Location of innovative activity in the pharmaceutical industry

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Innovation by firms is an important driver not only of their own business success, but also of national productivity, welfare and growth. A wide range of government policies are aimed at encouraging and facilitating firms' ability to innovate and to exploit innovation by others. These policies are largely formed in the context of a national innovation system. But firms operate globally - undertaking research and producing and selling products and services in many locations. Productivity and growth in the national economies depends not only on what firms do within the national boundaries, but also on what they do abroad.

Firms have traditionally been thought of as locating innovative activity near their headquarters at home, but they are increasingly relocating innovative activity abroad. This is indicated by a series of different statistics. These changes could be in response to a number of factors. Traditional models of the multinational firm focus on firms seeking to access foreign markets, and need to adapt technologies to local conditions. The public finance literature emphasises the important of R&D tax credits. Changes in technology, for example the rapid increase in the use of Information and Communication Technology (ICT), may have led to a reduction in the costs of moving innovative activity abroad. The availability and cost of skilled workers are likely also to play a role in firms' decisions to move R&D activities offshore. The management literature and theoretical work in economics has emphasised the importance of international technology sourcing in productivity growth.

Despite the widespread interest in these issues there is a scarcity of robust evidence on where inventive activity is locating, the relative importance of these various factors and what the implications are for policy. In this paper we consider the extent to which firms in the pharmaceutical industry from different countries have relocated their innovative activities offshore and we examine in particular the role of technology sourcing in influencing these decisions. This is of direct interest for policy. If technology sourcing is the main driver, then policies to "bring R&D back home" may have counteracting negative effects, as firms no longer participate in leading edge research. We will use variation within firms and across countries; and also therapeutic class-location variation in the productivity of research activity.

We will exploit novel and rich internationally comparable micro-level data on firm-level innovative activity, as measured by patents and the location of the inventors of those patents, matched to accounting data for firms across a number of European countries and the US. To describe the extent to which firms based in different countries have located their innovative activities offshore we will use the location of the *applicant* and the *inventor* in firms' patents to measure the location where innovative activity was undertaken. This allows us to map the extent to which innovative activity has moved offshore over time and across countries. Matching the patents data to accounting data allows us to identify the ultimate parent firm of the *applicant* and to contrast the location of firms' inventive activity with the location of the parent company. The patents data are administrative data from the European Patent Office, sourced from PATSTAT. The accounting data come from Amadeus, and we will supplement this with Compustat and Icarus.

RENEWABLE ENERGY POLICIES AND TECHNOLOGICAL INNOVATION:

EVIDENCE BASED ON PATENT COUNTS [1]

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Renewable Energy Policies and Technological Innovation:

Evidence Based on Patent Counts

Abstract: This paper examines the effect of environmental policies on technological innovation in the specific case of renewable energy. The analysis is conducted using patent data on a panel of 26 countries over the period 1978-2003. It is found that public policy plays a significant role in determining patent applications. Different types of policy instruments are effective for different renewable energy sources.

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Renewable Energy Policies and Technological Innovation:

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1. Introduction

Investment in renewable energy sources – wind, solar, geothermal, wave-tide, biomass, and waste – can significantly contribute to the realization of public environmental objectives. In addition, it is sometimes argued that increased shares of renewable energy contribute to other public policy objectives, such as greater energy security in the face of uncertain markets for fossil fuels.

Currently, the penetration of renewables, although increasing, remains limited. In the absence of public intervention favoring their development, production costs remain higher than for substitute fossil fuels. Various government policies have been introduced in an effort to reduce costs and accelerate market penetration. As such, renewable energy is an interesting context in which to assess the effect of different types of policy measures on technological innovation.

According to the International Energy Agency [12] three generations of renewable energy technologies can be distinguished: (i) First-generation technologies which have already reached maturity, such as hydropower, biomass combustion, and geothermal energy; (ii) Second-generation technologies which are undergoing rapid development such as solar energy, wind power, and modern forms of bio-energy; and (iii) Third-generation technologies which are presently in developmental stages such as concentrating solar power, ocean energy, improved geothermal, and integrated bio-energy systems.

The contribution of different renewable energy sources to total energy supply remains limited. In 2004, among the three main regions of the OECD, Europe had the highest share of renewable use in total energy production (6.9%). In North America (Canada, United States and Mexico) the figure is 5.7% and for OECD Pacific (Japan, Korea, Australia and New Zealand) it is 3.4% [13]. Solid biomass is the single largest source of renewable energy supply (44.6%) followed by hydropower (34.6%). The rate of growth of renewable energy supply amongst the OECD countries between 1990 and 2004 has been particularly strong for wind power (23.9% annually, on average), combustible renewables and waste excluding solid biomass (i.e. renewable municipal waste, biogas, liquid biomass) (12.3%), and solar energy (incl. solar thermal and solar photovoltaic) (5.7%) [13]. However, the relative importance of slow-growing renewables, such as solid biomass (1.6%), hydropower (0.6%) and geothermal (0.2%), means that the overall rate of growth of renewables (1.3%) is marginally below the growth rate of total primary energy supply (TPES) (1.4%).

In order to increase the share of renewable sources in total energy supply, many governments have sought to encourage further development and adoption of renewable energy technologies (see [11]). For instance, a European Union Directive of 2001 (Directive 2001/77/EC) provides a framework for the development of renewable energies in Europe. In March 2007 EU heads of state have agreed to set a binding target for renewable energy use at 20 percent of the EU's total energy needs by 2020. Precisely how this will be met remains to be determined. In the United States, federal tax credits for renewable energy were extended in 2006, granting production tax credits for bio-energy, geothermal, wind, solar, and other renewable energy sources [27].

In addition to production tax credits, other measures introduced in different countries include mandatory production quotas, differentiated tariff systems, and tradable certificates.[2] With the exception of support for research and development, most policies which have been introduced do not provide explicit support for technological innovation. However, by either decreasing the relative price of the use of renewable energy relative to fossil fuels, or by

[2] For details see the IEA 'Renewable Energy Policies and Measures Database' [17].

increasing demand for electricity generated from renewable sources, such policy measures will provide increased returns on the identification of more efficient forms of electricity generation using renewable energy sources.

While there are no previous studies which have used patent data to examine the case of renewable energy, there is some limited empirical evidence to support the more general finding that environmental policies lead to increased patent activity (see Jaffe, Newell and Stavins [18] for a review of the empirical literature). For instance, Lanjouw and Mody [20] examined the relationship between the number of patents granted and environmental policy stringency, measured in terms of pollution abatement expenditures at the macroeconomic level for Japan, US, and Germany. They found that pollution abatement cost affects the number of patents successfully granted with 1- to 2-year lag. However, their study is not entirely satisfactory because other factors that are likely to affect technical innovation were not controlled for in the analysis.

Using US industry-level data, Jaffe and Palmer [19] extended Lanjouw and Mody's study by incorporating various factors that potentially affect environmental innovation. As a measure of innovation, they examined R&D expenditures and the number of patents granted. The study confirmed that environmental regulation increases R&D expenditures. But it did not support the hypothesis that the number of patents increased in response to environmental regulation. They also stressed the necessity to assess the relative strength of the effects of flexible versus prescriptive environmental policy regulation regarding environmental innovation.

Brunnermeier and Cohen [2] used US manufacturing industry data and empirically analyzed factors that determined environmental technological innovation. They paid close attention to the fact that emission reduction pressures come not only from domestic regulatory authorities, but also evolve from international competition. As indicators of emission reduction pressures, they use pollution abatement costs and the number of inspections undertaken by the direct regulatory institutions. As a measure for environmental innovation, they used counts of environment-related patents. They found that environmental innovation becomes more active as pollution abatement expenditures increase. Moreover, they found that international competition stimulates environmental innovation. However, the effect of inspections was not confirmed.

Very few studies have examined the role of policy instrument choice. Using patent data, Popp [24] examined the effects of the introduction of the tradable permit system for SO_2 emissions as part of US Clean Air Act Amendments on the technological efficiency of flue-gas desulphurization. Comparing patent applications prior to the introduction of the tradable permit scheme with those submitted under the previous technology-based regulatory system, he found evidence of the improved removal efficiency of scrubbers. A later paper by Popp [26] looks at the experience of the US, Japan and Germany with respect to patents for SO_2 and NO_x abatement technologies. He found: (a) a strong influence of 'home bias' in the effect of domestic environmental regulations on patenting; but, also (b) an important role played by foreign innovation in the development of such patents.

In one of the few cross-country studies, de Vries and Withagen [4] investigated the relationship between environmental policy regarding SO_2 and patent applications in relevant patent classifications. Applying three different models which vary according to the manner in which policy stringency is modeled, they found some evidence that strict environmental policies lead to more innovation. However, they recognize that the modeling of environmental policy in their analysis requires further refinement. Moreover, they expressed concerns about their ability to identify all relevant patent classes.

In this paper, an assessment is made of the effects on innovation of different policies implemented to favor the development of renewable energy. In addition to the focus on renewable energy the study contributes to the literature in that it has a cross-country focus[3] and is the first to report on the effects of a wide variety of policy types. And finally, the paper uses a much richer set of data than has been used in previous studies, with a panel of 26 countries and 26 years. This allows for wide variation in the data, particularly with respect to policy frameworks.

The next section presents data used in the analysis, including data on patents with respect to renewable energy technologies, data on public policy introduction, and other explanatory variables. The third section discusses the specification and methodological issues involved. The fourth section presents the empirical results. The paper concludes with a summary of the main policy implications.

2. Data

2.1. Patent applications for renewable energy

Given the importance of technological innovation in modern economies, identifying reliable measures of technological innovation has long preoccupied economists. However, there are still very few such measures available. Many potential candidates (e.g. research and development expenditures, number of scientific personnel, etc.) are at best imperfect indicators of the innovative performance of an economy since they focus on inputs.

In this context patents, as an output measure, have emerged as a valuable source of information, reflecting the innovative performance of a firm or an economy in a manner which is attractive to researchers (Griliches [8]). Patent applications provide a wealth of information on the nature of the invention and the applicant. The data is both readily available (if not always in a convenient format), discrete (and thus easily subject to statistical analysis),

[3] Studies by Popp [26] and de Vries and Withagen [4] are the only cross-country studies available.

and can be disaggregated to specific technological areas. Significantly, there are very few examples of economically significant inventions which have not been patented [5,6].

Patents, issued by national patent offices (usually specialized agencies), give the holder the right to exclude others from the production of a specific good (or from using a specific process) for a defined number of years, which may vary depending upon the nature of the innovation. In order to be eligible for a patent, the innovation must be novel, involve a non-obvious inventive step, and be commercially viable [5,6].

However, patents are an imperfect measure of technological innovation for a variety of reasons: (a) It is difficult to distinguish between the 'value' of different patents on the basis of patent applications. Most clearly, the use of unweighted patent counts would attribute the same importance to patents for which there were no successful commercial applications with those which are highly profitable; (b) There is variation in the propensity to patent across countries and sectors. This is due in part to the level of protection afforded by the patent, but also to the possibility of protecting monopoly rights by other means depending upon market conditions; and, (c) Differences in patent regimes across countries mean that it is difficult to be certain that one is comparing 'like with like'. For instance, some countries would require multiple patents for the same innovation which could be covered by a single patent in other countries.

