112	264	1,272	672	267	4,340	7,040
Finland	277	154	134	1,155	2,122	37	1,142	5,021
France	3,208	1,845	998	6,312	5,942	491	10,387	29,183
UK	10,569	799	774	2,302	13,104	396	7,836	35,780
Greece	5	2	1	59	192	0	678	937
Ireland	44	0	15	103	27	4	293	486
Island	0	0	0	4	0	0	244	248
Italy	798	204	132	1,396	3,605	143	2,313	8,591
Liechtenstein	7	60	58	103	223	11	50	512
Luxembourg	29	18	44	168	91	0	42	392
Netherlands	1,339	223	194	1,267	5,800	244	4,157	13,224
Norway	89	140	441	332	698	352	1,740	3,792
Portugal	0	4	3	85	16	17	432	557
Sweden	490	1,317	525	1,433	1,861	317	4,482	10,425
TOTAL	30,166	13,526	6,516	47,146	112,651	3,717	92,962	306,684

Table 2: Number of renewable energy patent applications for each country (15 EU and 4 EFTA) over 1960-2007

	AT	BE	CH	DE	DK	ES	FI	FR	GB	GR	IE	IS	IT	LI	LU	NL	NO	PT	SE
1960	2	0	25	0	0	4	0	10	10	0	0	0	0	0	0	1	0	0	0
1961	0	0	24	7	0	0	0	0	9	0	0	0	2	0	0	0	0	0	0
1962	0	0	27	15	0	0	0	10	6	0	0	0	0	0	0	0	0	0	0
1963	2	0	73	42	0	2	0	0	8	0	0	0	0	0	0	0	0	0	2
1964	10	0	43	12	2	0	0	7	2	0	0	0	0	0	0	0	2	0	1
1965	2	0	32	28	2	2	0	9	7	0	0	0	0	0	0	7	0	0	3
1966	3	0	49	28	0	0	0	5	18	0	0	0	0	0	0	22	0	0	19
1967	15	1	38	65	0	0	0	0	4	0	0	0	0	0	0	6	0	0	12
1968	5	4	35	76	0	0	0	61	11	0	0	0	0	0	0	44	0	0	5
1969	0	1	45	21	0	0	0	30	20	0	0	0	0	0	0	4	0	0	31
1970	0	1	7	16	0	0	0	39	18	0	0	0	0	0	0	18	0	0	7
1971	2	2	1	11	0	0	0	20	13	0	0	0	1	0	0	34	0	0	0
1972	3	12	13	40	0	0	2	54	13	0	0	0	3	0	0	10	0	0	2
1973	1	0	20	115	0	0	0	57	23	0	0	0	0	0	0	4	2	0	34
1974	25	0	53	52	7	0	0	433	14	0	0	0	1	0	0	1	0	0	56
1975	15	3	114	72	49	0	6	394	53	0	0	0	19	0	8	10	0	0	42
1976	26	1	140	319	34	6	2	287	137	0	0	0	76	4	13	33	3	14	87
1977	50	4	99	332	18	22	6	388	77	0	6	0	76	8	7	82	18	4	50
1978	69	24	229	428	62	9	17	249	106	0	0	4	192	8	9	60	92	12	83
1979	26	4	131	618	0	60	6	437	59	0	0	0	131	0	12	43	9	24	154
1980	53	14	101	1526	20	94	38	606	78	5	10	0	201	3	12	110	29	12	174
1981	65	32	111	1421	23	173	9	640	167	2	8	0	104	2	2	77	21	22	229
1982	26	40	223	1115	27	72	38	544	200	2	0	0	132	10	8	73	23	4	236
1983	48	74	62	750	30	46	22	378	110	0	0	0	138	4	13	110	30	10	272
1984	40	16	74	668	57	62	52	283	45	14	0	0	21	0	0	35	4	10	199
1985	32	70	70	580	49	58	40	202	368	0	2	0	24	2	6	20	24	5	145
1986	16	66	14	779	60	41	63	236	233	0	0	0	24	24	5	113	0	21	142
1987	24	6	108	575	25	46	109	137	340	0	0	0	23	0	0	52	4	64	130
1988	61	3	88	1052	52	28	46	173	421	12	0	0	163	0	3	45	12	28	164
1989	36	6	21	952	66	34	130	354	206	4	2	0	275	0	38	176	22	0	57
1990	11	10	119	1236	144	106	127	189	220	4	7	0	85	15	5	272	11	6	28
1991	51	66	141	1141	82	75	25	227	395	29	3	0	85	27	2	253	16	8	83
1992	103	11	117	1652	147	55	72	186	530	134	0	0	124	11	1	24	44	34	63
1993	45	22	169	1601	50	87	264	252	801	5	0	0	24	2	3	65	73	4	54
1994	119	70	143	2249	84	131	260	208	482	10	3	0	107	5	2	159	111	20	81
1995	166	110	93	2403	144	160	326	164	943	0	0	36	264	0	12	80	81	10	107
1996	69	18	184	2550	261	115	202	388	567	0	21	0	72	1	2	244	118	8	131
1997	259	116	218	2863	101	138	115	631	661	7	36	0	183	66	0	198	210	2	243
1998	122	59	117	3519	240	62	214	618	493	3	0	12	339	0	1	465	231	14	218
1999	132	54	176	4350	513	170	371	493	716	64	7	0	134	13	14	602	173	13	430
2000	160	120	232	5427	525	494	160	644	690	8	16	0	176	10	13	690	330	4	482
2001	187	115	292	6484	378	338	154	580	798	1	31	0	137	13	7	702	231	19	428
2002	156	35	291	5902	592	364	93	747	1085	7	26	0	251	32	20	424	154	10	343
2003	293	27	223	4523	709	302	188	566	997	7	5	0	510	8	21	378	194	0	153
2004	228	49	212	3443	622	291	87	615	1312	5	1	0	133	1	6	319	141	0	151
2005	149	44	98	3063	627	478	93	567	816	0	4	0	340	1	6	292	157	4	208
2006	131	28	52	2674	241	475	44	225	510	7	22	0	146	8	8	71	95	8	53
2007	64	6	24	996	175	173	30	71	323	13	7	0	88	2	8	66	8	5	16

Notes: The following 15 EU and 4 EFTA countries are included in the table: AT=Austria, BE=Belgium, CH=Switzerland, DE=Germany, DK=Denmark, ES=Spain, FI=Finland, FR=France, GB=United Kingdom, GR=Greece, IE=Ireland, IS=Island, IT=Italy, LI=Liechtenstein, LU=Luxembourg, NL=Netherlands, NO=Norway, PT=Portugal, SE=Sweden.

Table 3A: Biomass

IPC code	IPC name	World	EU-EFTA
C10L 5/42	Solid fuels essentially based on materials of non-mineral origin	196	
C10L 5/44	Solid fuels essentially based on materials of non-mineral origin	3,121	
F02B 43/08	Plants characterized by the engines using gaseous fuel generated in the plant from solid fuel	0	
B01J 41/16	Anion exchange; Use of materials, cellulose or wood	0	
C10L 1/14	Liquid carbonaceous fuels - organic compounds	11,657	
	TOTAL	14,974	11,405

Table 3B: Geothermal

IPC code	IPC name	World	EU-EFTA
F24J 3/00	Other production or use of heat, not derived from combustion	15,520	
F24J 3/02	Other production or use of heat, not derived from combustion	0	
F24J 3/04	Other production or use of heat, not derived from combustion	0	
F24J 3/06	Other production or use of heat, not derived from combustion - using natural heat	454	
F24J 3/08	Other production or use of heat, not derived from combustion	2,272	
F03G 4/00	Devices for producing mechanical power from geothermal energy	2,147	
F03G 4/02	Devices for producing mechanical power from geothermal energy- with direct fluid contact	163	
F03G 4/04	Devices for producing mechanical power from geothermal energy- with deep-well turbo-pump	74	
F03G 4/06	Devices for producing mechanical power from geothermal energy- with fluid flashing	239	
H02N 10/00	Electric motors using thermal effects	0	
	TOTAL	20,869	4,934

Table 3C: Hydro

IPC code	IPC name	World	EU-EFTA
F03B 3/04	Machines or engines of reaction type; Parts or details - substantially axial flow throughout rotors	773	
F03B 3/10	Machines or engines of reaction type - functioning alternatively as pumps or turbines	1,082	
F03B 3/12	Machines or engines of reaction type; Parts or details - Blades; Blade-carrying rotors	2,018	
F03B 3/18	Machines or engines of reaction type; Parts or details	2,081	
F03B 11/02	Machines or engines for liquids - Parts or details - Casings Adaptations of machines or engines	0	
F03B 13/06	Stations or aggregates of water-storage type	0	
F03B 13/08	Machine or engine aggregates in dams	0	
F03B 13/10	Submerged units incorporating electric generators or motors	0	
F03B 15/04	Machines or engines for liquids - Controlling	0	
F03B 15/08	Machines or engines for liquids - Controlling	0	
F03B 17/00	Machines or engines for liquids - Other machines or engines	0	
F03B 17/06	Machines or engines for liquids - Other machines or engines	0	
E02B 9/00	Water-power plants; Layout, construction or equipment	8,465	
E02B 9/02	Water-power plants; Layout, construction or equipment	943	
	TOTAL	15,362	3,599

