The Determinants of Innovation in Electricity Generation Technologies

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Abstract

This paper focuses on the determinants of innovation in electricity generation technologies. It takes into account energy-efficient technologies for both fossil-fuel based and renewable electricity generation. The analysis is conducted using patent data on 18 countries over the period 1978-2005. Separate estimations are done for the two technology types to find that the main drivers of innovation in electricity generation technologies are fossil fuel prices and R&D expenditure. Additionally, by doing a joint estimation for the two technology types, it is found that above certain fossil-fuel price levels there is switching from fossil-fuel based to renewable technologies.

1. Introduction

In the past years we have seen increasing political efforts to tackle the problem of climate change. Nevertheless, the results of the policies chosen so far have been scarce. Furthermore, with emissions from new rising economies consistently increasing, climate targets, such as the ones proposed by the International Panel on Climate Change Agreement (IPCC), appear hard to achieve. In this context, the importance of the development and use of new energy-efficient technologies for the production of electricity is crucial. In fact, the electricity production sector accounts for about a quarter of the overall anthropogenic CO_2 emissions, thus greatly contributing to the problem of climate change. Investment in new energy-efficient technologies for power generation, both fossil-fuel based and renewables, is essential for the realisation of policy objectives. Plants based on fossil-fuel inputs are still more diffused, thus it is very important that new technologies for the combustion of fossil fuels are invented. The use of renewables is still limited but it is also very important that these technologies are developed further as they permit to produce electricity without the use of fossil fuels, which are a limited and highly polluting resource. For this reason, it is important not just that energy-efficient technologies are invented for both technology types, but also that electricity generation switches from fossil fuels towards renewables.

The present work attempts to study the determinants of innovation in these two technological sectors. It aims at finding out which economic variables lead to the production of more energy-efficient technologies. Furthermore, it aims at finding which factors lead to the switching from fossil-fuel based towards renewable technologies.

We aim at empirically studying the impact of economic factors on innovation, as measured in patenting activity. The main hypothesis is that innovation is caused by three major factors. First of all, it is determined by the R&D resources invested in the development on the technologies. The hypothesis for what regards R&D is that the higher is the R&D expenditure, the higher is the innovation in terms of patented technologies. Second, innovation depends on the size of the sector and of the market it is serving. If a market is large, it will be necessary to innovate more to be able to saturate the demand. Therefore, we expect innovation to be higher in bigger markets. Finally, fuel prices are expected to drive innovation. In fact, as fossil fuels are an input in the production of electricity in combustion plants, higher fuel prices should stimulate investment in the development of new technologies requiring the use of less fossil fuel. At the same time, with electricity production becoming more expensive with fossil-fuel based technologies, we expect innovative activity to grow in renewable technologies. This switching from one technology type to the other is expected to depend on the level of the fossil fuel prices.

Other previous studies have attempted to analyse the determinants of innovation, generally focusing on environmental policy. Lanjouw and Mody (1996) for example examined the relationship between patenting activity and stringency of environmental policy measured in terms of pollution abatement. They found that pollution abatement induces innovation by increasing the number of patents. Jaffee and Palmer (1997) use R&D expenditure and patents to study whether changes in regulatory stringency lead to innovation. They do not find evidence that patenting activity responds to environmental regulation. More recently, studies such as Popp (2006) have focused on the effect that different policy instruments have on innovation. He finds that command-and-control policy instruments are less effective than market-based instruments. Instead of focusing on environmental regulation, Popp (2002) considers the effect of energy prices on innovation in energy-efficient technologies. He shows that energy prices are a determinant of innovation.

Most of these studies are country-specific or consider a limited number of countries. De Vries and Withagen (2005) use cross-country data to investigate the relationship between environmental policy for limiting SO_2 emissions and patenting activity. They find some evidence that stringency of environmental policies induces innovation. A recent study by Johnstone et al. (2008) uses a panel of OECD countries, data on patents and R&D for different renewable technologies and on different types of environmental regulations, to check for the presence of induced innovation. They find that different types of policies are effective for different types of renewable technologies.

This paper follows the work by Johnstone et al. (2008) but it focuses on innovation induced by fossil fuel prices instead of environmental policy. This is important in a moment in which fossil fuel, and especially oil prices, play such an important role in influencing consumer behaviour, as well as government choices. Furthermore, by considering both fossil-fuel based and renewable technologies, it also analyses the induced switching effect between the two technology types. We find that fossil fuel prices drive innovation in both sectors, and that above certain price levels there is a technology switching from fossil fuels to renewables. We also find that R&D expenditure drives innovation, although this is more so for the renewable technologies. We do not find evidence that electricity consumption is a driver of innovation.

The paper is organised as follows. Section 2 describes the data used, by explaining the variable selection and the data sources. Section 3 explains the model specification and the estimation method chosen. Section 4 presents the empirical results. Section 5 concludes.