Despite their shortcomings patent counts are still the best available source of data on innovation which is readily available and comparable across countries. Relevant patents in different subject areas can be identified using the International Patent Classification (IPC) codes, developed at the World Intellectual Property Organisation. This classification system is a hierarchy of codes, structured into different levels. Table 1 gives an idea of the hierarchical structure, taking the example of solar concentrating devices used for the generation of mechanical power. While other classification systems (e.g., commodity or sectoral classifications) may be suitable to study innovation in general, the advantage of the IPC classification is that it is application-based – and thus facilitates identification of ‘environmentally-relevant’ technology classes.

Based upon an extensive literature review of technology developments in the area of renewable energy, a set of keywords were identified for this study. These were used to determine appropriate IPC codes which relate directly to renewable energy in the areas of wind, solar, geothermal, wave-tide, biomass, and waste (the complete list of the relevant codes and their definitions is included in Table A1 in the Appendix).

Two possible types of error are possible when searching for relevant patents – inclusion of irrelevant patents and exclusion of relevant patents from the selected classifications. In contrast to some other ‘environmental’ technologies, renewable energy technologies have the advantage that these types of errors are largely minimized because the definition of the relevant patent classifications allows easy identification of the relevant patents.

Patent counts were generated for each of the IPC classifications using the Triadic Patent Family database of the OECD’s Directorate for Science, Technology and Industry. The database allows for empirical analysis of innovation trends across a wide cross-section of the OECD countries, with time-series of patent applications to the US Patent and Trademark Office (USPTO), the Japanese Patent Office (JPO) and the European Patent Office (EPO), stretching back to the 1970s. Two filters are applied to ensure commensurability and inclusion of only high-quality patents in the database (see [6]): a consolidation filter which adjusts for differences in patent regimes (a particular problem with applications filed at JPO), and a geographic filter which includes only patent applications filed at all of the three patent offices. While such filters are useful to improve the quality of a patent dataset, application of the geographic filter may considerably restrict variation of the data - a common problem for the assessment of environmental innovation.

Consequently, for this study only patent applications deposited at the European Patent Office (EPO) were included. Through the EPO, the applicant designates as many of the EPO member states for protection as it desires, rather than applying to individual European patent offices among the 32 contributing countries. If the application is successful, the patent is transferred to the individual national patent offices designated for protection in the application. Given that EPO applications are more expensive than applications to national patent offices, inventors typically first file a patent application in their home country, and then apply to the EPO if they desire protection in multiple European countries. However, costs will be much lower by filing with the EPO than if individual applications are made to each country (see [25]). For the purpose of this paper, the EPO data is thus superior to data from national patent offices because the difference in costs provides a quality hurdle which eliminates applications for low-value inventions.

In this paper, the patent count represents the number of patent applications to the EPO, classified by inventor country and priority date. Counts were obtained for all major patenting countries, including non-European countries. While the European market is significant, it is still expected that there will be some bias toward applications from European inventors (see [5]). In the empirical analysis undertaken in this study this bias is addressed through the inclusion of both country fixed effects and a control variable reflecting data on total EPO applications for all technology areas.

Figure 1 shows the total number of patent applications for six renewable energy sources. Geothermal applications fell off dramatically after the late 1970s, while there has been continuous growth in patenting for solar power technologies. Wind power and waste-to-energy exhibit even more rapid growth, particularly since the mid-1990s. There are relatively few patents for wave-tidal and biomass energy, but they have been also increasing.[4]

Figure 2 compares total patent applications for a selection of OECD countries which have exhibited significant levels of innovation. Germany has the highest number of patents, but relative to the US and Japan, this partly reflects the ‘home bias’ in EPO applications. France and the UK both have at least 200 patent applications over the period.

In addition to these countries, there are specific areas in which individual countries have been important innovators for specific renewables. In addition to Germany, Japan and the US (countries which are consistently important for most renewables), other significant innovators for particular sources have included Denmark (wind), Switzerland (solar, geothermal), France (geothermal, biomass, waste), the UK (wave-tide, biomass and waste), Italy (wave-tide), Netherlands (wind), and Sweden (wave-tide).

However, a comparison of patenting activity across countries needs to account for relative differences in the size of countries’ economies. In Table 2, the counts are weighted by country’s GDP to yield a measure of patent intensity. On this basis, a number of smaller countries such as Denmark, Switzerland, Austria, and Sweden achieve the highest innovation output per unit of GDP. Of the three countries which have the highest absolute counts, only Germany continues to rank consistently in the top five. Japan and the US remain first and third among non-EPO countries, with Australia second.

Differences in general propensity to patent may also affect country’s innovative output through its effect on direction of innovation. Since national environmental policies generally complement innovation policies (IPR regimes, etc.), it is the question of direction of

[4] Interestingly, EPO applications for patents in total increased approximately ten-fold over the period in question, while patents for renewables increased just over four-fold. However, in recent years the rate of growth in the area of renewables has been higher than the rate of growth of total EPO applications.

innovation rather than the overall volume of innovation that is central to this paper. In Table 3, the counts are weighted by the volume of country's patenting activity overall (in all technological areas). On this basis, countries such as Denmark, Spain, Australia, Austria and Norway achieve the highest innovation output in renewables. Moreover, several non-EPO countries achieve relatively high innovation output, with Australia, Taiwan and Canada leading the group.

2.2. Public policy as a driver of innovation

In this paper, a database of public policies aimed at developing renewable energy sources compiled at the International Energy Agency (IEA) was used to construct alternative policy indicators. Figure 3 provides a graphical representation of the introduction of alternative policy types in various countries [11].

While different countries have adopted different approaches, the data indicate that different policy types have been introduced with some temporal regularity. First, in the 1970s, a number of countries introduced support for R&D. This was followed by investment incentives (third-party financing, investment guarantees), taxes (exemptions, rebates), and price-support policies (tariffs, guaranteed prices). More recently, a number of countries have introduced quantity obligations, often followed by certificates in which the obligations are tradable across generators.

In addition to differences in terms of the point of incidence of a policy, it is also important to distinguish between policy types according to the precise nature of the instrument being applied, with the following criteria being potentially important determinants of their impacts on innovation: (a) whether the measure is price-based (i.e. taxes, exemptions, subsidies, etc.) or quantity-based (obligations, procurement, etc.); and (b) whether the measure is mandatory or voluntary.

Figure 4 gives a first descriptive indication of the relative importance of public policy factors on patenting (total renewable energy patent applications) in selected countries. There is no obvious correlation between the introduction of different policies and 'spikes' in patent activity, except perhaps the introduction of tariffs in Germany (with some lag), obligations and taxes in Denmark, and investment credits in Japan.

In the estimated empirical models three different sets of policy variables are used based upon the data in Figure 3. First, *binary* variables are constructed for the different policy types, including R&D support, tax measures, investment incentives, differentiated tariffs, voluntary programs, quantity obligations, and tradable certificates. The variables take on a value of 0 prior to introduction of the policy, and 1 thereafter. Second, cluster analysis is applied to construct *clusters* of policy instruments based upon the policy dummies described above. Third, principal component analysis is applied to construct a *composite* policy variable. These policy variables provide a representation of environmental policy framework which is useful for studying the effects of instrument choice on innovation. They complement the range of measures used previously to reflect regulatory stringency (e.g., pollution abatement and control expenditures, inspection frequency, etc.).

2.3. Other explanatory variables

Aside from public policy, there are other important determinants of patenting activity for renewable energy technologies. Patent activity is clearly a result, in part, of national scientific capacity. While it is difficult to get a precise measure of national capacity for innovation, data on national public sector *expenditures on R&D* disaggregated by type of renewable energy were obtained from the IEA's Energy Technology Research and Development Database [14]. The sign on this variable is expected to be positive.

Returns on innovation are affected by the potential market for this innovation. In the case of renewable energy this is best reflected in trends for *electricity consumption*. A growing market for electricity should increase incentives to innovate with respect to renewable energy technologies. Data on household and industry sector electricity consumption was obtained from the IEA's Energy Balances Database [15].

The commercial viability of renewable energy is dependent in large part upon the *price of electricity*. Since the costs of electricity production using renewable energy sources are generally greater than for fossil fuels, an increase in the price of electricity should increase incentives for innovation in the area of renewable energies. Since renewable sources represent a relatively small proportion of total electricity generation, it is assumed that the price of electricity can be considered exogenous. Data on residential and industry end-user prices was obtained from IEA's Energy Prices and Taxes Database [16]. The electricity price variable was constructed by weighting price indices for residential and industrial use by consumption levels. The sign is expected to be positive.

The propensity of inventors from a particular country to patent is likely to change over time, both because different strategies may be adopted to capture the rents from innovation and because legal conditions may change through time. In particular, inventors from non-European countries are less likely to patent at the EPO (home bias). As such a variable was included reflecting overall *EPO patent applications* filed across the whole spectrum of technological areas [22].[5] This variable thus serves as a 'trend' variable in that it controls for the changes in general propensity to patent over time and across countries. The sign is expected to be positive. Table 4 provides basic descriptive statistics for the policy dummies and other explanatory variables.

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[5] The assistance of Hélène Dernis, OECD Directorate for Science, Technology and Industry in the collection of the data is gratefully acknowledged.

3. Empirical model

3.1. Specification

Based on the induced innovation literature (e.g., Binswanger [1]) an empirical model is developed in order to evaluate the effects of environmental policy and market-related determinants on patenting activity in renewable energy technologies. The following reduced-form equation is specified:

$$\begin{aligned}\left(PATENTS_{i,t}\right) = \beta_1\left(POLICY_{i,t}\right) + \beta_2\left(R\&D_{i,t}\right) + \beta_3\left(CONS_{i,t}\right) \\ + \beta_4\left(PRICE_{i,t}\right) + \beta_5\left(EPO_{i,t}\right) + \alpha_i + \varepsilon_{i,t}\end{aligned} \tag{1}$$

where $i = 1,\ldots,26$ indexes the cross-sectional unit (country) and $t = 1978,\ldots,2003$ indexes time. The dependent variable, patenting activity, is measured by the number of patent applications in each of the technological areas of renewable energy (wind, solar, geothermal, wave-tide, biomass, and waste). The explanatory variables include a vector of policy variables ($POLICY_{i,t}$), specific R&D expenditures ($R\&D_{i,t}$), electricity consumption ($CONS_{i,t}$), electricity price ($PRICE_{i,t}$) and total EPO filings ($EPO_{i,t}$). Fixed effects (α_i) are introduced to capture unobservable country-specific heterogeneity. All the residual variation is captured by the error term ($\varepsilon_{i,t}$).