Table 3D: Solar

IPC code	IPC name	World	EU-EFTA
F03G 6/00	Devices for producing mechanical power from solar energy	4,965	
F03G 6/02	Devices for producing mechanical power from solar energy - using a single state working fluid	48	
F03G 6/06	Devices for producing mechanical power from solar energy - with solar energy concentrating	1,036	
F03G 6/08	Devices for producing mechanical power from solar energy - Devices	0	
F24J 2/00	Use of solar heat	22,474	
F25B 27/00	Machines, plant, or systems, using particular sources of energy - sun	0	
F26B 3/28	Drying solid materials or objects by processes involving the application of heat by radiation	3,122	
H02N 6/00	Generators in which light radiation is directly converted into electrical energy	3,277	
E04D 13/18	Roof covering aspects of energy collecting devices	0	
B60L 8/00	Electric propulsion with power supply from force of nature, e.g. sun, wind	1,790	
	TOTAL	36,712	16,828

Table 3E: Waste

IPC code	IPC name	World	EU-EFTA
C10L 5/46	Solid fuels essentially based on materials of non-mineral origin	1,533	
C10L 5/48	Solid fuels essentially based on materials of non-mineral origin	1,642	
F25B 27/02	Machines, plant, or systems, using particular sources of energy using waste heat	0	
F02G 5/00	Hot gas or combustion - Profiting from waste heat of combustion engines	7,869	
F02G 5/02	Hot gas or combustion - Profiting from waste heat of exhaust gases	2,656	
F02G 5/04	Hot gas or combustion - Profiting from waste heat of exhaust gases	2,350	
F23G 5/46	Incineration of waste - recuperation of heat	9,551	
F01K 25/14	Plants or engines characterized by use of industrial and other waste gases	0	
C10J 3/86	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels	622	
F23G 7/10	Incinerators or other apparatus specially adapted for consuming field or garden waste	1,712	
H01M 8/06	Manufacture of fuel cells - Combination of fuel cell with means for production of reactants	42,525	
	TOTAL	70,460	35,727

Table 3F: Wave/Tide

IPC code	IPC name	World	EU-EFTA
F03B 13/12	Machines or engines characterized by using wave or tide energy	0	
F03G 7/04	Mechanical-power-producing mechanisms using pressure differences or thermal differences	1,949	
F03G 7/05	Mechanical-power-producing mechanisms using ocean thermal energy conversion	555	
F03B 7/00	Water wheels	2,688	
F03B 13/12	Machines or engines using wave or tide energy	0	
F03B 13/14	Machines or engines characterized by using wave or tide energy	0	
F03B 13/16	Machines or engines using the relative movement between a wave-operated and another member	0	
F03B 13/18	Machines or engines using wave or tide energy wherein the other member is fixed	0	
F03B 13/20	Machines or engines using wave or tide energy wherein both members are movable	0	
F03B 13/22	Machines or engines using wave or tide energy using the flow of water	0	
F03B 13/26	Machines or engines using tide energy	0	
E02B 9/08	Tide or wave power plants	919	
	TOTAL	6,111	1,608

Table 3G: Wind

IPC code	IPC name	World	EU-EFTA
F03D 1/00	Wind motors with r.a.s. in wind direction	9,286	
F03D 1/02	Wind motors with r.a.s. in wind direction having a plurality of rotors	962	
F03D 1/04	Wind motors with r.a.s. in wind direction having stationary wind-guiding means	1,669	
F03D 1/06	Wind motors with r.a.s. in wind direction - Rotors	3,455	
F03D 3/00	Wind motors with r.a.s. at right angle to wind direction	9,614	
F03D 3/02	Wind motors with r.a.s. at right angle to wind direction - having a plurality of rotors	1,166	
F03D 3/04	Wind motors with r.a.s. at right angle to wind direction - having stationary wind-guiding means	2,073	
F03D 3/06	Wind motors with r.a.s. at right angle to wind direction - Rotors	3,746	
F03D 5/00	Other wind motors	1,814	
F03D 5/02	Other wind motors - the wind-engaging parts being attached to endless chains	306	
F03D 5/04	Other wind motors - the wind-engaging parts being attached to carriages running on tracks	184	
F03D 5/06	Other wind motors - the wind-engaging parts swinging to-and-fro and not rotating	305	
F03D 7/00	Controlling wind motors	7,676	
F03D 7/02	Controlling wind motors - the wind motors having r.a.s. in wind direction	3,655	
F03D 7/04	Controlling wind motors - Regulation	2,595	
F03D 7/06	Controlling wind motors - the wind motors havingr.a.s. at right angle to wind direction	1,247	
F03D 9/00	Adaptations of wind motors for special use; Combinations of wind motors with apparatus driven	14,219	
F03D 9/02	Adaptations of wind motors for special use - the apparatus storing power	1,300	
F03D 11/00	Details, component parts, or accessories not provided	0	
F03D 11/02	Details, component parts, or accessories	0	
F03D 11/04	Details, component parts, or accessories	0	
B60L 8/00	Electric propulsion with power supply from force of nature, e.g. sun, wind	1,790	
B63H 13/00	Effecting propulsion by wind motors driving water-engaging propulsive elements	0	
	TOTAL	67,062	34,270

Table 4A: Count data results – dependent variable: Applications count

Variable	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
Constant: ω	0.03(0.116)	0.45(0.192)	–	–
Initial cond: κ	–	0.72^{***}(0.174)	–	-0.09^{***}(0.026)
AR(1) coeff: β	–	0.18^{***}(0.023)	–	0.14^{***}(0.012)
Exog vars: θ				
R&D$_t$	-0.20(0.215)	-0.21(0.180)	0.44^{*}(0.237)	0.42^{***}(0.078)
R&D$_{t-1}$	-0.77^{***}(0.166)	-0.72^{***}(0.163)	-0.67^{***}(0.175)	-0.60^{***}(0.048)
R&D$_{t-2}$	-1.44^{***}(0.260)	-1.50^{***}(0.267)	-1.22^{***}(0.261)	-1.24^{***}(0.072)
R&D$_{t-3}$	-1.97^{***}(0.314)	-1.87^{***}(0.317)	-1.82^{***}(0.323)	-1.69^{***}(0.121)
R&D$_{t-4}$	-0.31^{**}(0.140)	-0.07(0.146)	-0.24(0.155)	0.00(0.041)
R&D$_{t-5}$	-0.21(0.144)	-0.27^{**}(0.135)	-0.16(0.151)	-0.09^{**}(0.043)
R&D$_{wt}$	-3.20^{***}(0.782)	-3.26^{***}(0.847)	-3.03^{***}(0.800)	-3.59^{***}(0.167)
R&D$_{wt-1}$	-3.01^{***}(0.541)	-2.34^{***}(0.616)	-3.38^{***}(0.647)	-2.86^{***}(0.190)
R&D$_{wt-2}$	-2.57^{***}(0.283)	-1.93^{***}(0.413)	-2.71^{***}(0.461)	-2.19^{***}(0.175)
R&D$_{wt-3}$	-0.18(0.129)	0.24(0.153)	-0.37^{***}(0.137)	0.01(0.084)
R&D$_{wt-4}$	-0.80^{***}(0.164)	-0.78^{***}(0.152)	-1.08^{***}(0.163)	-1.02^{***}(0.079)
R&D$_{wt-5}$	0.02(0.136)	0.22^{**}(0.112)	-0.23^{*}(0.126)	-0.02(0.090)
R&D$_{bt}$	-0.62^{***}(0.184)	-0.60^{***}(0.111)	-0.28(0.182)	-0.37^{***}(0.101)
R&D$_{bt-1}$	-1.50^{***}(0.100)	-1.28^{***}(0.101)	-1.59^{***}(0.106)	-1.42^{***}(0.046)
R&D$_{bt-2}$	-1.23^{***}(0.090)	-0.99^{***}(0.093)	-1.21^{***}(0.093)	-1.03^{***}(0.038)
R&D$_{bt-3}$	-1.01^{***}(0.080)	-0.87^{***}(0.080)	-1.08^{***}(0.084)	-0.95^{***}(0.048)
R&D$_{bt-4}$	-0.79^{***}(0.077)	-0.67^{***}(0.072)	-1.01^{***}(0.079)	-0.86^{***}(0.056)
R&D$_{bt-5}$	-1.33^{***}(0.101)	-1.34^{***}(0.079)	-1.52^{***}(0.100)	-1.47^{***}(0.059)
Employees	4.82^{***}(0.059)	4.07^{***}(0.106)	6.20^{***}(0.183)	5.77^{***}(0.087)
P(Oil)$_t$	0.64^{***}(0.177)	0.37^{**}(0.180)	0.03(0.198)	-0.19^{***}(0.071)
P(Oil)$_{t-1}$	-1.32^{***}(0.220)	-1.15^{***}(0.219)	-1.50^{***}(0.222)	-1.23^{***}(0.101)
P(Oil)$_{t-2}$	0.46^{*}(0.274)	0.39^{*}(0.227)	-0.23(0.274)	-0.16(0.107)
P(Oil)$_{t-3}$	-0.06(0.166)	-0.26(0.256)	-0.16(0.206)	-0.26^{***}(0.061)
P(Oil)$_{t-4}$	3.10^{***}(0.453)	3.11^{***}(0.272)	1.88^{***}(0.478)	2.15^{***}(0.265)
P(Oil)$_{t-5}$	4.06^{***}(0.535)	3.23^{***}(0.229)	5.89^{***}(0.554)	4.81^{***}(0.347)
Electr prod	5.68^{***}(0.360)	4.95^{***}(0.367)	6.74^{***}(0.496)	6.19^{***}(0.304)
Hydro cons	-5.08^{***}(0.323)	-5.09^{***}(0.394)	-5.16^{***}(0.443)	-5.15^{***}(0.073)
Nuclear cons	-4.80^{***}(0.413)	-4.51^{***}(0.429)	-6.78^{***}(0.502)	-6.39^{***}(0.179)
Primary cons	5.55^{***}(0.651)	5.00^{***}(0.480)	4.14^{***}(0.731)	3.54^{***}(0.114)
Mean LL	-525.90	-524.64	-328.68	-327.65