2. Data Description

The data used to measure technological innovation is based on patent data. Patents are an output measure of innovation, and as such reflect the innovative performance of firms and economies (Griliches, 1990). Patents are issued by national offices and answer the necessity to protect new technologies with property rights which excludes others from the production for a defined number of years, which varies upon the nature of innovation and the rules of the national offices.

Patent data can be disaggregated by technology, which proves useful for the selection of the technological areas of interest. The International Patent Office (IPO) supplies patent classification codes developed by the World Intellectual Property Organisation (WIPO), thanks to which patents are classified into different technological areas and at several hierarchical levels. The International Patent Classification (IPC) (WIPO, 2006) is application-based, thus facilitating the identification of specific technology classes, and particularly for the scope of the present work, of classes including energy-efficiency patents.

Relevant patent classes have been selected after a careful and extensive review of technological developments in the area of energy-efficient fossil fuel technologies. Thanks to this review a set of technology-specific keywords have been identified. These were then used to determine the appropriate IPC codes related to each of the fossil fuel technologies considered, namely gas turbines, compressed ignition engines, cogeneration, combined cycles, fuel cells, superheaters, steam engines, boilers, burners and fluidised beds. Technology classes for the renewable technologies have been taken from previous selections (Johnstone, Hascic and Popp, 2008) which provide codes for the relevant renewable electricity generation technologies. These include energy-efficient technologies which are not based on the use of fossil fuels, namely wind, solar, geothermal, ocean, biomass and waste.

With the use of the selected IPC classifications and using the EPO/OECD Worldwide Patent Statistical Database (usually referred to as PATSTAT) we have created a database for energy-efficient technologies. The PATSTAT database includes patent data from 73 offices world-wide and post-grant data from about 40 offices. It is an extensive and comprehensive database which answers the needs of researchers and policy-makers to combine different datasets for patent-related information. Using this database, patent counts for claimed priorities were generated. The use of claimed priorities instead of overall patent counts, allows us to select only those technologies which have been filed in at least two countries, and which are thus believed to have an impact on the market and on energy-efficiency in electricity generation. Claimed priority counts are generated separately for fossil-fuel based technologies and for renewable technologies. This allows us to study the behaviour of the two different types of technologies for electricity generation. Figure 1 shows the time line in 3-year moving average for the claimed priority counts for fossil-fuel and renewable technologies. The trends are similar and show a steep increase in the number of patents from the early 1990s. The number of patents in renewables also had a peak in the early 1980s, coinciding with the first oil crisis as well as the development of the first-generation solar and wind technologies. The top technology producers for both technology types are the US, Japan and Germany, followed by France and Korea. Figure 2 shows how patents are distributed across different countries, whereas Figures 3 and 4 show the time trends in 3-year moving average for the top technology producers respectively for fossil-fuel and renewable technologies.

In order to capture the general propensity to patent and the country-specific characteristics in patenting, total claimed priority counts are also included in the database. Figure 5 shows the patent distribution across countries as normalised by the total number of claimed priorities. Once normalised, it is possible to see that countries such as Denmark, Spain, Finland and Greece achieve the highest innovation output in the selected energy-efficiency technologies.

To understand why there is innovation in these sectors, two main explanatory variables are included, that is R&D investments and fuel input prices. The former is the input investment necessary to obtain new technologies; therefore in this case the number of patents also represents the returns from R&D investments. The latter is a measure of induced innovation. In fact, higher fuel prices are expected to induce innovation in energy efficiency as more energy efficient technologies would reduce the fuel input requirements lowering the firms' production costs. This applies both to fossil fuel and to renewable technologies, although it is possible to hypothesise that after certain input price levels some firms would switch to more investments in renewable, rather than continuing to invest in fossil fuels.

The R&D measure used here is from the International Energy Agency (IEA)'s Energy Technology Research Development Database (IEA, 2006). This database collects data on national public sector expenditures on R&D disaggregated by type of technology, both for fossil fuel and renewable technologies, thus permitting to create two separate measures for the two technology types. It is generally expected that the sign on this variable is positive, as more investment in R&D should lead to higher technology output and thus patents.

The input fuel prices have been constructed using the IEA Energy prices and taxes database (IEA, 2006b). The fuel prices have been constructed for the three fossil fuel inputs, namely coal, oil and gas. They have been constructed as a combination of the fuel input price index for the industry and the input prices to industry which are used to attribute a monetary value to the price index[1].

Finally, to control for the electricity market size, which can influence the potential market for innovation, electricity consumption is also included as an explanatory variable. Data on household and industry sector electricity consumption are obtained from the IEA's Energy Balances Database (IEA, 2006c).

The final dataset includes data relative to 18 countries and 28 years (1978-2005) and the sample size is between 400 and 450 observations for each of the two equations under the different specifications[2]. Table 1 summarises the descriptive statistics for the explanatory variables included in the panel.