3.2. Estimation method

A negative binomial model is used to estimate the equation in (1). Count data models, such as the Poisson and negative binomial, have been suggested for estimating the number of occurrences of an event, or event counts (Maddala [21] p. 51; Cameron and Trivedi [3]). In this paper, an event count is the number of patent applications deposited at the EPO. Formally, an event count is defined as a realization of a nonnegative integer-valued random variable. We suppose that the number of patents ($PATENTS_{i,t}$) follows a negative binomial distribution, i.e. the patent count is modeled as a Poisson process with an unobserved error parameter (u) introducing heterogeneity in the variance, and an intensity parameter (μ) explained (in log) by a vector of explanatory variables (X):

$$PATENTS_{i,t} \rightarrow NegBin(\mu;\sigma)\text{, that is} \tag{2}$$

$$PATENTS_{i,t} \rightarrow Poisson(\mu)\text{ with}\begin{cases} \mu = \tilde{\mu}\cdot u = \exp(\beta X) \\ u \rightarrow \Gamma\left(\dfrac{1}{\sigma};\dfrac{1}{\sigma}\right) \end{cases} \tag{3}$$

Therefore, $E\left(PATENTS_{i,t}\right)=\mu$ and $V\left(PATENTS\right)=\mu\left(1+\sigma^2\mu\right)$. It follows that as $\sigma^2 \rightarrow 0$ the model converges to the Poisson distribution with intensity μ. Maximum likelihood method is used to estimate the parameters.[6]

4. Empirical results

Using data on patent counts the determinants of patenting activity for renewable energy are assessed. In total, a panel of 26 countries and 26 years (1978-2003) is available, but the presence of missing observations and all-zero outcomes of patent count for some countries and some technologies reduce the size of the samples to between 400 and 500 in most models estimated.[7]

Several alternative specifications of the model were estimated. Table 5 presents the estimation results when all policy dummies are included in the regressions, except the dummy for R&D programs (due to correlation with the intercept).[8] The coefficient of electricity price has a positive sign in every equation. It is statistically significant at the 1% and 5% levels in

[6] For further details on negative binomial models, see [3, 9].

[7] The variation in the number of observations used in the regression models is due (a) to a small number of missing values in the specific R&D variable, but (b) is mostly caused by all-zero outcomes of patent counts leading to data for individual countries being dropped from the regression.

[8] Most countries introduced R&D support programs as early as the 1970s. Since our data begin in 1978, this policy variable is (almost perfectly) correlated with the intercept (fixed effects).

the solar and biomass equations, respectively. This suggests that higher electricity prices provide an incentive for increased patenting activity in the solar and biomass technologies. The results also suggest that renewable-specific R&D spending is a significant determinant of patenting in renewable energy overall, and especially in wind and wave-tide technologies.[9] The estimated coefficient of electricity consumption is negative in every equation and statistically significant only in the waste-to-energy equation. One possible explanation of the negative sign could be related to the fact that policies aimed at renewables are often concurrent with policies aimed at encouraging energy efficiency. The estimated coefficient of the total number of EPO filings is positive and statistically significant at the 1% level in every technological area, suggesting that a part of the variation in patenting activity in renewable energies is due to changes in the general propensity to patent.[10]

The results on the policy dummies suggest that public policy plays a significant role in inducing innovations in renewable energies. For wind technology and for renewable energies overall, tax measures, obligations, and tradable certificates are statistically significant (at the 5% level and higher) policy instruments. However, the efficacy of alternative policy instruments in inducing innovations varies by renewable energy source. For example, the variable reflecting the provision of investment incentives is statistically significant for innovations in solar power. Investment incentives, as well as voluntary programs, are statistically significant policy instruments for waste-to-energy incineration. Finally, putting in place preferential tariff structures, and to a lesser extent tax measures, are statistically significant for patent activity with respect to biomass energy.

[9] The negative and significant coefficient in the biomass equation is counter-intuitive. It is not statistically significant in any of the alternative models.

[10] The coefficient is insignificant in the wave-tide equation. This is most likely due to the low variation in wave-tide patent counts.

There are two concerns related to including all policy dummies in the regression. First, correlation among the dummies may cause multicollinearity problems. In particular, dummies representing investment incentives, tax measures, and tariffs are correlated (correlation coefficient 0.53 and 0.57).[11] Similarly, obligations and tradable permits are correlated (0.48).[12] Second, it is possible that there are interaction effects among alternative policy instruments (e.g., investment incentives for capital goods may be accompanied by preferential tax rates for final goods). In an alternative specification, the individual policy dummies were included one-by-one in the regressions. The results (not reported) suggest that the key qualitative findings remain unaffected. Policies which are found to be statistically significant when all dummies are included in the regression remain statistically significant, and with the same signs, when they are included separately.

Including all policy dummies may cause multicollinearity. However, including policy dummies one-by-one may lead to incorrect conclusions due to omitted variables and possible interaction effects among the different policies. Two approaches are adopted in order to address these issues: (a) clusters of policy variables are developed by clustering similar policies in groups (to address possible multicollinearity and classification error); and (b) a composite policy variable is constructed using principal component analysis. This latter variable also allows assessing dynamic impacts in a more satisfactory manner.

Hierarchical cluster analysis is a method that can be applied in order to reduce a set of correlated variables into a smaller number of cluster components, with little loss of information. This allows for the identification of 'clusters' of policy instruments which are then used as explanatory variables. The variables are clustered in such a manner that variables

[11] The negative and statistically significant coefficient of tariffs in the wind energy equation could be considered a consequence of multicollinearity. However, it remains robust even if the tax dummy is dropped.

within one group are correlated, but uncorrelated with variables in the other groups (see, for example, [10]).

The choice of the number of clusters to retain must be made *ad hoc*. We chose to use the clustering of policy variables which yields three conceptually distinct groups of policies: (1) price-based policy instruments (including investment incentives, tax measures, and tariffs), (2) voluntary programs; and (3) quantity-based policy instruments (obligations and tradable certificates). We note that the dummy variable for voluntary programs is approximately equally correlated with the remaining two clusters. The estimated scoring coefficients were used to compute the component scores for each cluster.

Table 6 shows the regression estimates when policy variables are divided into three clusters. The estimated coefficients on the key regressors remain close to those obtained with individual policy variables. The results suggest that innovation effects of alternative policy instruments differ by the type of renewable energy technology. The evidence of differential policy effectiveness is particularly straightforward for wind, solar, biomass and waste-to-energy technologies. For wind power, the coefficient of quantity-based policy instruments (cluster 3) is positive and statistically significant at the 1% level. For solar, biomass and waste energy, the coefficients of price-based policy instruments (cluster 1) are positive and statistically significant at the 1% level. In addition, the coefficient of voluntary programs (cluster 2) in the waste equation is positive and statistically significant at the 5% level or higher. For wave-tide energy, none of the policy cluster variables are significant. Overall, for all renewables, the innovation effects of both price- and quantity-based instruments are highly statistically significant. Voluntary approaches seem to play a minor role.

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[12] In spite of this, we get a positive and significant coefficient even for tradable certificates. This suggests that allowing obligations to be traded provides a strong incentive for innovation.

As an alternative to cluster analysis, principal components analysis (PCA) was used to reduce the dimensionality of the set of individual policy variables. PCA transforms a number of correlated variables into a (smaller) number of uncorrelated variables (principal components). The first principal component accounts for as much of the variability in the data as possible, and in descending order each succeeding component accounts for as much of the remaining variability as possible (see, for example, [10]).

In this study, we chose to keep only the first principal component for two reasons: (a) it explains a good share of the variance (the inertia criterion), and (b) it is a true composite variable since all variables have a positive sign, while the second principal component opposes two clusters. In the first principal component, the estimated coefficients of all the policies are positive which means that the variable captures national tendencies to develop environmental policies to support renewable energy, but does not significantly disentangle policy types from each other. As a result, this variable does not help to draw conclusions on the efficacy of the different kinds of policies, but is a good indicator of the intensity of environmental regulation. The advantage of this approach is that the composite variable addresses the problem of multicollinearity, as well as potential interaction effects among policy instruments. Moreover, it can be lagged to analyze dynamic issues.

Table 7 presents the estimation results using the composite policy variable. The coefficients remain close to those obtained previously. The estimated coefficient of the composite policy variable is positive and statistically significant at the 5% level in every equation. This suggests that public policy is a significant driver of innovative activity in renewable energy overall, as well as for specific renewable energy sources.

Using the same model, the dynamic aspects of innovative activity were analyzed using 1- to 4-year lags. In addition, for the composite policy variable a 1-year leap was tested since inventors may anticipate the introduction of policies in support of the use of renewable energy sources. The coefficients remain robust to such changes. The coefficient of the composite policy variable is most significant with lags between 0 and 2 years, suggesting that the impact of public policy on patenting is rather fast. This is consistent with the findings in Popp [23] who found that energy patents followed energy price changes with little lag.

Finally, there is a concern that variables such as electricity consumption, EPO patent filings, and fixed effects may all, to a certain extent, reflect the same national tendencies. Including all of these variables in a regression may cause 'over-fitting' of the model. However, when country-specific fixed effects are dropped from the regression the key qualitative findings remain robust.

In sum, the major finding of this paper is that different policies have a greater effect on patent activity for some renewable energy sources than for others. In particular, quantity-based policy instruments such as obligations and tradable certificates are most effective in inducing innovations in wind power technology. Price-based instruments such as investment incentives, tax measures and tariffs are most effective in encouraging innovation in solar, biomass, and waste-to-energy technologies. Voluntary programs are not significant, except perhaps in the case of waste. These findings are robust to alternative policy measures and model specifications.[13]

Interpretation of these results is complicated by the fact that it is difficult to clearly distinguish the relevance of the policy variable by type of renewable. For instance, some of the measures reflected in the IEA database from which the policy variables are derived only relate to a sub-set of renewable energy sources, and thus the non-significance of a particular policy type for a particular type of renewable energy may relate to this factor, rather than to

[13] In addition to the models described above, random effects negative binomial models were estimated and the results confirm robustness of the major findings.

its efficacy or inefficacy.[14] However, there are good economic reasons to explain some of the findings. For instance, the significance of investment incentives for solar energy is likely due to the fact that solar installations are the most capital intensive (in terms of investment costs required per kW) among the studied renewable energy technologies (see, for example, [7] p. 51). The relative importance of voluntary programs for waste may be explained by the importance of the public sector in waste management, perhaps obviating the need for mandatory regulations. The importance of obligations and tradable certificates in the case of wind might be explained by their more recent application, co-existing with significant dynamic development of wind energy technologies. However, further work is required to support (or reject) these hypotheses.

5. Conclusions

This paper examines the effects of public policies on innovation in the area of renewable energies in a cross-section of OECD countries over the period 1978-2003. Patent counts are used as the most suitable proxy for innovation and the effects of a wide variety of different policy types are assessed.

The descriptive data indicates rapid growth in wind and waste-to-energy patent activity, particularly since the mid-1990s. There continues to be innovation with respect to solar energy, perhaps reflecting the opportunities presented by developments in concentrating solar power. Innovation with respect to biomass and wave-tide energy are also growing, but from a very low base. And finally, there appears to have been little innovation in the area of geothermal energy since the 1970s.

[14] As a counter-example, the models were estimated for a subsample of data (e.g., excluding Denmark from the wind energy equation) and the results confirm our qualitative findings.

At the same time, significant changes have occurred in the public policy framework put in place to support renewable energy. Initially R&D programs were introduced in a number of countries. This was followed by investment incentives, and later, tax incentives and preferential tariffs. Next, voluntary programs were developed. More recently, quantitative obligations, and finally tradable certificates, have been applied.