Notes: Standard errors are reported in parentheses. The ***, ** and * denote parameter significant at the 1%, 5% and 10% level, respectively. The – denotes parameter not identified. The Mean LL denotes mean log-likelihood. The following specifications are presented in the table:

Basic Poisson:	Basic Poisson-AR(1):	Fixed effects:	Fixed effects-AR(1):
$\ln \lambda_{it} = \omega + \theta Z_{it}$	$\ln \lambda_{it} = \omega + \beta \ln \lambda_{it-1} + \theta Z_{it}$	$\ln \lambda_{it} = \omega_i + \theta Z_{it}$	$\ln \lambda_{it} = \omega_i + \beta \ln \lambda_{it-1} + \theta Z_{it}$

Table 4B: Country, time and industry effects – dependent variable: Applications count

Country effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
D(AT)	$-0.89^{***}(0.127)$	$-0.96^{***}(0.126)$	–	–
D(BE)	$-2.83^{***}(0.196)$	$-2.83^{***}(0.203)$	–	–
D(CH)	$0.65^{***}(0.122)$	$0.35^{**}(0.156)$	–	–
D(DE)	$-8.46^{***}(0.611)$	$-7.67^{***}(0.516)$	–	–
D(DK)	$-0.34^{**}(0.160)$	$-0.72^{***}(0.238)$	–	–
D(ES)	$-2.07^{***}(0.201)$	$-2.03^{***}(0.194)$	–	–
D(FI)	$-1.43^{***}(0.126)$	$-1.53^{***}(0.153)$	–	–
D(FR)	$-2.14^{***}(0.262)$	$-1.74^{***}(0.227)$	–	–
D(GB)	$-5.61^{***}(0.426)$	$-5.29^{***}(0.389)$	–	–
D(IT)	$-4.23^{***}(0.292)$	$-3.89^{***}(0.243)$	–	–
D(LU)	$-3.16^{***}(0.428)$	$-3.04^{***}(0.359)$	–	–
D(NL)	$-3.26^{***}(0.221)$	$-3.21^{***}(0.210)$	–	–
D(NO)	$2.43^{***}(0.215)$	$2.24^{***}(0.173)$	–	–
D(SE)	–	–	–	–

Time effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
$D_{1987 \leq t \leq 2002}$	–	–	–	–
$D_{t=2003}$	$0.27^{***}(0.095)$	$0.24^{***}(0.070)$	$0.56^{***}(0.092)$	$0.46^{***}(0.059)$
$D_{t=2004}$	$-0.71^{***}(0.136)$	$-0.68^{***}(0.065)$	$-0.26^{**}(0.131)$	$-0.34^{***}(0.073)$
$D_{t=2005}$	$-1.51^{***}(0.084)$	$-1.27^{***}(0.082)$	$-1.25^{***}(0.084)$	$-1.08^{***}(0.036)$
$D_{t=2006}$	$-2.06^{***}(0.118)$	$-1.81^{***}(0.095)$	$-1.70^{***}(0.114)$	$-1.57^{***}(0.052)$
$D_{t=2007}$	$-2.82^{***}(0.174)$	$-2.42^{***}(0.134)$	$-2.16^{***}(0.176)$	$-1.93^{***}(0.080)$

Industry effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
D(1-paper and printing)	$0.66^{***}(0.092)$	$0.58^{***}(0.074)$	–	–
D(2-chemicals)	$0.50^{***}(0.057)$	$0.45^{***}(0.045)$	–	–
D(3-rubber and plastics)	$-0.04(0.130)$	$-0.01(0.087)$	–	–
D(4-wood and misc.)	$-1.01^{***}(0.132)$	$-0.81^{***}(0.115)$	–	–
D(5-primary metals)	$0.59^{***}(0.071)$	$0.52^{***}(0.057)$	–	–
D(6-fabricated metals)	$-0.86^{***}(0.129)$	$-0.68^{***}(0.114)$	–	–
D(7-machinery)	$0.65^{***}(0.069)$	$0.58^{***}(0.056)$	–	–
D(8-electrical machinery)	$-0.04(0.033)$	$0.00(0.026)$	–	–
D(9-autos)	$-0.11^{***}(0.036)$	$-0.08^{***}(0.034)$	–	–
D(10-aircrafts and other trans.)	$0.35^{***}(0.052)$	$0.33^{***}(0.042)$	–	–
D(11-textiles and leather)	–	–	–	–
D(12-pharmaceuticals)	$-0.36^{***}(0.071)$	$-0.27^{***}(0.064)$	–	–
D(13-food)	$-0.01(0.136)$	$0.03(0.128)$	–	–
D(14-computers and inst.)	$-0.26^{***}(0.051)$	$-0.18^{***}(0.046)$	–	–
D(15-oil)	$0.28^{***}(0.043)$	$0.26^{***}(0.035)$	–	–
D(16-non-manufacturing)	$-0.31^{***}(0.044)$	$-0.26^{***}(0.042)$	–	–

Notes: Standard errors are reported in parentheses. The ***, ** and * denote parameter significant at the 1%, 5% and 10% level, respectively. The – denotes parameter not identified. The country names see in Table 2.

Table 5A: Count data results – dependent variable: Applications count + Citations count