3. Model Specification and Estimation Method

A. Model Specification

The basic model estimated is a reduced form equation which is estimated separately for fossil fuels and renewable technologies:

$$(CP_{i,t}) = \beta_1\,(R\&D_{i,t}) + \beta_2\,(P_{i,t}) + \beta_3\,(CONS_{i,t}) + \beta_4\,(CP\_TOT_{i,t}) + \alpha_i + \varepsilon_{i,t} \qquad (1)$$

where $i = 1,\ldots 18$ indexes the cross-sectional unit (country) and $t = 1978,\ldots,2005$ indexes time. The dependent variable, patenting activity $PATENTS_{i,t}$, is measured by the number of patent applications in the relevant technology areas. The explanatory variables include specific R&D expenditures ($R\&D_{i,t}$), fossil fuel prices ($P_{i,t}$), electricity consumption ($CONS_{i,t}$) and total patent counts ($CP\_TOT_{i,t}$). Fixed effects (α_i) are introduced in order to capture unobservable country-specific heterogeneity. All residual variation is captured by the error term ($\varepsilon_{i,t}$).

[1] Prices of oil and gas are highly correlated, thus only price of oil is included. The price of coal is not correlated to the other two fuel input prices, and it is rather stable over time. The coal prices data are scarce in terms of number of countries covered and they consistently lower the number of observations in the sample. Thus, as coal price is never found significant in the regressions, and as its omissions does not significantly change the results, it is omitted from the regressions, leaving the price of oil to be the unique measure of fuel input prices.

[2] The limited sample size is due to some countries having zero patent counts and being thus dropped from the sample, and from limited and incomplete data on R&D expenditures.

Given that expectations on energy prices could influence the decision making of firms in their choices to invest into R&D and into new technologies, alternative specifications will be tried with lagged values of the prices.

The two models are first estimated separately and then pooled together. Whilst the two equations are meaningful on their own, they are also correlated. In fact, there is strong correlation between R&D expenditure in fossil fuels and R&D expenditure in renewable as well as patents in renewable. Furthermore, it is reasonable to believe that there are technological spillovers between the two sectors. Evaluating the two equations together allows us to consider these cross effects, as well as to capture the simultaneous effects that oil price and the other explanatory variables have on patent counts in the two different technology groups. In fact, pooling the two models allows us to obtain common coefficients for the control variables such as total claimed priorities, while obtaining separate coefficients for fossil-fuel based and renewable technologies for the main variables of interest. At the same time pooling the two dataset together increases the sample size and the efficiency of the estimation.

B. Estimation Method

Patent data are usually estimated with techniques for count data models, namely data for which the dependent variable is non-negative[3]. The classical approach to count data is to use the Poisson regression thus assuming that the conditional distribution of the dependent variable follows a Poisson distribution, as in El Sayyad (1973) and Maddala (1983). However, the Poisson regression is based on the strong assumption of variance-mean equality, which has been rejected in numerous application. A relaxed version of this assumption is allowed by the Poisson quasi-maximum likelihood estimator (QMLE), which allows the variance-mean ratio to be any positive constant σ^2. When $\sigma^2<1$, the mean of the distribution is greater than the variance, and there is underdispersion in the sample. When instead $\sigma^2>1$, the mean of the distribution is smaller than the variance, and there is overdispersion. In the latter case, the distribution corresponds to a NegBin I, which is a particular parameterisation of the negative binomial distribution, as explained in Cameron and Trivedi (1986). Given that our sample has a high number of zero counts, it is likely to be overdispersed, and thus the negative binomial estimation is preferable to the Poisson.

Whilst count data models were initially designed for cross-sectional data, extensions have been developed for panel data model, starting with the pioneering work by Hausman, Hall and Griliches (1984), who studied patent application by firms in terms of R&D spending. We follow their work in using a fixed effect negative binomial estimation technique.

[3] For an overview of count data models see Cameron and Trivedi (1998) or Woolridge (2002).

A further problem with the data is that, it is not just heteroskedastic because of its count data nature, but it is also heterosckedastic across countries. In fact, because most innovation takes place in a limited number of countries (as it is possible to see from Figure 2), there is a further problem of heterosckedasticity. This is corrected for by applying a robust estimation.

4. Empirical Results

The models are first estimated separately. Tables 2 and 3 show respectively the results for the fossil fuel and the renewable models. In both models results are as expected. Oil price has a positive on claimed priorities for both technology groups. This positive and strongly significant relationship between fossil fuel prices and innovative activity measured as patent counts shows that higher fuel prices can be an incentive to develop new energy-efficient technologies. The relationship is also robust to different specification of price lags. The effect of the lagged prices is however decreasing over time for both models, showing that there is likely to be an expectation component to the price variable. Note that the positive effect of oil prices applies also to renewables, where the relationship is less intuitive. This supports the hypothesis that development of renewable technologies is stimulated by higher costs in the production of electricity by means of the substitute fossil-fuel technologies.

R&D expenditures also have a positive effect on innovation, although R&D is non-significant in some specifications. For the low significance of the R&D variable, it is important to point out that the data used is limitative because it only regards public governmental expenditure in R&D. Due to the limitations of the data, it has not been possible to include private R&D. This would have been particularly important for some countries such as the US, or the UK where the percentage of private R&D spending, particularly in the energy sector, is very high.