Our empirical results indicate that public policy has had a very significant influence on the development of new technologies in the area of renewable energy. Using the composite policy variable, statistical significance at the 1% level is found for all renewable energy sources, except biomass (where it is significant at the 5% level). However, the results suggest that instrument choice also matters. With respect to patent activity in renewable energy overall, taxes, obligations and tradable certificates are the only statistically significant policy instruments.

Interestingly however, source-specific models indicate that there is variation in the effects of instrument type on different renewables. Broadly, investment incentives are effective in supporting innovation in solar and waste-to-energy technologies, tariff structures are important for biomass, obligations and tradable certificates (which are closely related) support wind technology, and voluntary programs are helpful in inducing waste-to-energy innovations. Overall, only tax incentives have wide influence on innovation for a number of renewable energy sources.

While the results are interesting and robust, further work in the area could be undertaken. This includes accounting for variation in natural conditions as determinants of patenting in renewable energy technologies, and better examination of dynamic issues, with a particular focus on addressing the possible simultaneity of R&D expenditures and patenting activity.

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Table 1. International patent classification (IPC) system

Subdivision	Number of subdivisions	Example of an IPC code	
		Symbol	Title
Section	8	F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
Subsection	21	F0	Engines or Pumps
Class	120	F03	Machines or Engines for Liquids; Wind, Spring, or Weight Motors; Producing Mechanical Power or a Reactive Propulsive Thrust, Not Otherwise Provided For
Subclass	628	F03G	Spring, Weight, Inertia, or Like Motors; Mechanical-Power-Producing Devices or Mechanisms, Not Otherwise Provided For; or Using Energy Sources Not Otherwise Provided For
Main group	ca. 6,900	F03G 6	Devices For Producing Mechanical Power From Solar Energy….
Subgroup	ca. 62,100	F03G 6/08	With Solar Energy Concentrating Means

Table 2. Number of EPO Patent Applications in Renewable Energy Technologies per Unit of GDP (1978-2003)

	Wind	Solar	Geo-thermal	Wave-tide	Biomass	Waste	All renewables	1978-2003 Total
AT	2.54	**6.55**	**6.76**	0.85	**1.48**	**5.07**	**23.24**	110
AU	0.49	**4.82**	1.08	0.49	0.29	1.08	8.26	84
BE	**4.17**	2.26	1.91	0.17	0.70	1.39	10.60	59
BR	0.00	0.00	0.00	0.04	0.13	0.04	0.22	5
CA	0.88	0.82	0.35	0.12	0.18	1.76	4.05	66
CH	2.66	**11.07**	**6.97**	0.41	0.82	**6.97**	**28.90**	138
DE	**8.14**	**7.51**	**4.10**	0.41	**2.07**	**6.90**	**28.99**	1285
DK	**27.16**	3.70	1.54	**3.40**	**1.23**	**5.86**	**42.91**	137
ES	1.49	1.25	0.12	0.71	0.00	0.12	3.69	61
FI	2.55	3.27	1.09	0.73	0.00	4.73	12.37	34
FR	1.42	1.51	2.23	0.27	**1.27**	1.48	8.15	267
GB	1.65	1.10	0.78	0.81	**4.59**	1.62	10.41	322
GR	1.27	1.27	0.00	0.51	0.00	0.51	3.55	14
HU	0.68	1.71	1.71	0.68	0.34	0.00	5.13	15
IE	2.95	2.36	0.00	**2.95**	0.00	0.00	8.27	14
IT	0.97	1.10	0.75	0.50	0.25	1.06	4.63	148
JP	0.64	2.68	0.64	0.16	0.29	**5.00**	9.41	656
KR	0.66	0.08	0.00	0.08	0.08	0.33	1.23	15
NL	**5.74**	**4.53**	**2.76**	0.55	0.99	3.42	17.78	161
NO	2.51	2.20	1.57	**3.76**	0.31	0.94	11.29	36
NZ	0.59	0.00	0.59	0.59	0.59	1.77	4.13	7
PL	0.11	0.23	0.23	0.00	0.11	0.11	0.80	7
PT	1.37	1.37	0.00	0.27	0.00	0.27	3.29	12
SE	**6.86**	3.14	**5.69**	**3.14**	0.78	2.16	**21.76**	109
TW	0.70	0.56	0.14	0.14	0.00	0.70	2.25	16
US	0.52	0.81	0.51	0.28	1.19	1.60	4.92	925
Total	942	1079	616	216	566	1285	4702	

Note: The table gives the annual mean number of patent applications for renewables during 1978-2003, classified by inventor country, and normalized by country's GDP (in trillions of US dollars, using 2000 prices and PPP). Countries in the top five for each renewable are indicated in bold face.

Table 3. Number of EPO Patent Applications in Renewable Energy Technologies, Normalized by Overall Patenting Activity (1978-2003)

	Wind	Solar	Geo-thermal	Wave-tide	Biomass	Waste	All renewables
AT	0.67	**1.75**	**1.76**	0.22	**0.39**	**1.33**	**6.13**
AU	0.39	**3.75**	**0.86**	**0.42**	0.25	0.84	**6.50**
BE	**1.31**	0.69	0.61	0.06	0.17	0.44	3.28
CA	0.73	0.68	0.30	0.08	0.16	**1.38**	3.34
CH	0.29	1.15	**0.75**	0.03	0.08	0.74	3.03
DE	1.10	1.01	0.55	0.05	0.27	0.93	3.91
DK	**7.65**	1.03	0.44	**0.92**	**0.35**	**1.64**	**12.04**
ES	**2.62**	**2.29**	0.24	**1.31**	0.00	0.24	**6.70**
FI	0.47	0.60	0.20	0.13	0.00	0.85	2.25
FR	0.37	0.39	0.60	0.07	**0.33**	0.39	2.15
GB	0.51	0.35	0.24	0.25	**1.46**	0.50	3.32
IT	0.53	0.61	0.42	0.28	0.14	0.59	2.57
JP	0.16	0.65	0.16	0.04	0.07	**1.21**	2.29
KR	0.62	0.08	0.00	0.08	0.08	0.31	1.16
NL	1.11	0.88	0.55	0.10	0.20	0.68	3.52
NO	**1.68**	**1.41**	**1.01**	**2.39**	0.20	0.61	**7.31**
SE	1.05	0.49	**0.90**	**0.49**	0.11	0.31	3.36
TW	**1.48**	**1.19**	0.30	0.30	0.00	**1.48**	4.75
US	0.21	0.33	0.21	0.11	**0.48**	0.66	2.01

Note: The table gives the total number of patent applications for renewables during 1978-2003, classified by inventor country, and normalized by country's total number of patent applications in all technology areas (in millions of EPO filings). Only countries with a minimum of 2,600 EPO patent filings overall (25th percentile) are included in the table. Countries in the top five for each renewable are indicated in bold face.

Table 4. Descriptive statistics of explanatory variables (1978-2003)

Variable	Obs.	Mean	Std. Dev.
Policy dummies			
R&D support	676	0.8432	0.3639
Investment incentives	676	0.4127	0.4927
Tax measures	676	0.2722	0.4454
Tariffs	676	0.3151	0.4649
Voluntary programs	676	0.1050	0.3068
Obligations	676	0.2130	0.4097
Tradable certificates	676	0.0577	0.2333
Technology-specific R&D expenditures (10e9 USD, 2005 prices and PPP)			
Wind R&D	478	0.0063	0.0140
Solar R&D	479	0.0237	0.0702
Ocean R&D	477	0.0016	0.0077
Bioenergy R&D	478	0.0086	0.0157
Renewables R&D	482	0.0481	0.1261
Electricity price (US$/unit, using PPP)	583	0.0849	0.0345
Electricity consumption (millions GWh)	624	0.0158	0.0323
Total EPO patent filings (thousands)	673	2.3964	4.9912

Table 5. Estimated coefficients of the negative binomial fixed effects models with individual policy variables

	Wind	Solar	Wave-tide	Biomass	Waste	All renewables
Electricity price	3.187	18.718**	2.181	14.769*	2.957	0.994
	(0.488)	(0.000)	(0.737)	(0.035)	(0.469)	(0.683)
Specific R&D expenditures	17.789**	0.966	13.889*	-7.473*	0.479	1.063**
	(0.000)	(0.153)	(0.038)	(0.043)	(0.249)	(0.000)
Electricity consumption	-9.630	-8.060	-15.200	-15.900	-13.600**	-5.030
	(0.123)	(0.141)	(0.335)	(0.115)	(0.005)	(0.162)
Total EPO filings	0.106**	0.074**	0.069	0.121**	0.122**	0.081**
	(0.001)	(0.000)	(0.188)	(0.001)	(0.000)	(0.000)
Policy dummies						
Investment incentives	-0.214	0.626**	-0.097	-0.176	0.723**	0.145
	(0.292)	(0.000)	(0.740)	(0.481)	(0.000)	(0.146)
Tax measures	0.371*	-0.021	0.538	0.500*	0.083	0.235*
	(0.040)	(0.881)	(0.089)	(0.050)	(0.578)	(0.017)
Tariffs	-0.434	0.116	0.015	0.783**	0.192	-0.043
	(0.053)	(0.547)	(0.964)	(0.000)	(0.336)	(0.717)
Voluntary programs	0.089	0.020	-0.066	-0.240	0.334*	0.119
	(0.718)	(0.898)	(0.863)	(0.307)	(0.043)	(0.318)
Obligations	1.157**	0.181	0.472	-0.212	0.045	0.384**
	(0.000)	(0.214)	(0.155)	(0.372)	(0.761)	(0.001)
Tradable certificates	0.485*	0.064	0.192	-0.081	0.245	0.305*
	(0.034)	(0.718)	(0.597)	(0.798)	(0.159)	(0.016)
Intercept	-0.214	0.267	15.394	1.012	0.372	0.995**
	(0.598)	(0.685)	(0.992)	(0.371)	(0.509)	(0.000)
Observations	452	427	450	334	441	463
Log-likelihood	-477.65	-488.20	-238.56	-289.98	-482.30	-926.40
Wald chi2	250.63	209.21	33.22	80.03	337.01	398.90
(Prob > chi2)	(0.000)	(0.000)	(0.000)	(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 patent count (successful and unsuccessful applications) in a given technological area. Intercept represents the average value of the country-specific fixed effects. Results for geothermal energy are not reported because they represent a significant outlier.