Variable	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
Constant: ω	$-0.17(0.173)$	$0.17(0.168)$	–	–
Initial cond: κ	–	$0.39^{***}(0.089)$	–	$-0.01(0.018)$
AR(1) coeff: β	–	$0.17^{***}(0.012)$	–	$0.10^{***}(0.014)$
Exog vars: θ				
R&D$_t$	$0.36^{**}(0.148)$	$0.17(0.161)$	$0.75^{***}(0.139)$	$0.62^{***}(0.145)$
R&D$_{t-1}$	$-1.12^{***}(0.111)$	$-1.13^{***}(0.116)$	$-1.02^{***}(0.113)$	$-1.02^{***}(0.116)$
R&D$_{t-2}$	$0.04(0.076)$	$0.06(0.079)$	$0.17^{**}(0.080)$	$0.20^{***}(0.080)$
R&D$_{t-3}$	$-1.74^{***}(0.173)$	$-1.87^{***}(0.183)$	$-1.70^{***}(0.167)$	$-1.74^{***}(0.171)$
R&D$_{t-4}$	$-0.39^{***}(0.093)$	$-0.19^{**}(0.096)$	$-0.38^{***}(0.098)$	$-0.20^{**}(0.100)$
R&D$_{t-5}$	$-0.12(0.088)$	$-0.13(0.093)$	$-0.10(0.090)$	$-0.04(0.089)$
R&D$_{wt}$	$-32.17^{***}(1.938)$	$-35.91^{***}(2.424)$	$-29.07^{***}(2.195)$	$-32.17^{***}(2.417)$
R&D$_{wt-1}$	$-5.51^{***}(1.452)$	$-0.96(2.550)$	$-7.92^{***}(2.126)$	$-6.76^{***}(2.537)$
R&D$_{wt-2}$	$-11.31^{***}(1.309)$	$-3.96^{***}(1.224)$	$-12.08^{***}(1.399)$	$-6.92^{***}(1.561)$
R&D$_{wt-3}$	$0.39^{***}(0.093)$	$1.25^{***}(0.199)$	$0.12(0.093)$	$0.92^{***}(0.178)$
R&D$_{wt-4}$	$-0.24^{**}(0.108)$	$-0.26^{***}(0.108)$	$-0.57^{***}(0.110)$	$-0.55^{***}(0.113)$
R&D$_{wt-5}$	$-0.05(0.097)$	$0.13(0.105)$	$-0.34^{***}(0.104)$	$-0.19^{*}(0.104)$
R&D$_{bt}$	$-0.04(0.138)$	$-0.18(0.153)$	$0.11(0.133)$	$-0.03(0.137)$
R&D$_{bt-1}$	$-1.29^{***}(0.068)$	$-1.10^{***}(0.067)$	$-1.31^{***}(0.067)$	$-1.19^{***}(0.069)$
R&D$_{bt-2}$	$-0.84^{***}(0.059)$	$-0.67^{***}(0.059)$	$-0.83^{***}(0.058)$	$-0.73^{***}(0.060)$
R&D$_{bt-3}$	$-0.41^{***}(0.049)$	$-0.33^{***}(0.045)$	$-0.46^{***}(0.048)$	$-0.40^{***}(0.049)$
R&D$_{bt-4}$	$-0.07(0.052)$	$-0.02(0.048)$	$-0.18^{***}(0.049)$	$-0.12^{**}(0.050)$
R&D$_{bt-5}$	$-1.23^{***}(0.069)$	$-1.27^{***}(0.075)$	$-1.31^{***}(0.067)$	$-1.29^{***}(0.067)$
Employees	$5.30^{***}(0.045)$	$4.59^{***}(0.069)$	$5.36^{***}(0.101)$	$5.08^{***}(0.111)$
P(Oil)$_t$	$1.54^{***}(0.141)$	$1.35^{***}(0.141)$	$1.08^{***}(0.143)$	$0.97^{***}(0.139)$
P(Oil)$_{t-1}$	$-1.46^{***}(0.209)$	$-1.48^{***}(0.208)$	$-1.44^{***}(0.206)$	$-1.35^{***}(0.205)$
P(Oil)$_{t-2}$	$-0.09(0.199)$	$0.10(0.225)$	$-0.57^{***}(0.209)$	$-0.39^{*}(0.220)$
P(Oil)$_{t-3}$	$0.25(0.194)$	$-0.07(0.176)$	$0.24(0.200)$	$0.10(0.197)$
P(Oil)$_{t-4}$	$0.96^{***}(0.388)$	$1.40^{***}(0.436)$	$0.37(0.377)$	$0.77^{**}(0.391)$
P(Oil)$_{t-5}$	$4.91^{***}(0.432)$	$3.81^{***}(0.485)$	$5.90^{***}(0.417)$	$5.01^{***}(0.435)$
Electr prod	$-1.96^{*}(1.089)$	$-1.85^{*}(1.027)$	$-0.82^{*}(0.457)$	$-0.76^{*}(0.422)$
Hydro electr cons	$-3.66^{***}(0.362)$	$-3.85^{***}(0.349)$	$-3.83^{***}(0.356)$	$-3.82^{***}(0.347)$
Nuclear energ cons	$-3.56^{***}(0.380)$	$-3.58^{***}(0.353)$	$-4.21^{***}(0.390)$	$-4.14^{***}(0.365)$
Primary energ cons	$12.87^{***}(0.507)$	$11.88^{***}(0.486)$	$11.65^{***}(0.509)$	$11.03^{***}(0.493)$
Mean LL	-971.50	-968.11	-669.25	-668.16

Notes: Standard errors are reported in parentheses. The ***, ** and * denote parameter significant at the 1%, 5% and 10% level, respectively. The – denotes parameter not identified. The Mean LL denotes mean log-likelihood. The following specifications are presented in the table:

Basic Poisson:	Basic Poisson-AR(1):	Fixed effects:	Fixed effects-AR(1):
$\ln \lambda_{it} = \omega + \theta Z_{it}$	$\ln \lambda_{it} = \omega + \beta \ln \lambda_{it-1} + \theta Z_{it}$	$\ln \lambda_{it} = \omega_i + \theta Z_{it}$	$\ln \lambda_{it} = \omega_i + \beta \ln \lambda_{it-1} + \theta Z_{it}$

Table 5B: Country, time and industry effects – dependent variable: Applications + Citations count

Country effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
D(AT)	$-1.14^{***}(0.136)$	$-1.20^{***}(0.129)$	–	–
D(BE)	$-2.52^{***}(0.197)$	$-2.60^{***}(0.189)$	–	–
D(CH)	$1.16^{***}(0.145)$	$0.92^{***}(0.144)$	–	–
D(DU)	$-8.75^{***}(0.457)$	$-8.10^{***}(0.442)$	–	–
D(DK)	$0.57^{***}(0.219)$	$0.24(0.216)$	–	–
D(ES)	$-1.92^{***}(0.163)$	$-1.93^{***}(0.161)$	–	–
D(FI)	$-1.23^{***}(0.153)$	$-1.35^{***}(0.146)$	–	–
D(FR)	$-2.20^{***}(0.259)$	$-1.80^{***}(0.230)$	–	–
D(GB)	$-5.47^{***}(0.324)$	$-5.24^{***}(0.319)$	–	–
D(IT)	$-4.85^{***}(0.216)$	$-4.60^{***}(0.213)$	–	–
D(LU)	$-3.80^{***}(0.714)$	$-3.76^{***}(0.632)$	–	–
D(NL)	$-3.62^{***}(0.203)$	$-3.61^{***}(0.197)$	–	–
D(NO)	$2.55^{***}(0.162)$	$2.47^{***}(0.161)$	–	–
D(SE)	–	–	–	–

Time effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
$D_{1987\leq t\leq 2002}$	–	–	–	–
$D_{t=2003}$	$0.34^{***}(0.079)$	$0.26^{***}(0.078)$	$0.46^{***}(0.075)$	$0.37^{***}(0.073)$
$D_{t=2004}$	$-0.26^{**}(0.107)$	$-0.30^{***}(0.115)$	$-0.03(0.100)$	$-0.11(0.101)$
$D_{t=2005}$	$-1.70^{***}(0.063)$	$-1.51^{***}(0.063)$	$-1.56^{***}(0.061)$	$-1.46^{***}(0.062)$
$D_{t=2006}$	$-2.27^{***}(0.098)$	$-2.03^{***}(0.099)$	$-2.09^{***}(0.091)$	$-1.99^{***}(0.094)$
$D_{t=2007}$	$-3.07^{***}(0.141)$	$-2.73^{***}(0.146)$	$-2.67^{***}(0.135)$	$-2.53^{***}(0.137)$

Industry effects:

	Basic Poisson	Basic Poisson-AR(1)	Fixed effects	Fixed effects-AR(1)
D(1-paper and printing)	$0.91^{***}(0.078)$	$0.86^{***}(0.076)$	–	–
D(2-chemicals)	$0.57^{***}(0.040)$	$0.55^{***}(0.038)$	–	–
D(3-rubber and plastics)	$-0.11(0.125)$	$-0.09(0.120)$	–	–
D(4-wood and misc.)	$-1.57^{***}(0.123)$	$-1.41^{***}(0.120)$	–	–
D(5-primary metals)	$0.93^{***}(0.062)$	$0.88^{***}(0.060)$	–	–
D(6-fabricated metals)	$-1.49^{***}(0.129)$	$-1.33^{***}(0.125)$	–	–
D(7-machinery)	$0.64^{***}(0.042)$	$0.62^{***}(0.042)$	–	–
D(8-electrical machinery)	$-0.16^{***}(0.032)$	$-0.12^{***}(0.030)$	–	–
D(9-autos)	$0.42^{***}(0.040)$	$0.38^{***}(0.039)$	–	–
D(10-aircrafts and other trans.)	$0.72^{***}(0.050)$	$0.69^{***}(0.048)$	–	–
D(11-textiles and leather)	–	–	–	–
D(12-pharmaceuticals)	$-0.75^{***}(0.069)$	$-0.66^{***}(0.068)$	–	–
D(13-food)	$0.40^{***}(0.127)$	$0.39^{***}(0.119)$	–	–
D(14-computers and inst.)	$-0.43^{***}(0.047)$	$-0.36^{***}(0.045)$	–	–
D(15-oil)	$0.14^{***}(0.032)$	$0.14^{***}(0.029)$	–	–
D(16-non-manufacturing)	$-0.39^{***}(0.037)$	$-0.38^{***}(0.035)$	–	–

Notes: Standard errors are reported in parentheses. The ***, ** and * denote parameter significant at the 1%, 5% and 10% level, respectively. The – denotes parameter not identified. The country names see in Table 2.