Electricity consumption is mostly positive and non-significant. The positive relationship could indicate that larger markets have higher resources and thus are more able to invest in new technologies. The estimated coefficient of the total number of patents is positive and statistically significant at the 1% statistical level for both technology areas. This suggests that part of the variation in patenting activity is due to the general propensity to patent and the structure of the patent system in the different countries.

Fixed effects are included to control for country-specific heterogeneities. The US is chosen as reference country. Most country dummies are negative and significant, showing that most countries have a lower production of energy-efficient technologies than the US. This does not apply to the other top technology producers, such as Japan and Germany, for which the country dummies are non-significant[4].

[4] Clearly results on country dummies change according to the reference country. Choosing the US as a reference and checking results, shows that the fixed effects are relevant and that it is important to control for country-specific differences.

In order to check on the hypothesis of oil prices inducing innovation simultaneously on renewable and fossil fuel technologies, we have estimated the above models pooling the data together. Technology dummies (a dummy for the fossil fuel group and one for the renewable group) are created in order to control for technology-specific heterogeneities. Table 4 shows the results from the pooled estimation. In the first specification some of the variables are interacted with the technology dummies in order to obtain a technology-specific parameter estimates. This is done for oil prices and R&D expenditures, where it is expected that the effect will be different on the two technology groups. The other variables are left without interaction because there is no reason for believing that they should have different effects on the two groups. Fixed effects are again included to control for country-specific heterogeneities.

Results from this specification show that the price of oil has, consistently with the separate models, a positive effect on the innovative activity. The effect is stronger for renewable than for fossil-fuel technologies. This supports our initial hypothesis that not only increases in the price of fossil fuels lead to higher innovative activity in fossil fuel technologies, which are directly related to them, but also in renewable technologies, which are a substitute technology. R&D expenditures are positive and significant for both technology groups. The other results are also coherent with the previous results obtained. In fact, the total number of patents is positive and significant, electricity consumption is positive but non-significant and fixed effects, included for both technologies and countries, are generally significant.

An alternative specification also includes squared oil prices[5], in order to attempt to capture non-linearities in the relationship between patent counts and fossil-fuel prices. Results show that the additional squared terms are negative and significant. This means that, although prices will lead to higher patent counts, this effect is decreasing with the prices increase. This is most likely to be due to demand effects, i.e. as prices increase to very high levels, electricity prices will increase, demand for electricity will decrease, thus the production of electricity will decrease, so that there will be also less technologies being invented. Under this specification other results remain coherent with the previous specification, except that the R&D in renewable becomes insignificant, probably due to the pieces variables capturing more variability in the data.

It is possible to use the results from the last specification to draw the relationship between fossil fuel prices and innovative activity measured as patent counts *ceteris paribus*. The graph in Figure 6 illustrates this relationship[6]. Both curves are increasing and concave, though the renewable curve is steeper, meaning that an increase in price leads to a higher increase in renewable patents than fossil fuel patents.

[5] Woolridge (1997) shows that alternative functional forms such as exponential terms can be used for patent count models.

[6] Note that the intercept has been normalised, and that the graph shifts vertically according to the different country-dummies. The difference in the intercept between the two curves remain the same as it is determined by the technology dummies.

The two curves cross at a certain price level above which renewable patents are more numerous than fossil fuel ones. The crossing of the two curves is due to the fact that fossil fuel patents are higher at the start (the intercept is higher) but renewable patents grow faster. The price levels at which renewables patents become higher is at around 182 US$(PPP). We can compare this to actual recorded price levels for the countries included in the sample. For example, in the United States the 2007 end-user price for electricity generation was 289.04 US$, meaning that the innovative activity in renewable energy technologies is already higher than in fossil-fuel technologies. The price threshold seems to have been passed in 2004 when the price of oil was 203.08 US$ (it was 175.95 US$ in 2003). Although the threshold price has been surpassed at times, it generally falls back under the threshold, so that fossil fuel technologies are still more diffused and there has not been a real switching towards renewables.

For all regressions values of the likelihood ratio chi-squared test with three degrees of freedom are given and show that all models are statistically significant. Estimate of the log of the overdispersion parameter alpha are also obtained in order to check whether the negative binomial estimation is appropriate. The likelihood ratio chi-square tests support the use of negative binomial[7].

5. Conclusions

This paper analyses the determinants of innovation in energy-efficient technologies for both fossil-fuel based and renewable technologies for a cross-section of OECD countries for the period 1978-2005. Patent counts, of which we only consider claimed priorities in order to select the patents which mostly lead to innovation, are used to proxy for innovation.

The empirical results show that fossil fuel prices induce innovation in both fossil-fuel and renewable technologies. R&D expenditure is also a determinant of innovation, although it is more so for renewables. It is also found that electricity consumption, which control for the market size, is not significant, and that total patent counts, which control for overall innovative capacity and propensity to patent, are a significant determinant of innovation.