Table 6. Estimated coefficients of the negative binomial fixed effects models with clusters of policy variables

	Wind	Solar	Wave-tide	Biomass	Waste	All renewables
Electricity price	-2.465	20.112**	1.787	12.459	5.013	0.094
	(0.547)	(0.000)	(0.775)	(0.094)	(0.190)	(0.968)
Specific R&D expenditures	16.944**	1.100	15.028*	-6.705	0.490	1.069**
	(0.000)	(0.091)	(0.023)	(0.067)	(0.245)	(0.000)
Electricity consumption	-11.551	-7.088	-13.868	-9.658	-11.160*	-5.825
	(0.073)	(0.175)	(0.361)	(0.253)	(0.011)	(0.109)
Total EPO filings	0.121**	0.075**	0.064	0.094**	0.116**	0.087**
	(0.000)	(0.000)	(0.199)	(0.004)	(0.000)	(0.000)
Policy clusters						
Policy cluster 1 (incl. inv, tax, tar)	-0.018	0.614**	0.419	1.053**	0.728**	0.310**
	(0.941)	(0.000)	(0.216)	(0.000)	(0.000)	(0.005)
Policy cluster 2 (incl. vol)	-0.006	0.030	-0.075	-0.127	0.366*	0.072
	(0.980)	(0.843)	(0.842)	(0.573)	(0.031)	(0.521)
Policy cluster 3 (incl. oblig, trad)	1.632**	0.209	0.665	-0.508	0.219	0.639**
	(0.000)	(0.184)	(0.055)	(0.074)	(0.184)	(0.000)
Intercept	-0.132	0.006	13.727	0.346	-0.027	1.029**
	(0.726)	(0.991)	(0.982)	(0.646)	(0.955)	(0.000)
Observations	452	427	450	334	441	463
Log-likelihood	-483.95	-493.77	-239.69	-293.72	-487.22	-927.89
Wald chi2	216.29	200.81	31.89	64.08	297.49	393.14
(Prob > chi2)	(0.000)	(0.000)	(0.000)	(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 patent count (successful and unsuccessful applications) in a given technological area. The coefficient on the intercept represents the average value of the country-specific fixed effects. Policy cluster 1 includes investment incentives, tax measures, and tariffs; Policy cluster 2 includes voluntary programs; Policy cluster 3 includes obligations and tradable certificates.

Table 7. Estimated coefficients of the negative binomial fixed effects models with a composite policy variable

	Wind	Solar	Wave-tide	Biomass	Waste	All renewables
Electricity price	-4.679	19.671**	1.442	12.337	4.813	0.110
	(0.265)	(0.000)	(0.818)	(0.080)	(0.210)	(0.963)
Specific R&D expenditures	15.024**	0.956	13.824*	-7.415	0.483	1.088**
	(0.000)	(0.155)	(0.029)	(0.057)	(0.257)	(0.000)
Electricity consumption	-15.010**	-6.070	-17.008	-0.918	-9.462*	-7.669*
	(0.006)	(0.210)	(0.249)	(0.894)	(0.024)	(0.021)
Total EPO filings	0.106**	0.064**	0.055	0.063*	0.117**	0.087**
	(0.000)	(0.000)	(0.251)	(0.025)	(0.000)	(0.000)
Composite policy variable	0.366**	0.162**	0.226**	0.097*	0.223**	0.202**
	(0.000)	(0.000)	(0.000)	(0.047)	(0.000)	(0.000)
Intercept	0.168	0.275	17.660	0.276	0.251	1.284**
	(0.660)	(0.617)	(0.968)	(0.675)	(0.595)	(0.000)
Observations	452	427	450	334	441	463
Log-likelihood	-495.04	-495.35	-240.17	-299.37	-488.16	-930.27
Wald chi2	151.10	200.20	30.53	47.48	307.67	369.11
(Prob > chi2)	(0.000)	(0.000)	(0.000)	(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 patent count (successful and unsuccessful applications) in a given technological area. The coefficient on the intercept represents the average value of the country-specific fixed effects.

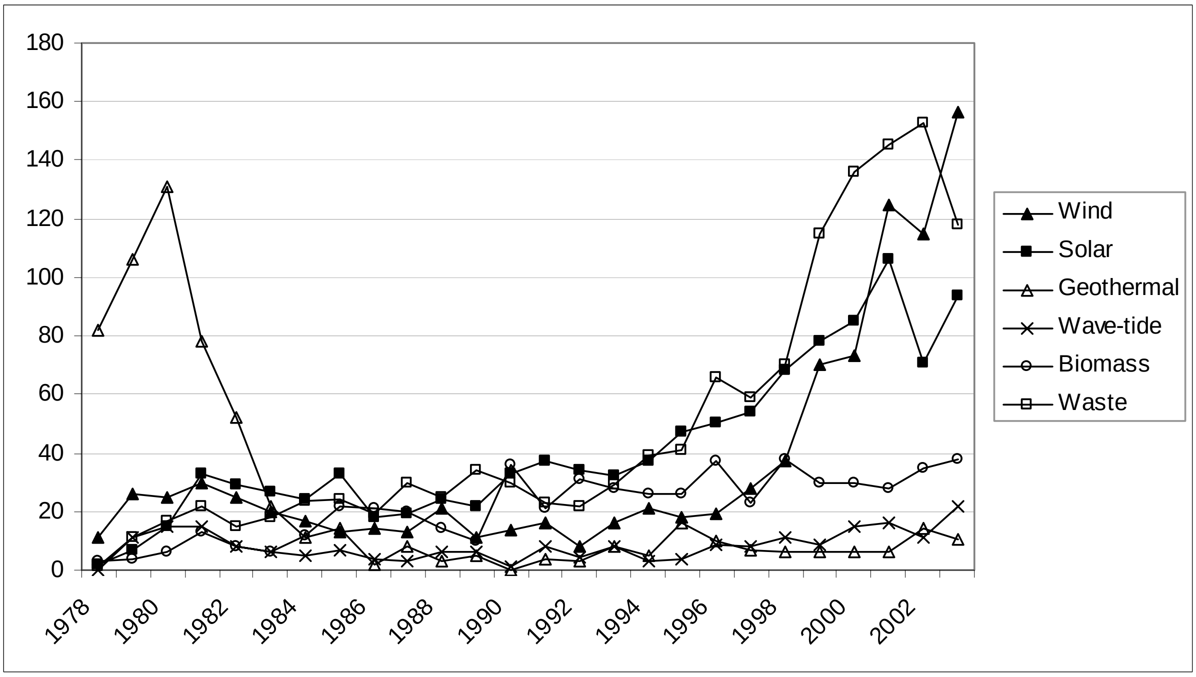


Figure 1. Number of EPO patent applications for renewables by type of technology

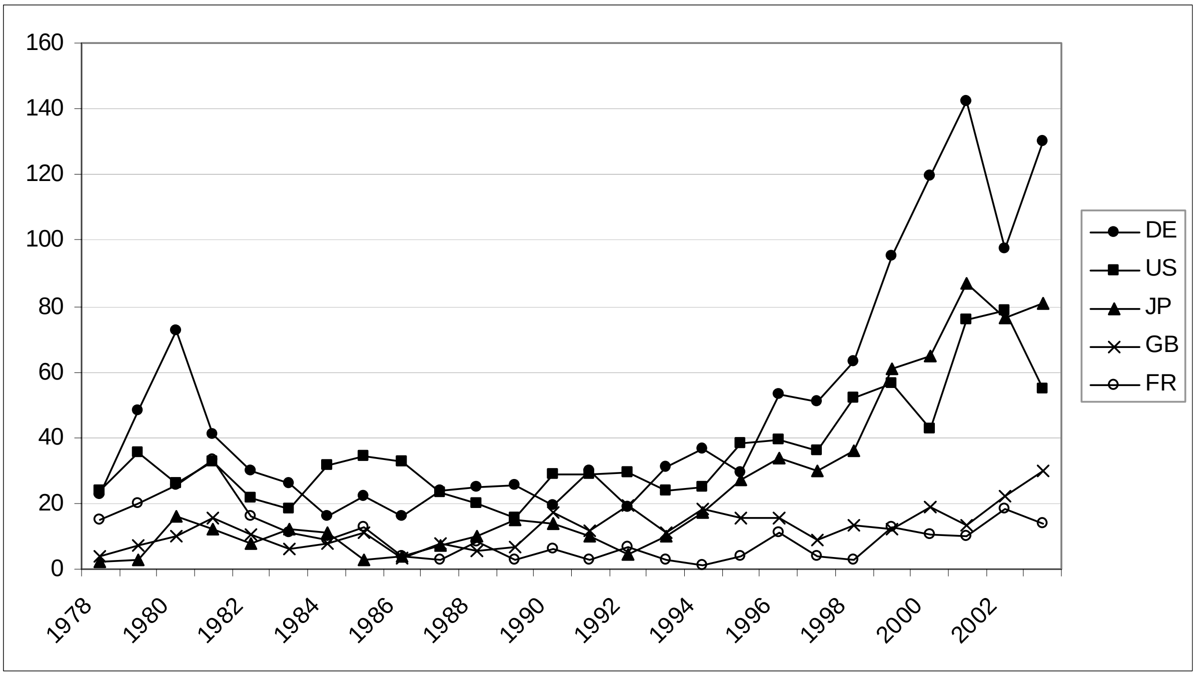
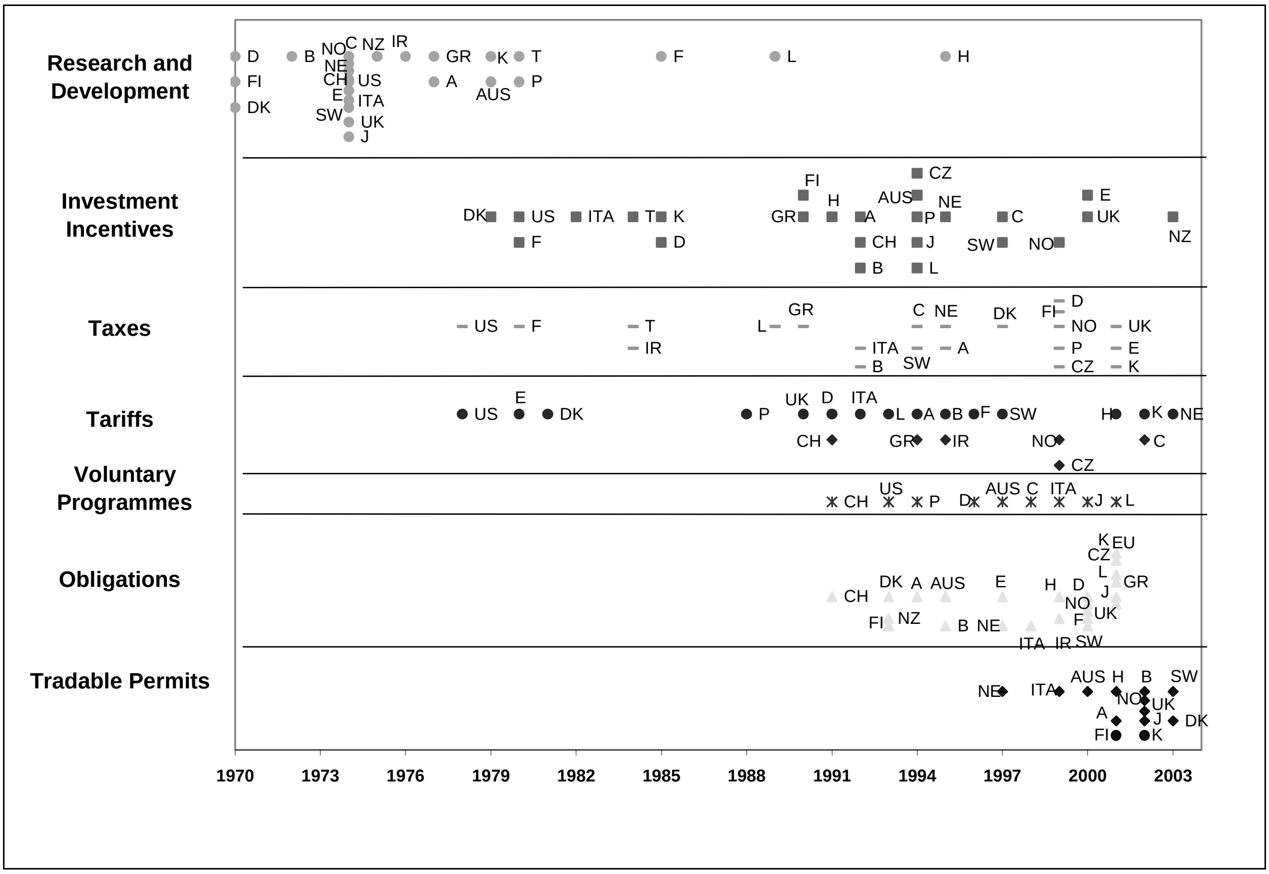