Table 6A: Basic panel data regression results

Firm perform.	ROA		Stock return	
Count model	Basic Poisson-AR(1)	Fixed effects-AR(1)	Basic Poisson-AR(1)	Fixed effects-AR(1)
Parameter	estim(st.dev)	estim(st.dev)	estim(st.dev)	estim(st.dev)
ζ	0.001^{**}(0.0005)	0.001^{**}(0.0004)	0.002(0.003)	0.0004(0.002)

Table 6B: PVAR(1) estimation results

Firm perform.	ROA		Stock return	
Count model	Basic Poisson-AR(1)	Fixed effects-AR(1)	Basic Poisson-AR(1)	Fixed effects-AR(1)
Parameter	estim(st.dev)	estim(st.dev)	estim(st.dev)	estim(st.dev)
ζ_{11}	0.07(0.046)	0.01^{***}(0.002)	0.09^{***}(0.009)	0.08^{***}(0.022)
ζ_{12}	0.00(0.005)	0.11^{***}(0.002)	-0.01(0.005)	0.11^{***}(0.002)
ζ_{21}	0.81^{***}(0.039)	0.10^{***}(0.002)	0.09^{***}(0.019)	0.05^{**}(0.024)
ζ_{22}	0.15^{***}(0.010)	0.80^{***}(0.003)	0.15^{***}(0.005)	0.65^{***}(0.005)
$\Omega_{\epsilon_{21}}$	1.87^{***}(0.117)	1.58^{***}(0.025)	0.12^{***}(0.011)	0.19^{***}(0.024)
$\Omega_{0_{21}}$	0.00(0.002)	0.00(0.002)	0.00(0.002)	0.000.002)
$\Omega_{\omega_{21}}$	1.89^{***}(0.131)	-1.02^{***}(0.022)	0.20^{***}(0.061)	-2.34^{***}(0.050)

Notes: Standard errors are reported in parentheses. The ***, ** and * denote parameter significant at the 1%, 5% and 10% level, respectively. In the first row of the table, the firm performance measure is presented. Consecutively, in the second row, we show the count data model used to derive the $\log \lambda_{it}$ values for the firm performance model. For all count data models of this table, we use the patent applications count variable (i.e. *not* the applications + citations counts!). The following specifications are presented in the table:

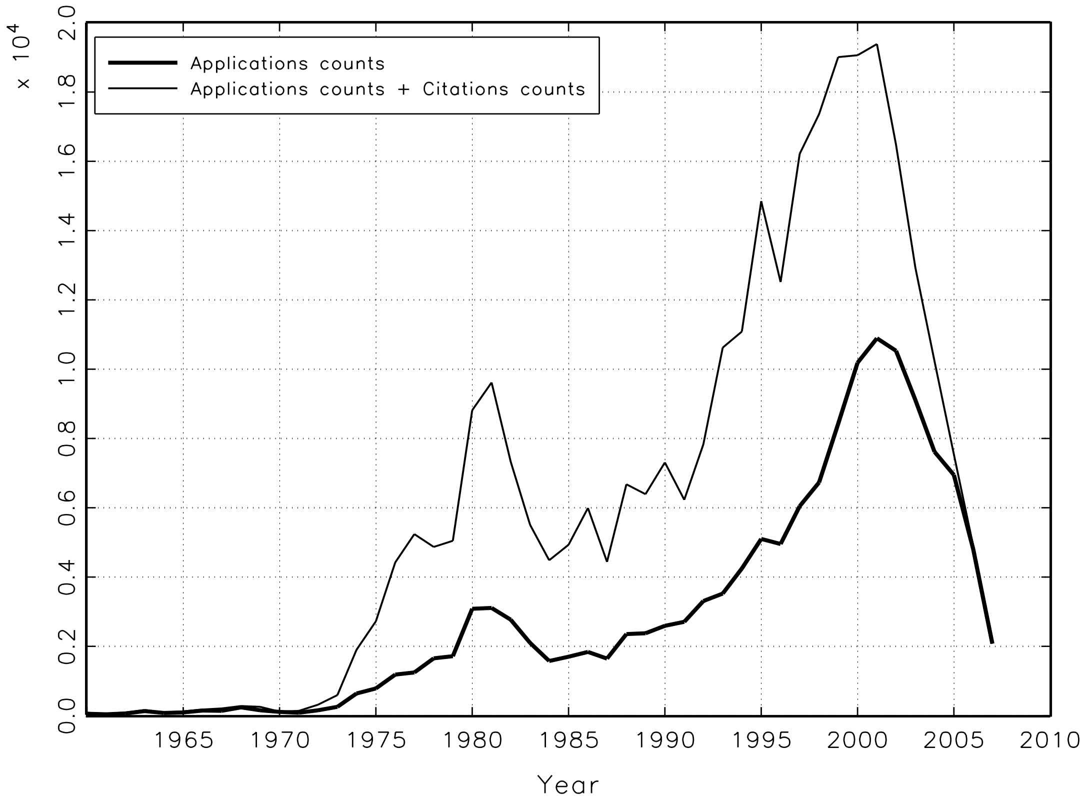
Basic panel data regression:

$$y_{it} = \omega_i + \zeta \log \lambda_{it} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_\epsilon^2)$$

PVAR(1) model:

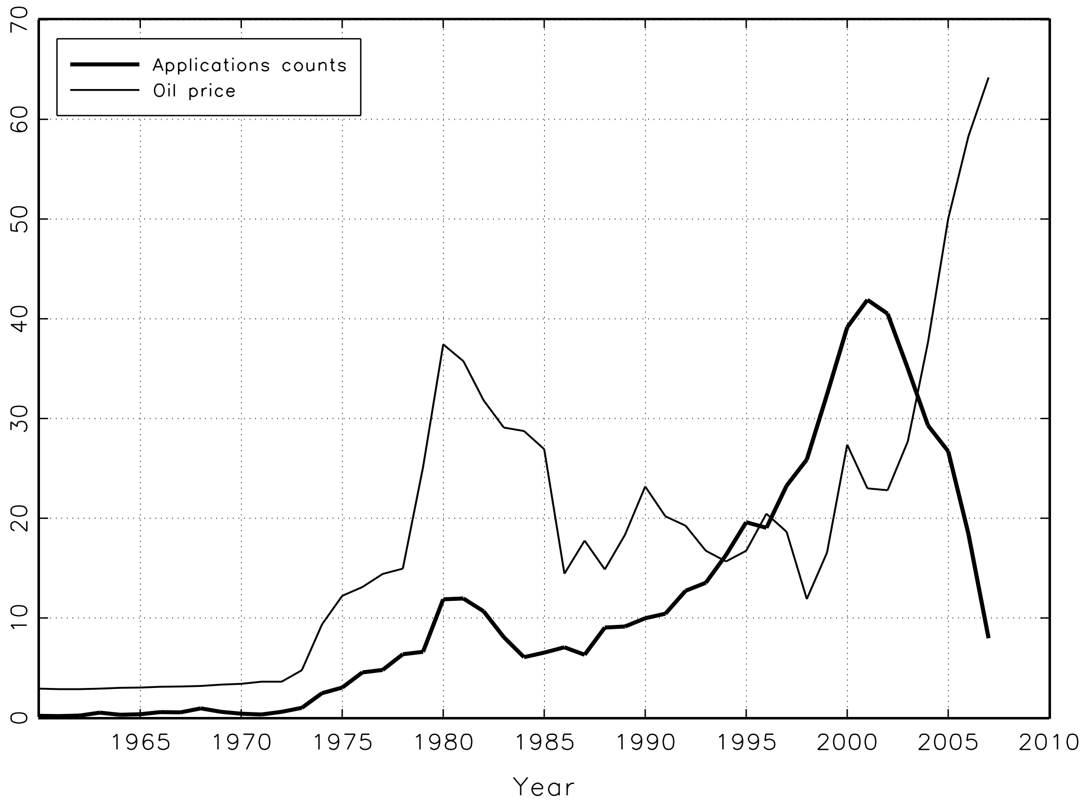
$$X_{it} = \omega_i + \delta_t + \zeta(X_{it-1} - \delta_{t-1}) + \epsilon_{it}, \quad X_{it} = (y_{it}, \log \lambda_{it})', \quad \epsilon_{it} \sim N(0, \Omega_\epsilon)$$

Figure 1. (1) Number of renewable energy patent applications and (2) number of renewable energy patent applications plus number of citations received of 15 EU and 4 EFTA countries over 1960-2007