It is also found that *ceteris paribus* at high levels of the fossil fuel prices there is a switching from fossil-fuel based to renewable technologies. This shows that not only fossil fuel prices induce innovation in all energy-efficient technologies, but that they can also lead to reduce the reliance on fossil fuel technologies by inducing relatively more innovation in renewable.

While these results are interesting, further work is needed both to improve the robustness of the result and to achieve other related results. First of all, better measures of R&D expenditures, which are not

[7] The test is used to verify whether the overdispersion parameter alpha is statistically significant from zero. If alpha equals zero, then there is no overdispersion. If the test is significant zero-truncated negative binomial is preferred to zero-truncated poisson. In all estimated models the test is significant supporting the choice of estimating with negative binomial.

available to date, could improve the results. In particular data relative to private and public expenditure in energy-efficient technologies for electricity generation would be ideal to account for the R&D input in the production of these technologies. Second, considering the empirical estimation method, a better methodology for estimating the system of equations should be found. An SUR system with negative binomial estimation could improve the reliability of the results by increasing the efficiency of the estimates. Finally, as future work, it would be interesting to apply these results, which show a strong linkage in innovation in the two types of technologies, to a detailed study of inter-technology spillovers, based on the construction of knowledge stocks. Such a study would also be of interest because of its applicability to applied climate-economy or general equilibrium models.

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Figure 1: Time trends for claimed priorities in fossil-fuel and renewable technology patents

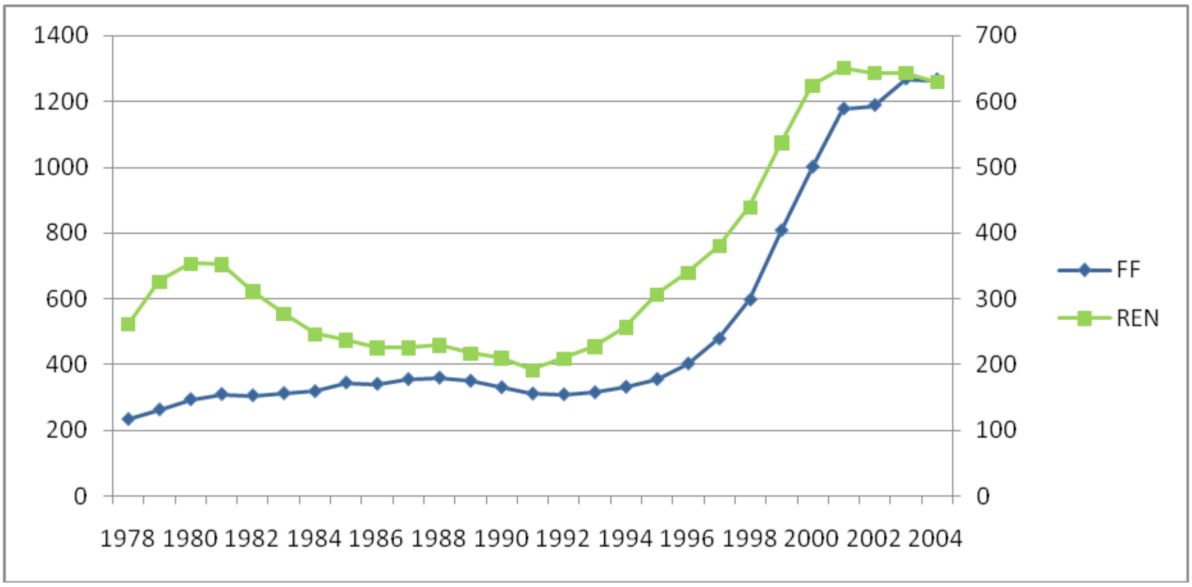

Figure 2: Number of claimed priorities in fossil-fuel and renewable technology patents by country (1978-2005)