Figure 2. Number of EPO patent applications for renewables by country

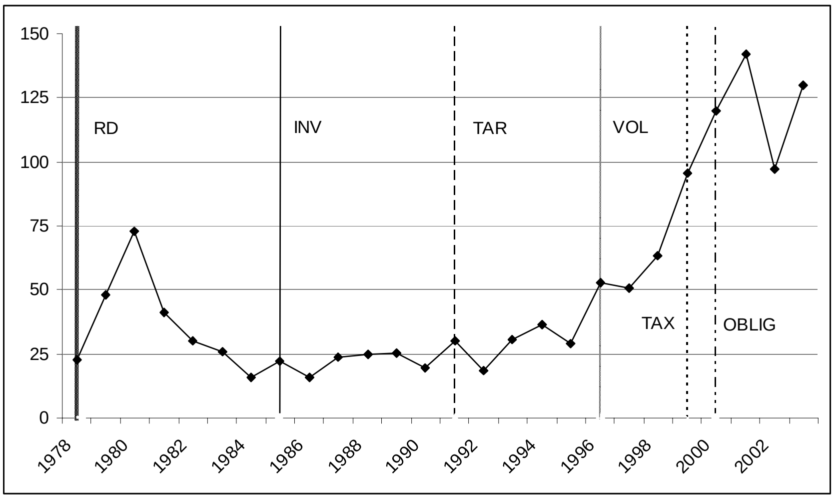


Source: IEA (2004)[15]

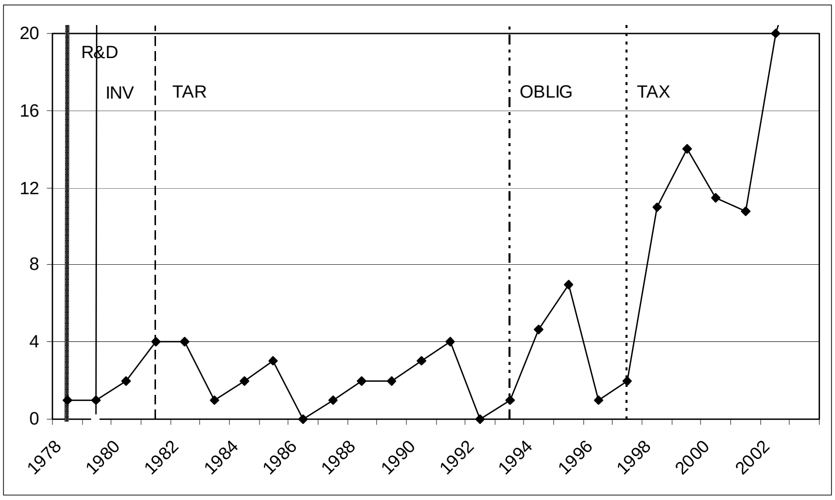
Figure 3. Introduction of renewable energy policies by type in OECD countries[16] (1973-2003)

[15] An updated version of the table published in IEA (2004) was kindly provided by Piotr Tulej of the International Energy Agency.

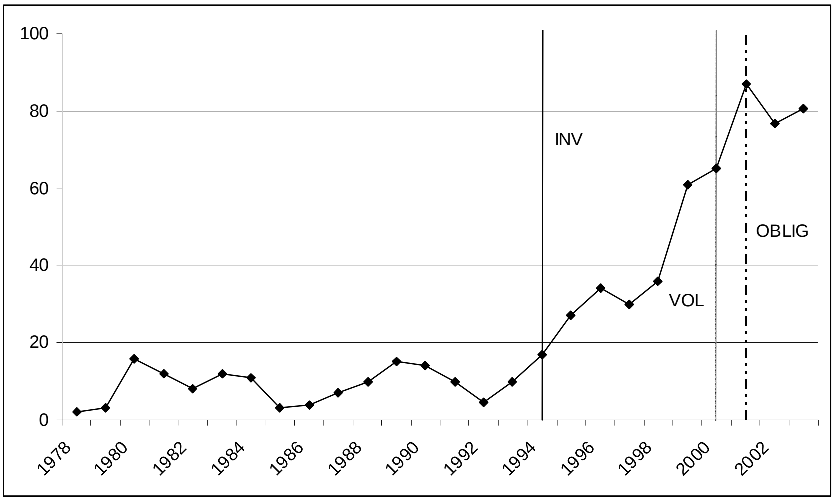
[16] AUS - Australia, C - Canada, FI - Finland, GR - Greece, ITA - Italy, L - Luxembourg, NO - Norway, SW - Sweden, UK - United Kingdom, A - Austria, CZ - Czech Rep., F - France, H - Hungary J - Japan, NE - Netherlands, P - Portugal, CH - Switzerland, US - United States, B - Belgium, DK - Denmark, DE - Germany, IR - Ireland, K-Korea, NZ - New Zealand, E - Spain, T - Turkey.



GERMANY



DENMARK



JAPAN

Figure 4. Relationship between point of introduction of policies and patent counts[17]

[17] RD = Research and Development; INV=Investment Incentive; TAR=Tariff Structure; VOL=Voluntary Agreement; OBLIG=Obligation or Quota; TAX=Tax Incentive

APPENDIX

Table A1. IPC codes for renewable energy technologies

WIND	**Class**	**Sub-Classes**
Wind motors with rotation axis substantially in wind direction	F03D	1/00-06
Wind motors with rotation axis substantially at right angle to wind direction	F03D	3/00-06
Other wind motors	F03D	5/00-06
Controlling wind motors	F03D	7/00-06
Adaptations of wind motors for special use;	F03D	9/00-02
Details, component parts, or accessories not provided for in, or of interest apart from, the other groups of this subclass	F03D	11/00-04
Electric propulsion with power supply from force of nature, e.g. sun, wind	B60L	8/00
Effecting propulsion by wind motors driving water-engaging propulsive elements	B63H	13/00
SOLAR		
Devices for producing mechanical power from solar energy	F03G	6/00-08
Use of solar heat, e.g. solar heat collectors	F24J	2/00-54
Machine plant or systems using particular sources of energy - sun	F25B	27/00B
Drying solid materials or objects by processes involving the application of heat by radiation - e.g. sun	F26B	3/28
Semiconductor devices sensitive to infra-red radiation - including a panel or array of photoelectric cells, e.g. solar cells	H01L	31/042
Generators in which light radiation is directly converted into electrical energy	H02N	6/00
Aspects of roofing for the collection of energy – i.e. solar panels	E04D	13/18
Electric propulsion with power supply from force of nature, e.g. sun, wind	B60L	8/00
GEOTHERMAL		
Other production or use of heat, not derived from combustion - using natural or geothermal heat	F24J	3/00-08
Devices for producing mechanical power from geothermal energy	F03G	4/00-06
Electric motors using thermal effects	H02N	10/00
WAVE/TIDE		
Adaptations of machines or engines for special use - characterized by using wave or tide energy	F03B	13/12-24
Mechanical-power producing mechanisms - ocean thermal energy conversion	F03G	7/05
Mechanical-power producing mechanisms - using pressure differentials or thermal differences	F03G	7/04
Water wheels	F03B	7/00
BIOMASS		
Solid fuels based on materials of non-mineral origin - animal or vegetable	C10L	5/42-44
Engines operating on gaseous fuels from solid fuel - e.g. wood	F02B	43/08
Liquid carbonaceous fuels - organic compounds	C10L	1/14
Anion exchange - use of materials, cellulose or wood	B01J	41/16
WASTE		
Solid fuels based on materials of non-material origin - refuse or waste	C10L	5/46-48
Machine plant or systems using particular sources of energy - waste	F25B	27/02
Hot gas or combustion - Profiting from waste heat of exhaust gases	F02G	5/00-04
Incineration of waste - recuperation of heat	F23G	5/46
Plants or engines characterized by use of industrial or other waste gases	F012K	25/14
Prod. of combustible gases - combined with waste heat boilers	C10J	3/86
Incinerators or other apparatus consuming waste - field organic waste	F23G	7/10
Manufacture of fuel cells - combined with treatment of residues	H01M	8/06

Capturing Nanotechnology's Current State of Development via Analysis of Patents

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This study aims at identifying major technological domains in nanotechnology based on analyses of patent applications. Patent applications designated to the European Patent Office were intensively analysed. Exogenous and endogenous approaches were applied. In the exogenous approach, nanotechnology patent applications were classified into six large domains with the help of the main International Patent Classification. In the endogenous approach, maps of patent applications were generated using linkages among nanotechnology patent applications which were observed in forms of citations in the patent applications. Approximately 4 300 nanotechnology patent applications were mapped and fifteen domains of nanotechnology patent applications were found in 2003. The domains cover a wide range of application fields; they are domains related to measurement and manufacturing; electronics; optoelectronics; biotechnology; and nano materials. It was found that the combination of exogenous and endogenous approaches provides us with rich information on the domains. Maps in several reference years registered the evolution of nanotechnology, where the breadth of application fields has been broadening over time. Direct and indirect knowledge flows among different domains of nanotechnology are seemingly small at the present. Each domain of nanotechnology is likely pushing the technological frontier within its own domain. The exception is sensing and actuating technologies on the nanometre scale. Direct and indirect knowledge flows to/from this domain describe their vital role in nanotechnology.

1 . Main part of this study was conducted in collaboration with Teruo OKAZAKI when the author was in the OECD.

IP and performance: an empirical analysis of the UK's small and medium sized enterprises*

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Harris Manchester College, Oxford University and
Oxford Intellectual Property Research Centre

PATSTAT Conference, Venice, October 2007

* Invaluable research assistance was provided by Christian.Helmers@wolfson.ox.ac.uk. The research was supported by the UK IP Office and UK Trade and Investment.