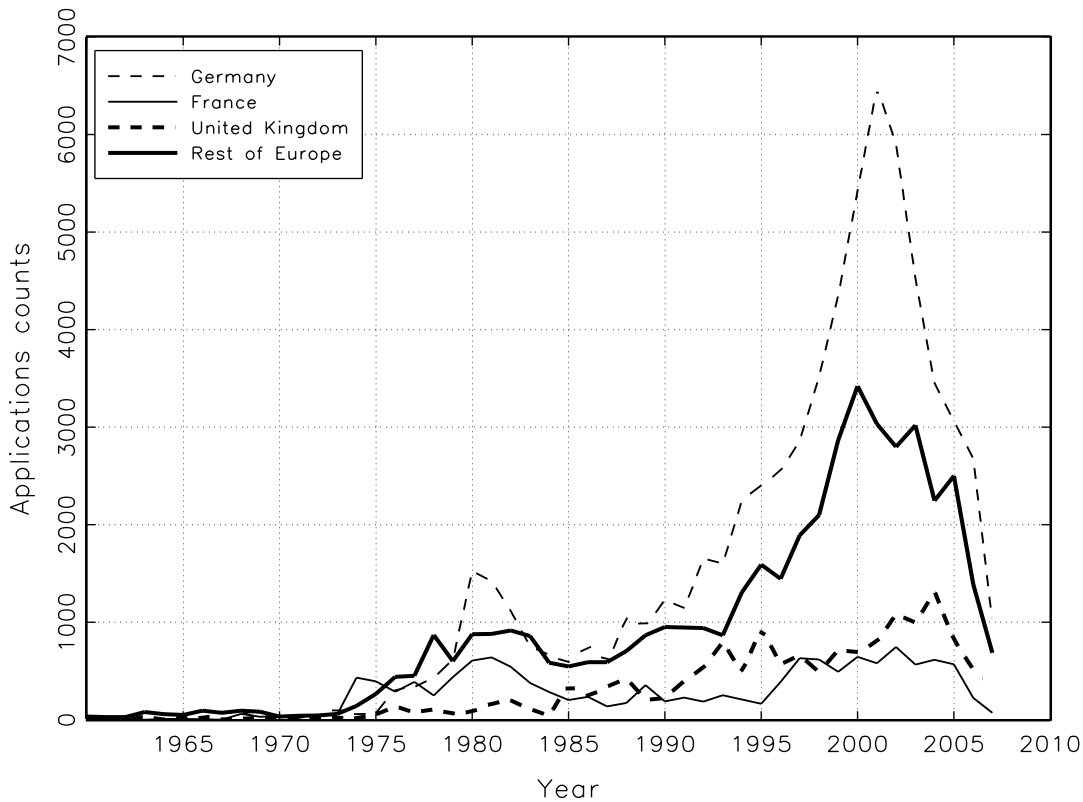
Notes: The sharp decrease in counts during the last years of the sample is due to the sample truncation bias. (See the Data section and Figure 6.)

Figure 2. (1) Total number of renewable energy patent applications of 15 EU and 4 EFTA countries and (2) Oil price USD over 1960-2007.



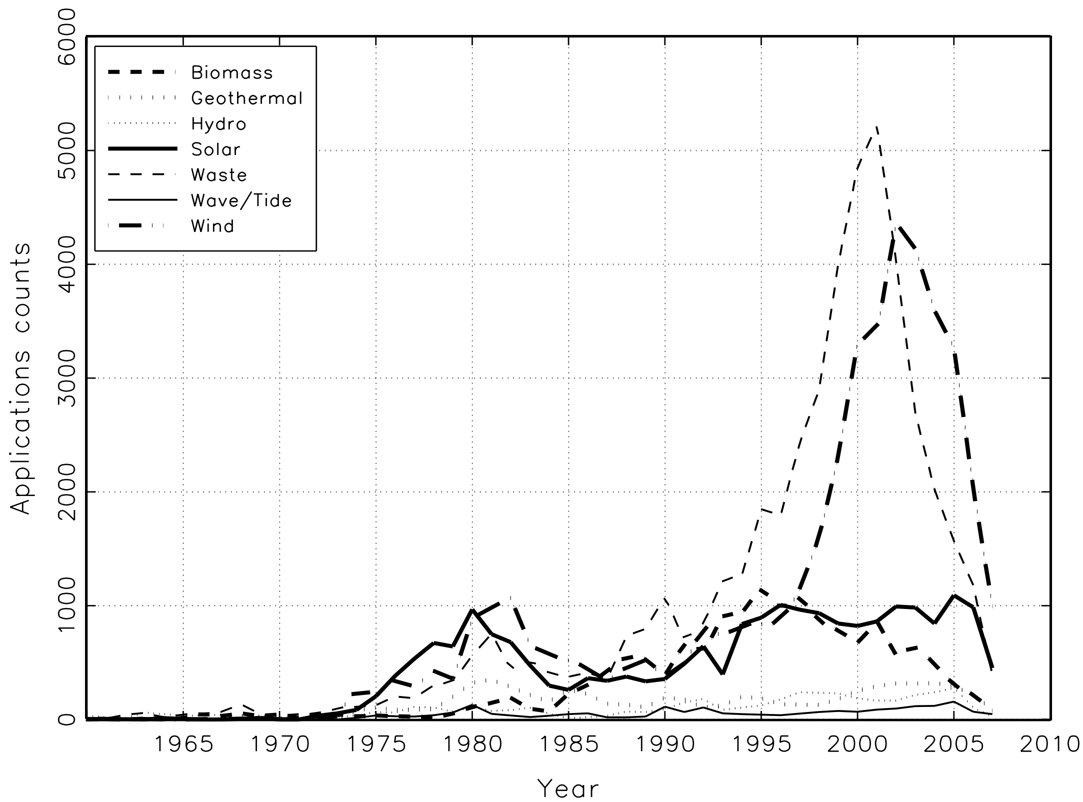
Notes: Notice that we rescaled both time series presented in the figure in order to observe better the comovements. The sharp decrease in patent application counts during the last years of the sample is due to the sample truncation bias. (See the Data section and Figure 6.)

Figure 3. Number of patent applications for the largest countries and the rest of Europe (EU-15 and EFTA-4) over 1960-2007.



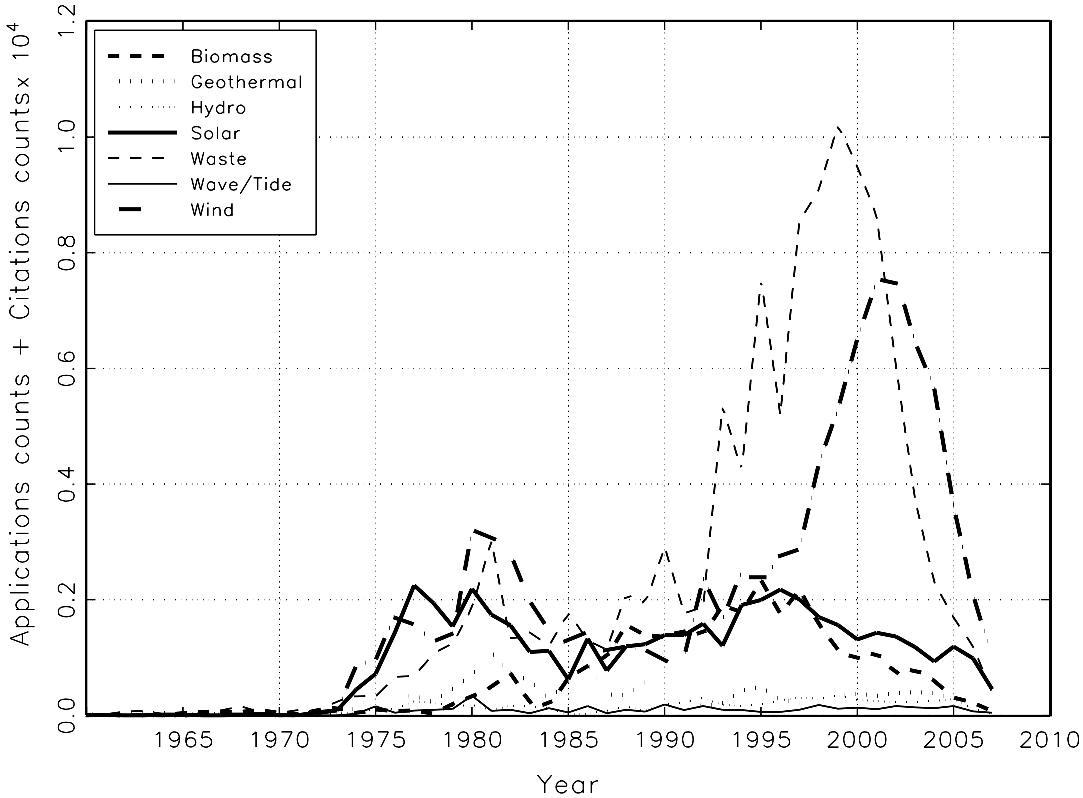
Notes: The sharp decrease in patent application counts during the last years of the sample is due to the sample truncation bias. (See the Data section and Figure 6.)

Figure 4. Total number of patent applications by renewable energy category over 1960-2007 of the EU-15 and EFTA-4 countries.