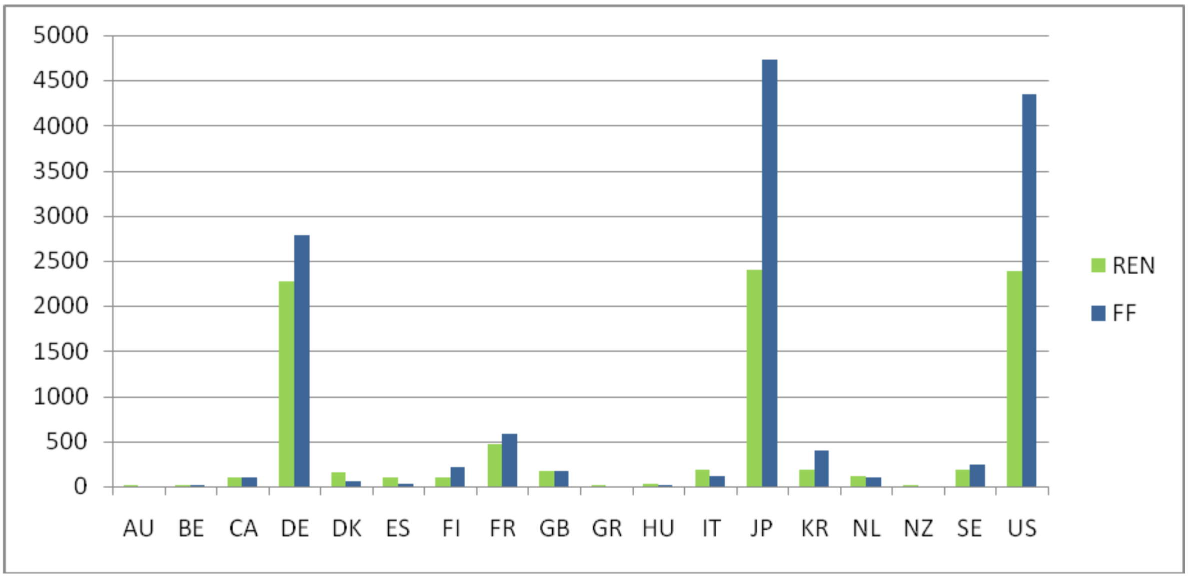

Figure 3: Number of claimed priorities in fossil-fuel technologies by country

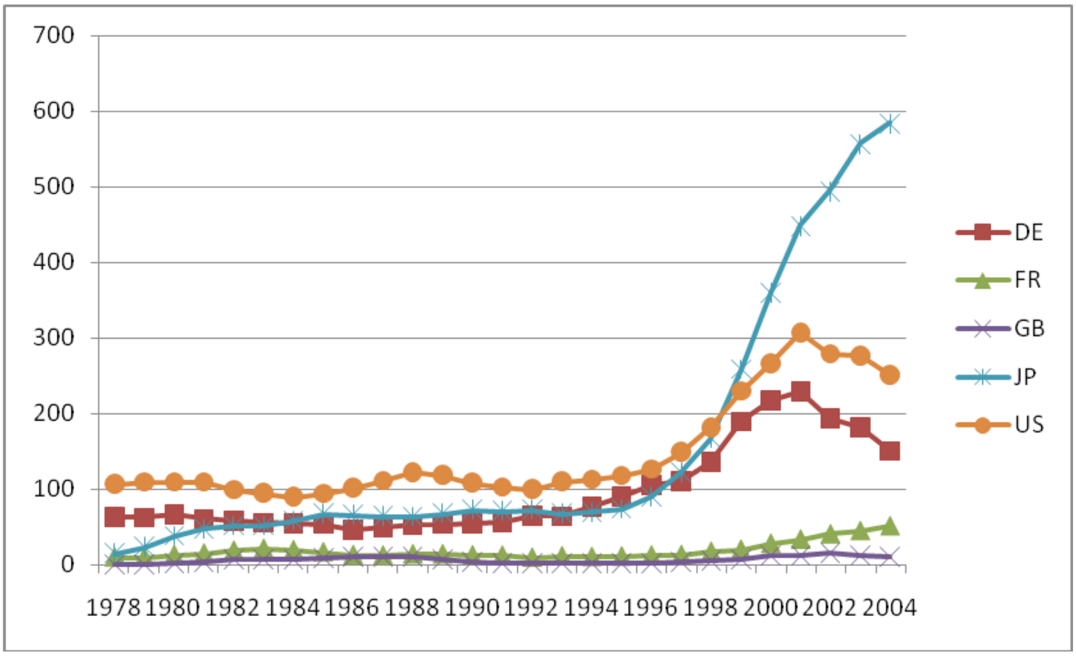

Figure 4: Number of claimed priorities in renewable technologies by country

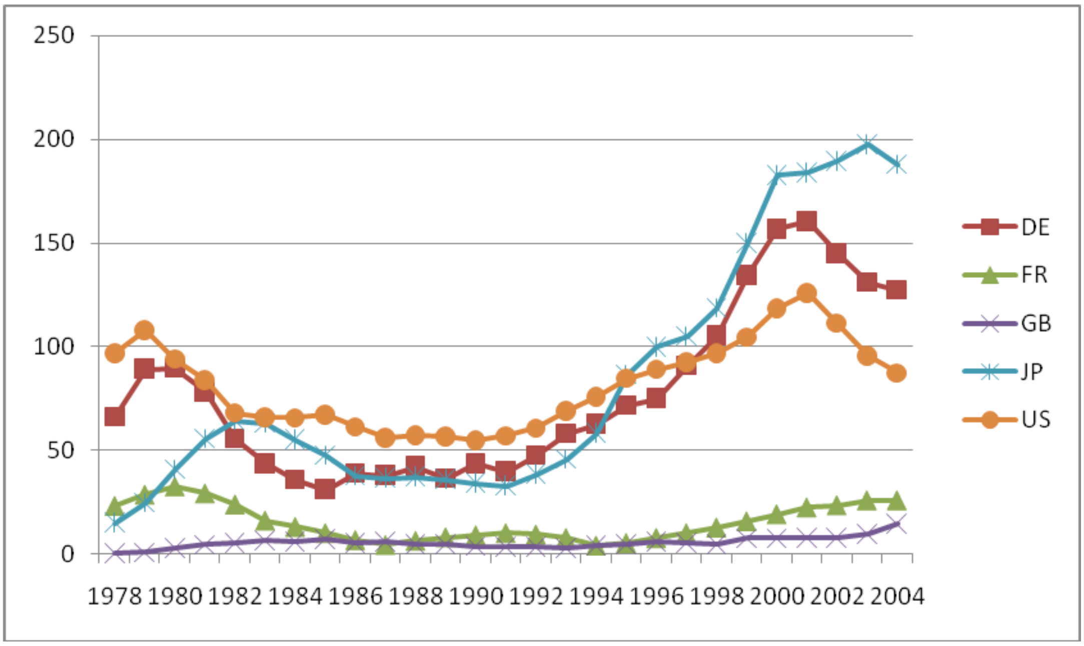

Figure 5: Number of claimed priorities in fossil-fuel and renewable technology patents by country normalised by overall patenting activity (1978-2005)