Research project outline

- Map IP activity of British SME’s using FAME data
- FAME data (all UK registered firms)
  - 2.1 million active companies (all sizes)
  - 0.9 million ‘inactive’ (dissolved, liquidated, non-trading, receivership)
- Match current and previous firm names to IP applicant
- Consider UK patents, UK trade marks, EPO patents (publications) Community trade marks (registrations)
- Main period 2001 to 2005 (but have more data for patents)

Definitions

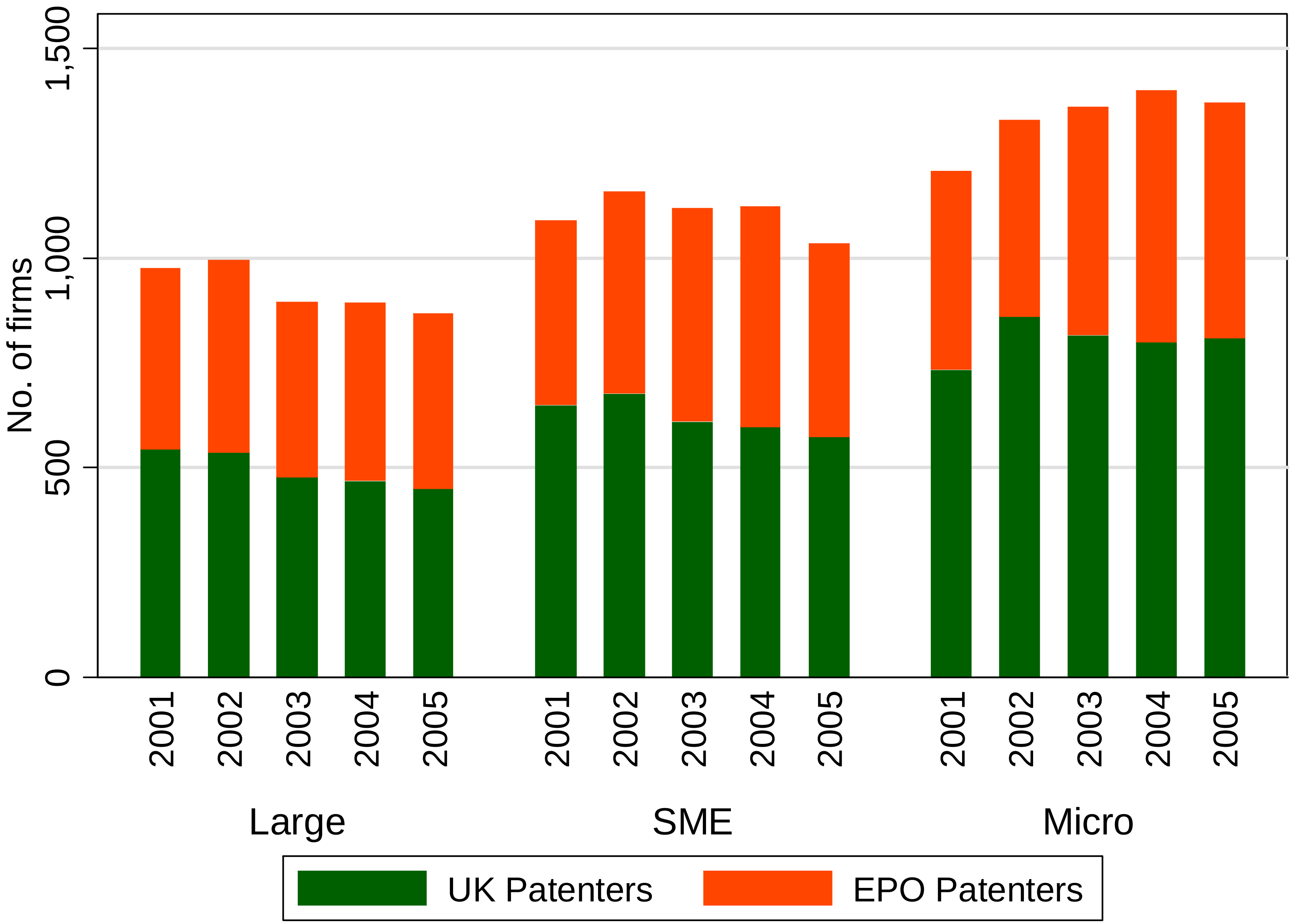
- Small and medium enterprises (SMEs)
  - Euro 2m < **total assets** < 43 million
  - 10 < employment < 250
  - Euro 10m < turnover < 50m
- Subsidiaries of large firms not SMEs
- Around 140k in 2001
- Micro firms have assets < 2m or missing (2 million)
- Large firms have assets >43m Euro (107k)
- Oxford Firm Level IP (OFLIP) data

Summary of matching outcomes

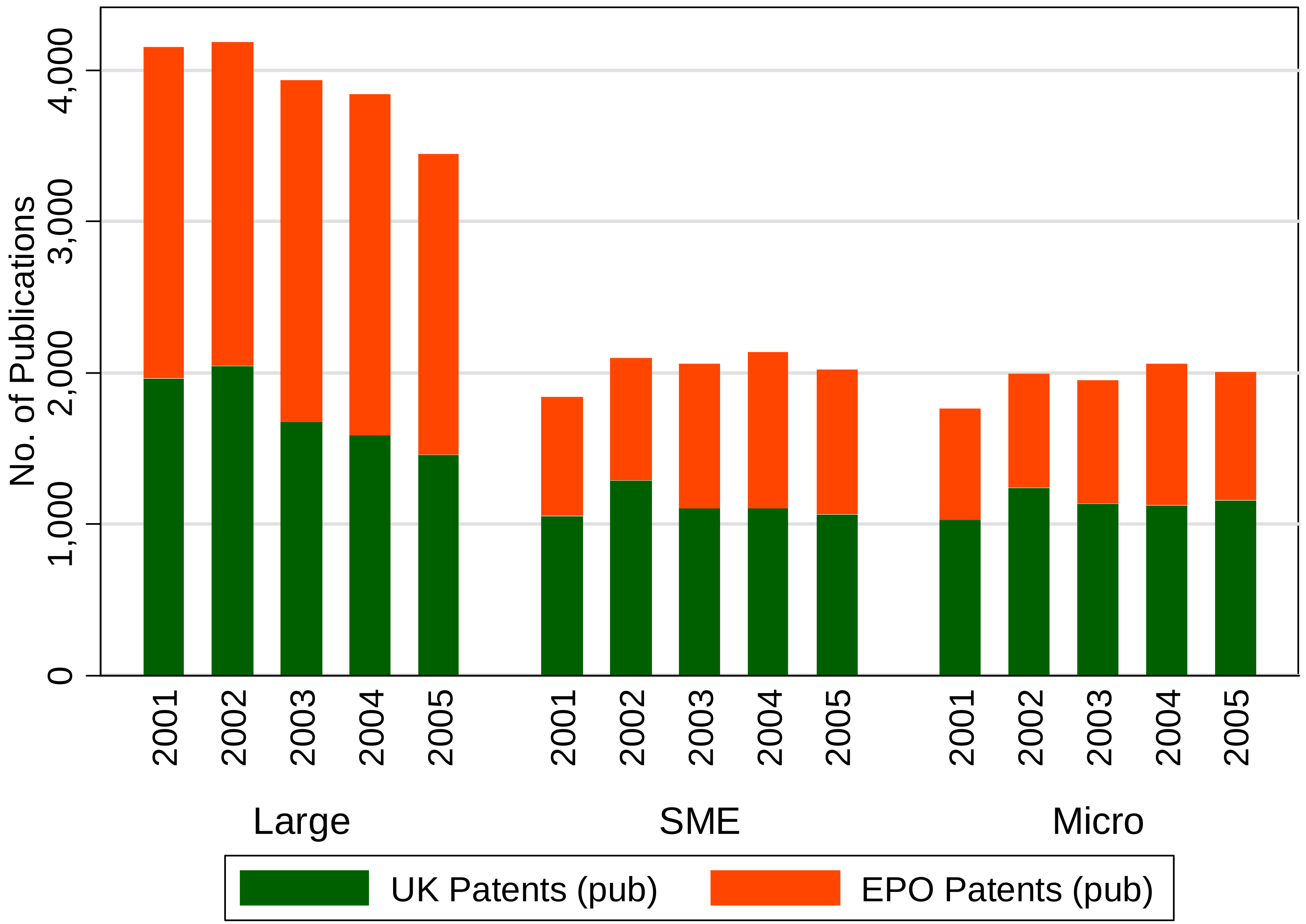
	Official Data	OFLIP Data	Percentage (%)
UKIP – patents	5,708	4,084	71.5
UKIP – trade marks	18,071	12,484	69.1
OHIM – Community marks	6,301	4,478	71.1
EPO – patents	4,361	4,132	94.7

- Official data is all publications – personal, corporate or governmental
- Some (micro) UK firms not registered
- EPO highest since dominated by larger firms