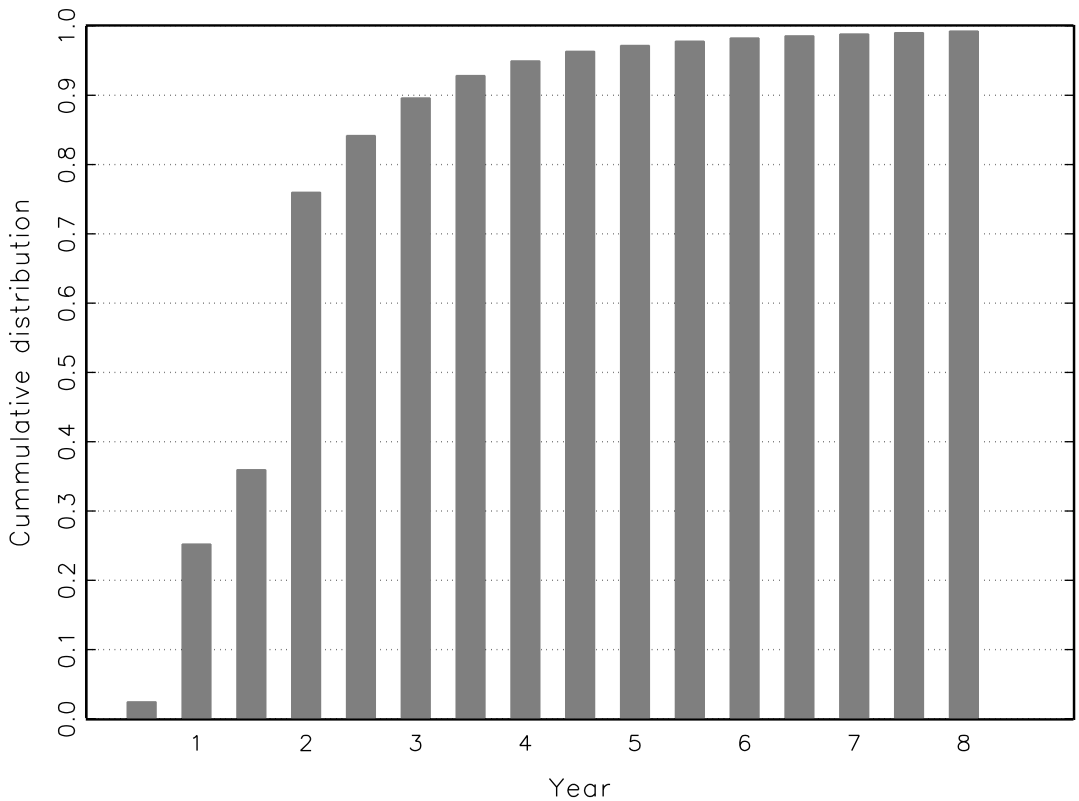
Notes: The sharp decrease in patent application counts during the last years of the sample is due to the sample truncation bias. (See the Data section and Figure 6.)

Figure 5. Total number of patent applications plus total number of citations received by renewable energy category over 1960-2007 of the EU-15 and EFTA-4 countries.



Notes: The sharp decrease in counts during the last years of the sample is due to the sample truncation bias. (See the Data section and Figure 6.)

Figure 6. (Publication date)-(Application date) duration empirical distribution



Notes: The figure shows the time duration between the application date and publication date of patents. Notice that the majority of patents are published in 5 years after submission to the EPO. This, motivates us to include time effects for the last 5 years of our sample: 2003-2007 and a constant for the years before 2003 in our patent count model. (See also Figure 11.)

Figure 7. Electricity production in TWh of the EU and Europe during 1990-2007.

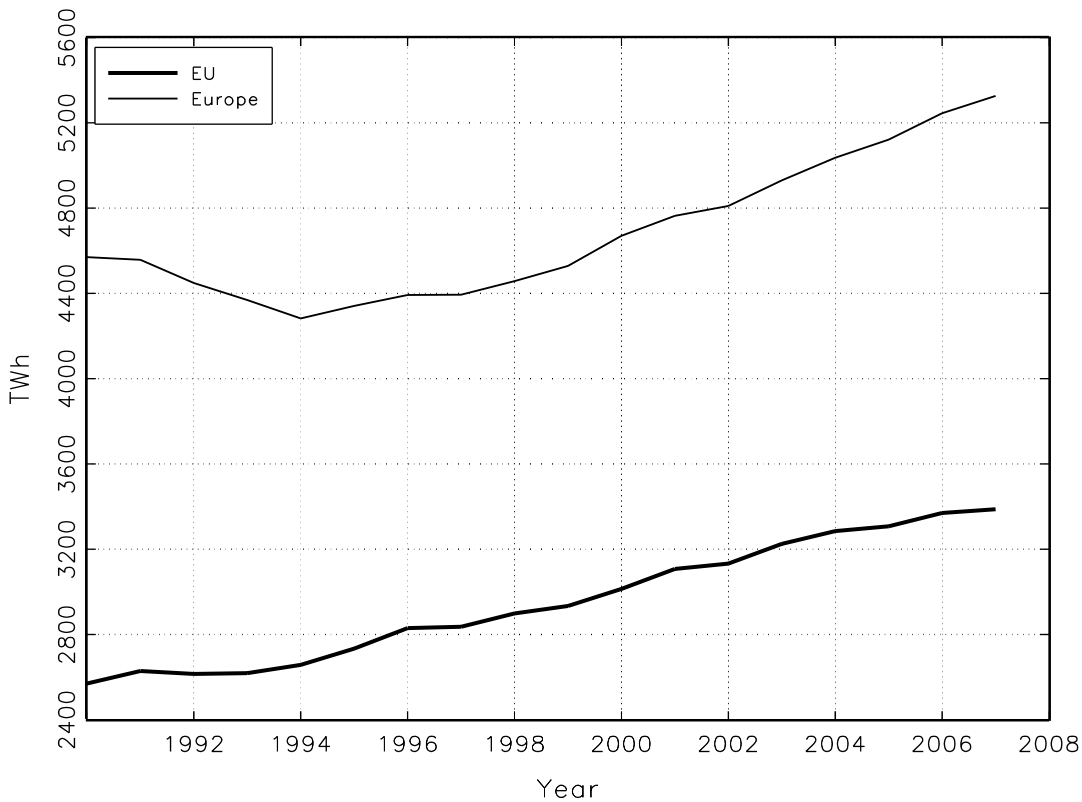


Figure 8. Hydroelectricity (TWh), nuclear energy (TWh) and primary energy (tonnes of oil equivalents, toe) consumption in the EU during 1965-2007.