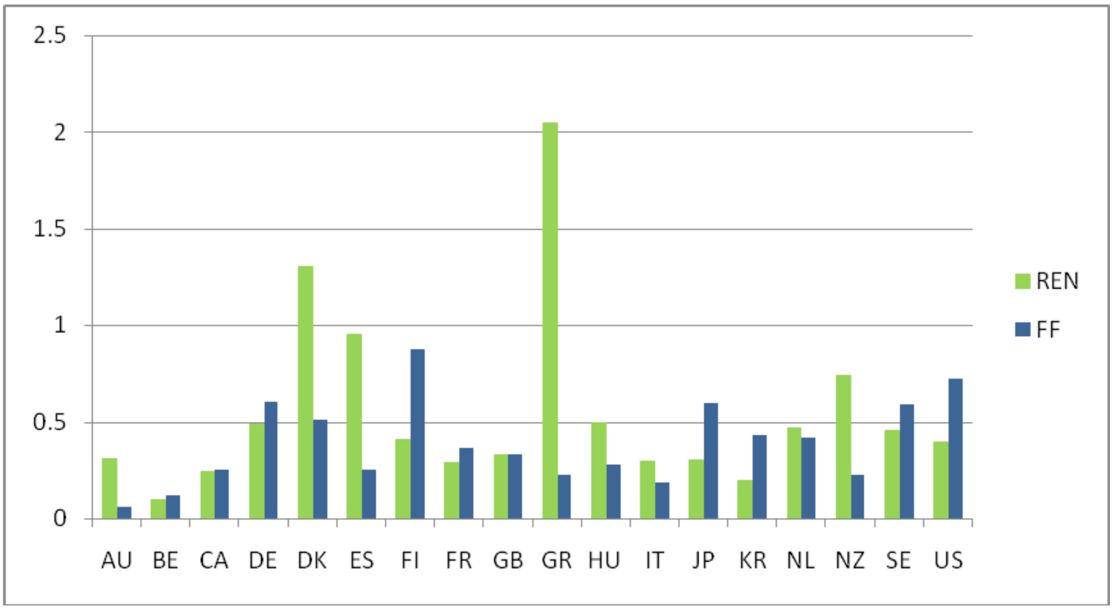

Figure 6: Claimed Priorities as a function of oil prices

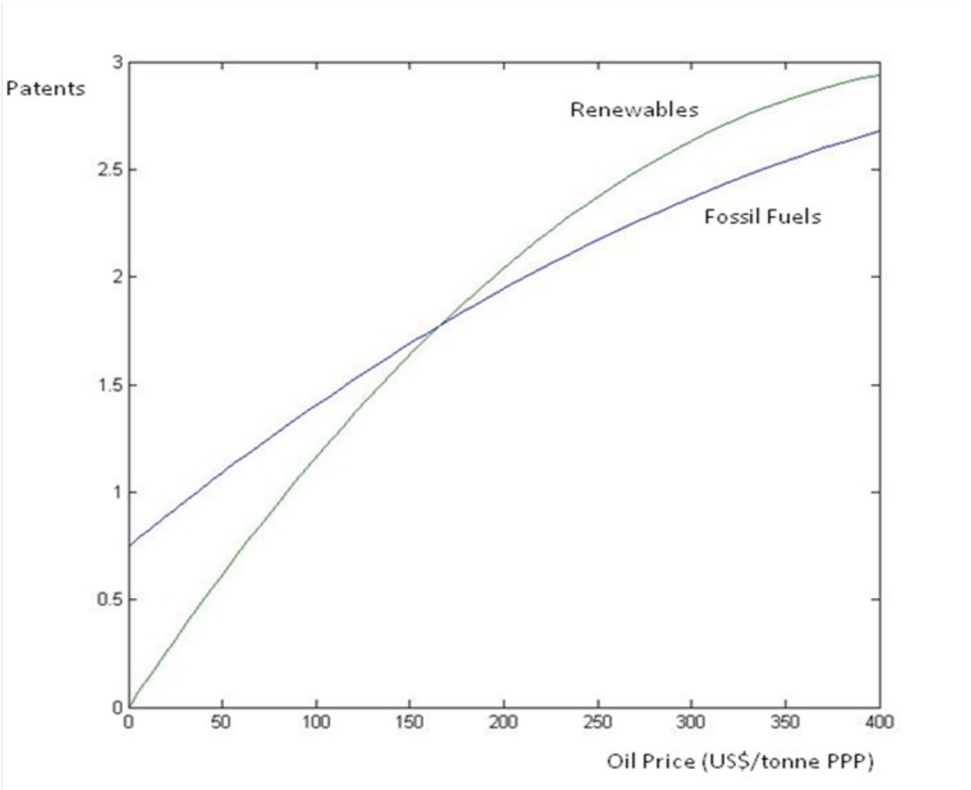

Table 1: Descriptive statistics of explanatory variables (1978-2005)

Variable	Unit of Measure	Obs	Mean	Std.De
Claimed Priorities – Fossil Fuels	Number of claimed priorities	560	4.68214	69.43652
Claimed Priorities – Renewables	Number of claimed priorities	560	5.80536	33.81751
Claimed Priorities – Total	Number of claimed priorities (thousands)	560	.289125	8.406336
Oil price	2000 US$/tonne - using PPP	560	208.6582	109.3546
Consumption of electricity	Thousand TWh	560	.337547	0.671126
R&D – Fossil Fuels	Billion 2000 US$ - Constant prices and PPP	436	0.090043	0.203072
R&D – Renewables	Billion 2000 US$ - Constant prices and PPP	431	0.049884	0.127507

Table 2: Results from the Fossil Fuel estimations with negative binomial fixed effects model

	FF (1)	FF (2)	FF (3)
Oil price	.0033**		
	(0.000)		
Oil price – lag 1		.0018**	
		(0.002)	
Oil price – lag 2			.00154**
			(0.002)
R&D expenditure	.1410	.3170*	.3771**
	(0.323)	(0.014)	(0.002)
Electricity consumption	.0147	.0808	.1079
	(0.900)	(0.478)	(0.351)
Total patents	.0909**	.0962**	.0985**
	(0.000)	(0.000)	(0.000)
Fixed Effect	Yes	Yes	Yes
Observations	436	435	434
Log-likelihood	-1100.60	-1103.87	-1103.34
Wald Chi2	9880.54	12495.29	11140.59
(Prob>chi2)	(0.000)	(0.000)	(0.000)

Notes: * and ** refer to 5% and 1% level of statistical significance. P-values are in parentheses. The dependent variable is claimed priorities in fossil-fuel based energy-efficient technologies. Country dummies are included to control for country-specific heterogeneities, omitting the dummy for the US which is taken as reference country.

Table 3: Results from the Renewables estimations with negative binomial fixed effects model

	REN (1)	REN (2)	REN (3)