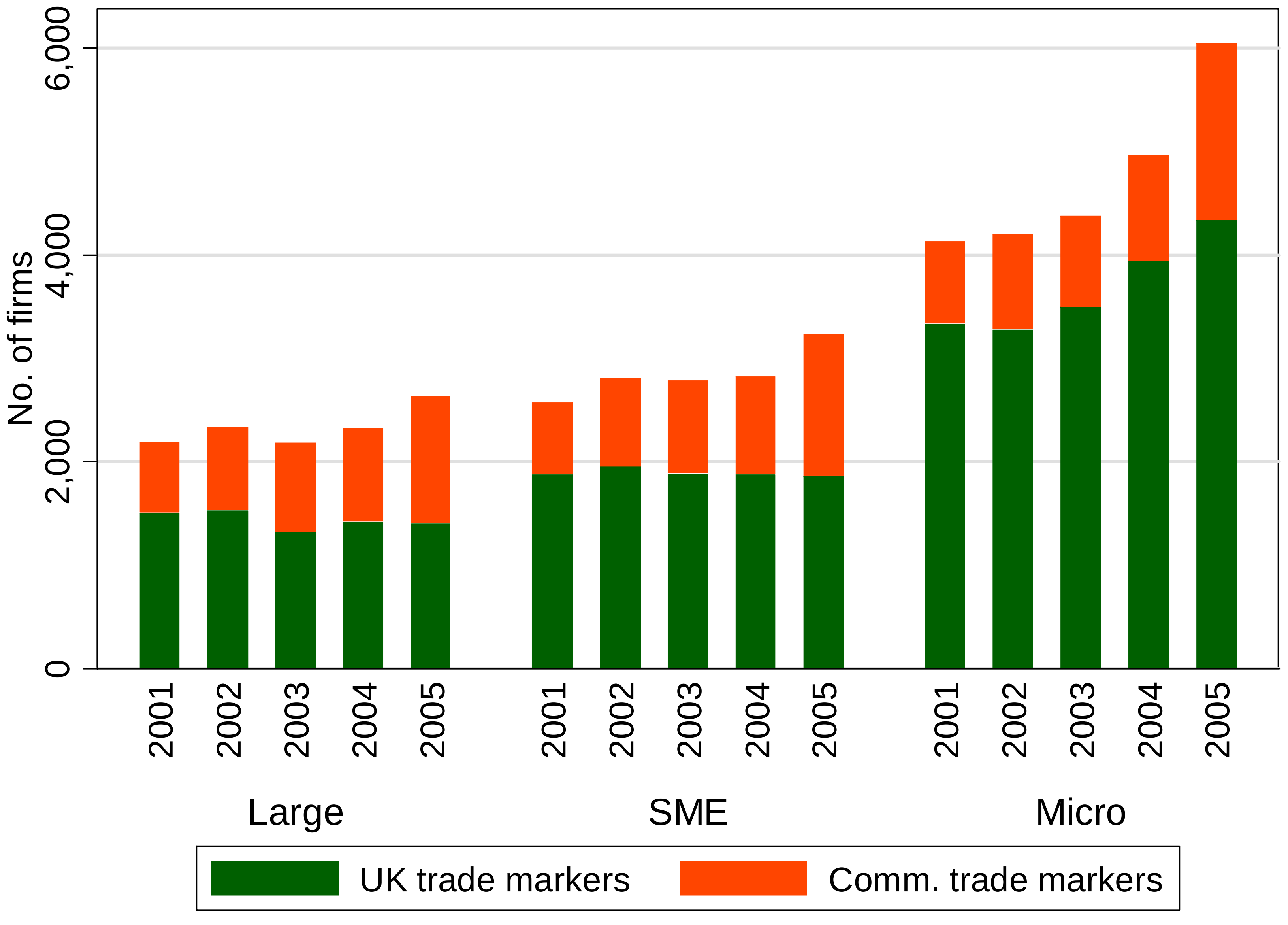
Patenting firms by size



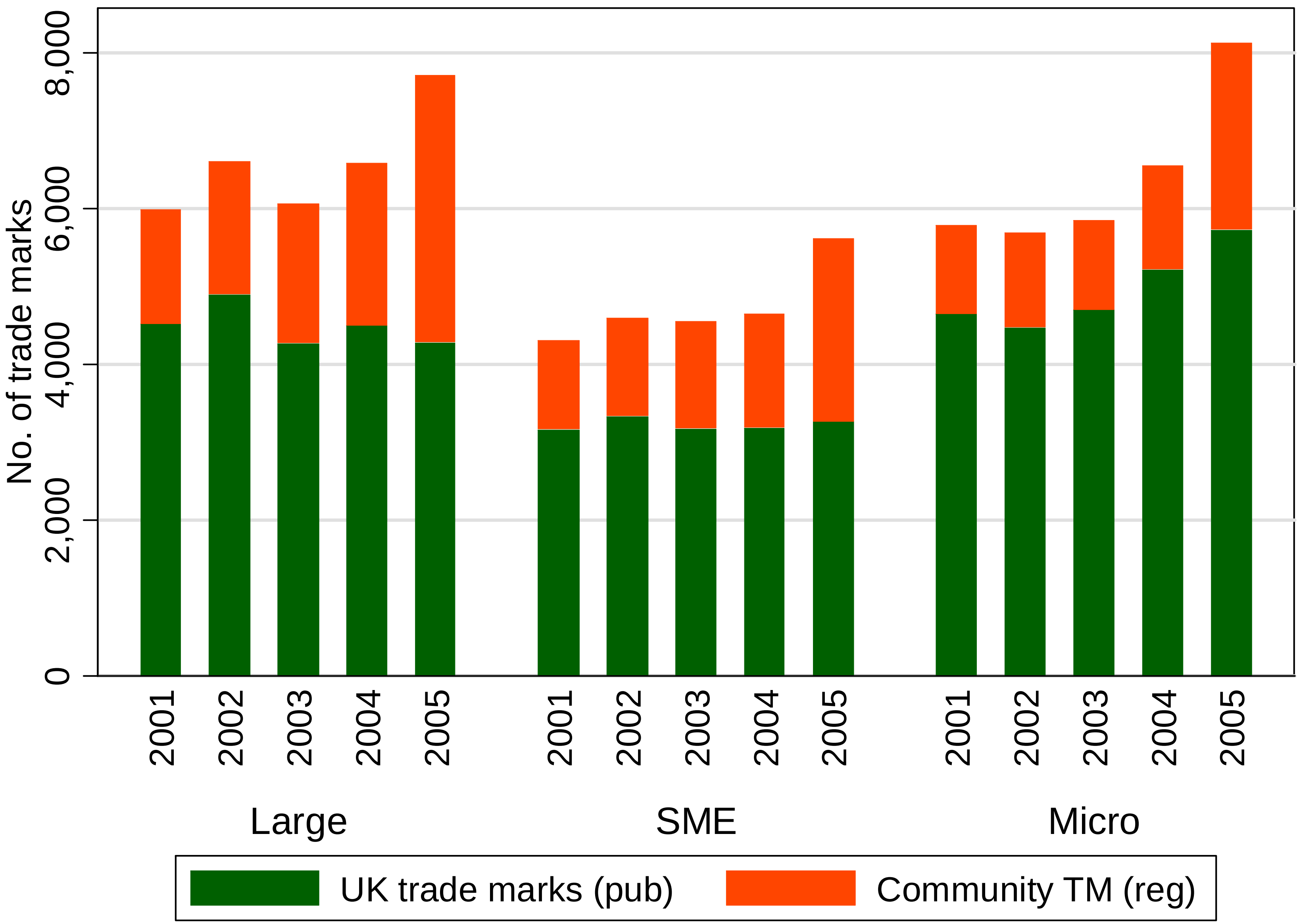
Patents published by size



Trade marking firms by size



Trade marks by size



Propensity of SMEs to use IP

- Around 4.4% of SMEs publish at some stage 2001-2005 (one of 4 IP types considered).
  - 5.4% of large; 0.8% of micro firms
- Older (age>10) SMEs tend to be more active, but 5-10 age also over-represented for patents
- 3,101 SMEs had one or more UK patent published
- 2,423 SMEs …… EPO patent published (2001-5)
- Average number of SME publications per year was 1.6 to 1.9

Other aspects of database

- Joint patenting (2004)
  - UK patent: SMEs 21% Large 31% Micro 29%
  - EPO patent: SMEs 6% Large 10% Micro 5%
- Joint patents with university (2004)
  - UK patents: SMEs 0.5% Large 0.5% Micro 3%
  - EPO patents: SMEs 0.7% Large 0.5% Micro 5%
- Also IP information on PCT, EPO (designations), classes, agents, grants, etc
- Firm-level information on industry, age, financials, etc

What are outcomes of the 2001 cohort of SMEs by 2004?

Outcome groups in 2004	IP active in 2001	%	Not IP active in 2001	%
Large	*240*	7.69	*8,684*	6.35
SME	*2,460*	78.8	*106,184*	77.6
Micro	*265*	8.49	*14,696*	10.7
Exited	*155*	4.97	*7,265*	5.31
Total	*3,120*	100	*136,829*	100

Outcomes depend on range of factors

- Firm-level
  - IP use, experience, strategy, human capital, etc
- Industry level
  - stage of product cycle, competition, growth rates, innovation, spillovers, etc
- Regional and macro level
- Initially use probit analysis: exit2004=1, 0
- DV all from 2001

Using IP to create industry variables

SIC3 large firm patent intensity	High values may indicate mature industry with extensive cross licensing.	Increase probability of SME exit
SIC3 large firm trade mark intensity	High values may indicate mature industry with high advertising and/or product innovation.	Increase probability of SME exit
SIC3 SME patent intensity	High values may indicate high technological opportunities on industry in early stage of product cycle.	Reduce probability of SME exit
SIC3 SME trade mark intensity	High values may indicate substantial product innovation by SMEs, hence competition between SMEs.	Increase probability of SME exit

Probit: exit=1, survive=0

2001 values	All SMEs	Age < 4	Age 5-10	Age 11 +
UK trade mark dummy	-0.015	0.000	-0.022	-0.017
	(3.86)**	(0.04)	(2.40)*	(3.69)**
Comm. Trade mark dummy	-0.003	0.025	-0.011	-0.016
	(0.45)	(1.67)	(0.76)	(1.91)
UK patent dummy	-0.011	-0.012	-0.008	-0.01
	(1.32)	(0.44)	(0.35)	(1.09)
EPO patent dummy	-0.01	0.015	-0.017	-0.011
	(1.12)	(0.54)	(0.87)	(1.13)
UK pat per mill. asset SIC3 Large firms	0.103	0.118	1.236	-0.37
	(0.23)	(0.12)	(1.35)	(0.61)
UK TM per mill. asset SIC3 Large firms	-2.453	-3.418	-4.344	-1.491
	(7.04)**	(3.04)**	(4.57)**	(4.13)**
UK pat per mill. asset SIC3 SME firms	-0.37	-0.466	-0.411	-0.328
	(1.96)*	(0.81)	(0.87)	(1.58)
UK TM per mill. asset SIC3 SME firms	0.336	0.577	0.644	0.156
	(3.36)**	(1.91)	(2.58)**	(1.41)
Joint patent dummy	0.02	0.014	-0.011	0.029
	(1.34)	(0.42)	(0.33)	(1.48)

Marginal effects shown (dF/dx at means)

Continued…

age	-0.002	0.03	0.007	-0.001
	(22.01)**	(4.05)**	(1.02)	(7.80)**
age2	0.000	-0.006	0.000	0.000
	(16.31)**	(4.31)**	(1.04)	(6.23)**
ln(number of directors)	0.022	0.011	0.024	0.024
	(25.34)**	(4.10)**	(11.31)**	(23.85)**
Dummy for foreign ownership	-0.029	-0.034	-0.039	-0.024
	(22.91)**	(10.73)**	(13.16)**	(16.36)**
Dummy for subsidiary (of SME)	-0.055	-0.085	-0.066	-0.043
	(47.40)**	(27.03)**	(24.26)**	(31.05)**
Dummy for university address	-0.027		-0.026	-0.02
	(2.26)*		(1.17)	(1.18)
4-firm concentration ratio (SIC3)	-0.014	-0.015	-0.024	-0.009
	(3.64)**	(1.63)	(2.72)**	(1.88)
Industry turnover growth SIC3 all firms	-0.003	-0.006	-0.005	-0.002
	(2.84)**	(2.06)*	(1.68)	(1.64)
Capital per worker, SIC3	0.000	0.000	0.000	0.000
	(7.26)**	(1.23)	(5.70)**	(4.91)**
Average 1st year firm / average size SIC3	0.042	0.781	-0.048	-0.013
	(0.12)	(0.61)	(0.05)	(0.04)
Price cost margin	0.003	0.006	0.005	-0.003
	(3.61)**	(3.25)**	(2.82)**	(1.66)
Observations	137860	26094	31643	80091

Plus regional and sector dummies

IP interpretation

- IP activity in 2001 not big factor
  - UK trade mark(s) reduces prob(exit) by 0.015
- Industry variables
  - More trade marking by large firms tends to reduce SME exit, but
  - More trade marking by SMEs increases exit
  - Magnitude? Skewed distributions.
  - A 50^{th} – 75^{th} change:
  - 0.002 prob (large) and 0.01 (sme)
  - SME industry patenting may imply spillovers (but none from large firms)

Conclusions

- Newly created OFLIP data: full population of UK registered firms IP activity (4-types)
- 4% of UK SMEs use IP in 2001-05 period
  – SME patenting activity static (2001-05)
  – Ditto SME trade marking, rise in 2005
  – Only micro firms' activity rose
- TM in 2001 increases survival to 2004
  – As does higher TM by large firms in industry
  – But higher SME competitor TM reduces survival