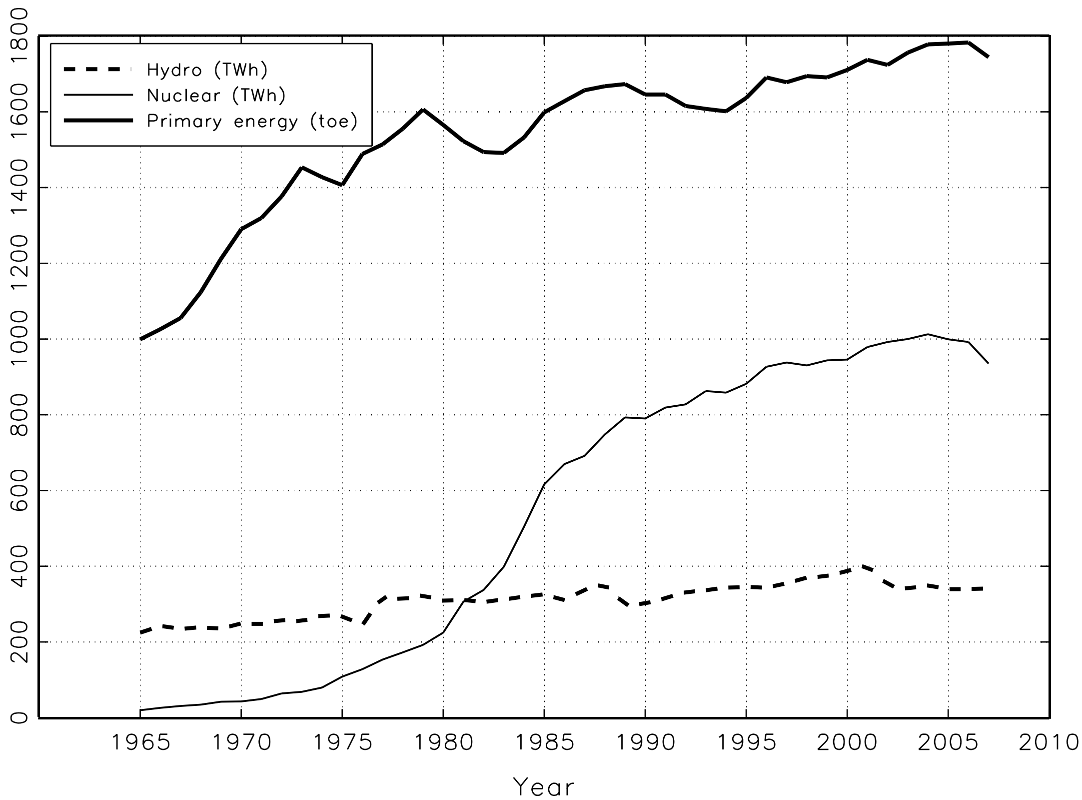
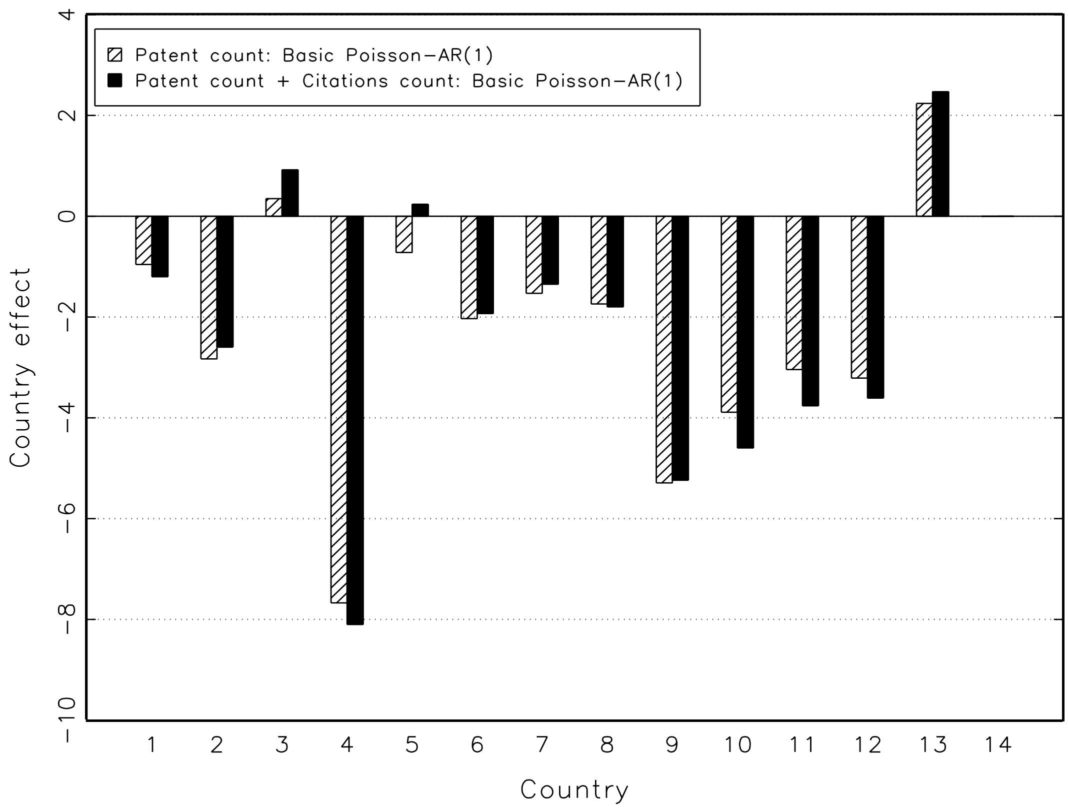
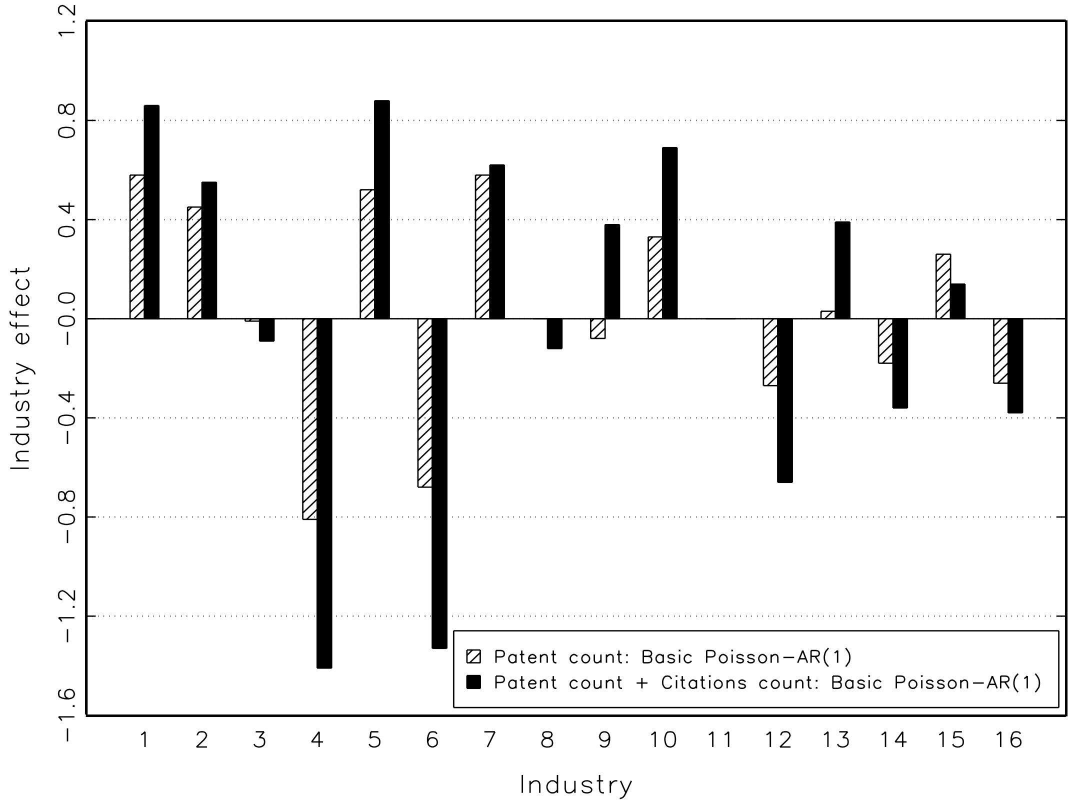


Figure 9. Country effects for the patent activity of firm i.



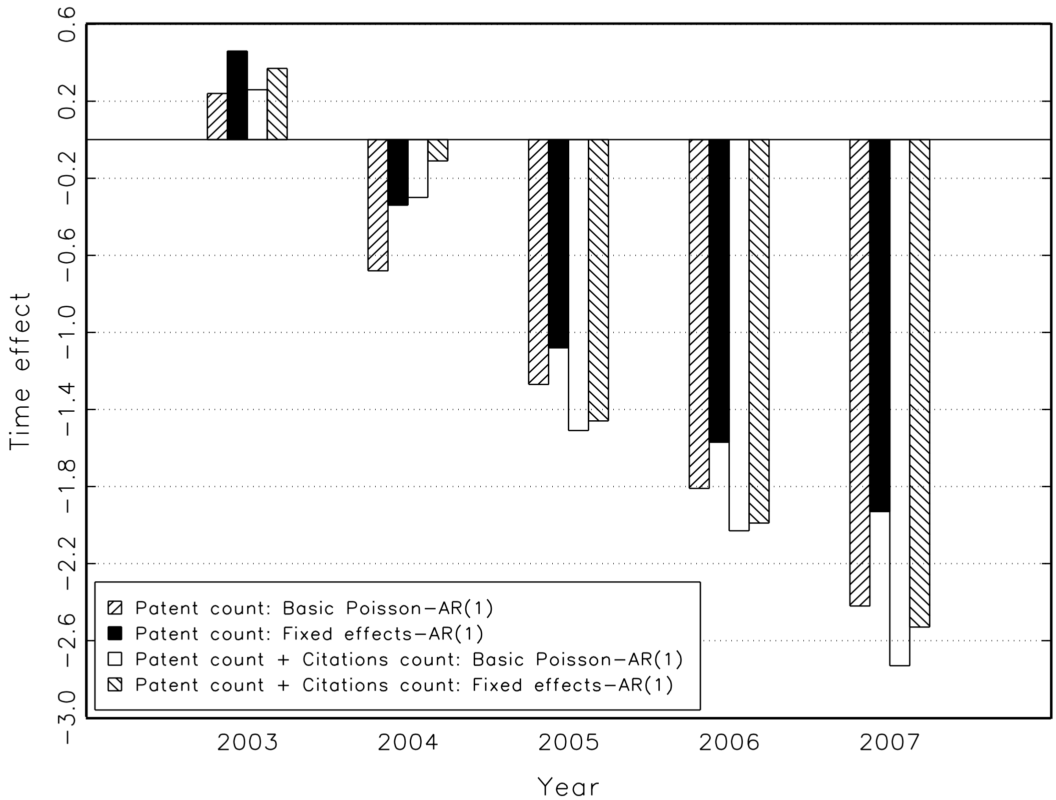
Notes: The following countries are included in the figure: 1-Austria, 2-Belgium, 3-Switzerland, 4-Germany, 5-Denmark, 6-Spain, 7-Finland, 8-France, 9-United Kingdom, 10-Italy, 11-Luxembourg, 12-Netherlands, 13-Norway and 14-Sweden. The parameter values presented in this figure can be also seen in Tables 4B and 5B.

Figure 10. Industry effects for the patent activity of firm i.



Notes: The following industries are included in the figure: 1-paper and printing, 2-chemicals, 3-rubber and plastics, 4-wood and misc., 5-primary metals, 6-fabricated metals, 7-machinery, 8-electrical machinery, 9-autos, 10-aircrafts and other trans., 11-textiles and leather, 12-pharmaceuticals, 13-food, 14-computers and inst., 15-oil and 16-non-manufacturing. The parameter values presented in this figure can be also seen in Tables 4B and 5B.

Figure 11. Time effects for the patent activity during the last five years of the sample.



Notes: The parameter values presented in this figure can be also seen in Tables 4B and 5B. The choice of five time effects for the last 5 years of the sample is motivated by Figure 6.