Oil price	.0044**		
	(0.000)		
Oil price – lag 1		.0024**	
		(0.005)	
Oil price – lag 2			.0018*
			(0.016)
R&D expenditure	.8208**	1.0376**	1.0509**
	(0.002)	(0.000)	(0.000)
Electricity consumption	.2000	.3277*	.3107
	(0.181)	(0.042)	(0.052)
Total patents	.0600**	.0643**	.0665**
	(0.000)	(0.000)	(0.000)
Fixed Effect	Yes	Yes	Yes
Observations	431	430	429
Log-likelihood	-1178.87	-1185.27	-1186.34
Wald Chi2	3146.72	3282.92	3206.90
(Prob>chi2)	(0.000)	(0.000)	(0.000)

Notes: * and ** refer to 5% and 1% level of statistical significance. P-values are in parentheses. The dependent variable is the claimed priorities in renewable technologies. Country dummies are included to control for country-specific heterogeneities, omitting the dummy for the US which is taken as reference country.

Table 4: Results from the Pooled model with negative binomial fixed effects model

	POOLED (1)	POOLED (2)
Oil price – Fossil Fuels	.0034**	.0071**
	(0.000)	(0.000)
Squared Oil price – Fossil Fuels		-5.85e-06*
		(0.044)
Oil price – Renewables	.0046**	.0131**
	(0.000)	(0.000)
Squared Oil price – Renewables		-.000014**
		(0.000)
R&D expenditure – Fossil Fuels	.0006**	.0006**
	(0.000)	(0.000)
R&D expenditure – Renewables	.0005*	.0004
	(0.025)	(0.143)
Electricity consumption	.1908	.2023
	(0.109)	(0.120)
Total patents	.0773**	.0792**
	(0.000)	(0.000)
Fixed Effect	Yes	Yes
Observations	860	860
Log-likelihood	-2340.57	-2328.07
Wald Chi2	5360.13	29004.64
(Prob>chi2)	(0.000)	(0.000)

Notes: * and ** refer to 5% and 1% level of statistical significance. P-values are in parentheses. The dependent variable is the claimed priorities in the two technology groups. Country dummies are included to control for country-specific heterogeneities. Technology dummies are also included to control for the effect of the single technology groups.