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INDUCED INNOVATION AND RENEWABLE ENERGY POLICIES FOR BIOENERGY

This paper employs a negative binominal count data model approach to investigate whether various renewable energy policies used in 14 OECD countries have affected innovation in the bioenergy field. Innovation have been estimated using patent counts for the period 1978-2009 and the policies examined are feed-in tariffs, quota obligations and different types of investment support schemes. The study finds that feed-in tariffs have affected innovation positively but quota obligations have not. The results regarding investment support programs are ambiguous. Another finding is that electricity prices seem to be an important determinant of innovation and that the accumulated stock of knowledge in the bioenergy sector also has a positive impact on bioenergy innovation.

Keywords: Economics; Renewable energy; Energy policy; Innovation; Patent, Bioenergy.

1. Introduction

The use of bioenergy is not a novelty in global energy production. Wood or derivatives of wood have been one of the most important energy sources throughout human history. With the introduction of coal and, later on, petroleum products, the use of bioenergy in industrialized countries faded. However, in the wake of the oil crises in 1973 and 1979, and lately the growing concern about global warming, the need for finding alternatives to traditional fossil fuels seems increasingly pressing. In this context, bioenergy is an energy source many countries are increasing their reliance on. The common arguments used for an increasing share of bioenergy are related to climate issues, security-of-supply and, in some cases, to rural development [EU 2009]. However, compared to many renewable energy sources, including bioenergy, fossil fuels still have cost advantages due to e.g., economies of scale, path dependencies in the energy systems and higher level of technological maturity [Neuhoff, 2005]. Nevertheless, bioenergy is beneficial for energy production in the sense that it is readily available in many countries, not only in the form of wood materials or

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cultivation of perennial crops, but also as by-products from forestry, agriculture and industrial processes. There is also a potential for energy extraction from municipal waste. In addition, since many of the areas of bioenergy technology are relatively immature, additional benefits might arise for first-movers. This could manifest itself for a country as becoming an exporter of bioenergy-related technology. Thus, in addition to the climate issues, security-of-supply and rural development arguments, the innovation aspect of bioenergy technologies might bring further benefits for a country.

Innovation is also one of the key factors in the development and deployment of bioenergy technology. Lower operating costs by continuous improvements of existing technology and the development of new technologies are results of the innovation process. Both aspects are necessary in order to increase the competitiveness of bioenergy and to make it a reliable substitute for fossil fuels. To speed up the deployment and development of bioenergy technologies, a variety of public support schemes such as feed-in-tariffs, renewable energy quotas, investment support schemes, tax support schemes and guaranteed electricity purchase obligations have emerged during the last three decades. However, the purpose of most related policy schemes have not explicitly been to stimulate innovation, but rather to achieve goals related to energy self-dependency and mitigation of carbon emissions. One of the first policy measure introduced was publicly financed research and development (R&D). This type of support for research on bioenergy started around middle to late 1970s and has increased considerably since then. For instance, the annual total sum of bioenergy R&D in the 14 countries included in this study has risen from 75 to 611 million USD between 1978 and 2010 (in 2012 USD).

The effect of different policy schemes on innovation has been theoretically and empirically investigated in a number of earlier studies [e.g., Brunnermeier and Cohen, 2003; Jaffe and Palmer, 1997; Johnstone et al., 2010; Lanjouw and Mody, 1996; Noailly and Batrakova, 2010; Walz, et al., 2008]. The majority of these studies have focused on the effect of environmental regulations i.e., policies designed to increase the cost of economic activities that are deemed environmental harmful. A few studies have investigated commonly used support schemes, but only a couple of them model the intensity of the implemented support, even fewer have considered the effect on bioenergy technology in particular. Thus, the empirical knowledge on how specific policy schemes affect bioenergy related innovations is lacking. The purpose of this study is therefore to estimate and analyze the effect energy and climate policies have had on the level of bioenergy innovation activity. Specifically the study aims to empirically test the hypothesis that innovation in bioenergy technology can be stimulated by appropriate policies or combinations thereof.

2. Patents as a proxy for innovation

A key issue in modeling policy-induced innovation is how to actually measure innovation. There is no direct measure; instead some sort of proxy must be used. One method to approximate innovation is to use either R&D expenditures or the number of employed scientific personnel. According to Rübbelke and Weiss [2011], these two proxies could be assumed to correlate with the level of innovations. However, they could hardly be seen as an output of the innovation process, but rather as an input.

Another approach is to use the number of patents as a proxy for the outcome of innovation activities. An explanation is made by Griliches [1990], innovation could be seen as the change in accumulated knowledge (which is the indiscernible variable) and is proportional to research expenditures and other unobserved influences. This accumulated knowledge, i.e., technique, is in turn a determinant of the change in an output measure which could be for example growth, productivity or the stock market value of a firm or industry. These last quantities are also determined by other measurable factors like capital-deepening and other but unobservable influences. The notion here is that patents could be seen as an indicator of the change in accumulated knowledge; if knowledge is constant no new patents should be applied for, if knowledge is growing at a constant rate patenting should increase with the same rate every year, and if the rate of technological change increases the rate of patenting should increase as well. Among the alternative proxies at hand, patents have so far shown to be the best indicator of the result of the innovation process [Johnstone et al. 2010; OECD 2009].

As all proxies, patents also have some problematic properties. Popp [2003; 2005], comments on the quality aspect of an innovation when studying innovations in the United States before and after the SO_2 permit trading system was introduced. He finds that the number of patents was actually higher before the 1990s. However, the effectiveness of the patented technologies, in terms of the amount SO_2 removed, was higher after trade begun. This is counterintuitive with the idea that a high number of patents are equal to a high rate of growth in technological knowledge. Furthermore, not all innovations will be patented, so patents are not a complete measure of the innovation activity. Moreover, the patent practices across countries are likely to be heterogeneous and the propensity to patent may differ between countries [Johnstone et al. 2010].

As could be seen in fig. 1 the number of bioenergy patents increase at a slow rate from the late 1970s until the mid-90s after which the patent activity started to increase exponentially. The ratio between bioenergy patents and total number of patents is not that encouraging though when the development for the first period between 1978 and 1996 is considered since the share of total number of patents is steadily decreasing. This can partly be explained by the decline in energy prices that occurred in the 1980s and 1990s, which would have lowered the interest for bioenergy. The explanation could be valid despite the fact that oil prices were still quite high at the beginning of the 1980s, findings by Popp [2002] for example show that the innovative effect of rising energy prices seems to linger of relatively fast after an initial price shock. The sharp increase in the number of bioenergy patents from the mid-90s until 2008 might be explained by the emergence of energy and climate policies related to renewable energy during the 1990s. Once again rising energy prices could also have played a role for the interest in bioenergy until they collapsed at the outbreak of the 2008 crisis.

3. Energy and climate policy measures

The policy areas of renewable energy and climate change are relatively new, even though the interest for the latter was originally awakened already after the oil crisis in the 1970s. In order to understand the fundamentals of the policy areas and their connection to bioenergy, a short description of the technological properties with economic relevance for renewable energy production is needed. Neuhoff [2005] argues that network externalities are one of the major obstacles for restructuring energy production in the industrialized world. An example of such could be the infrastructure built around petrol- and oil use, where the value of having a petrol driven car or any other type of oil consuming technical devise increases if many other people also are using the same type of technology. This since availability of the necessary technological support and infrastructure will be more widespread. Energy systems also exhibit a strong characteristic of lock-in[1] to established technologies, caused by factors as economies of scale, market-place barriers, accumulated learning-by-doing and learning-by-using of established technologies. Finally, energy systems tend to involve large-scale products and investments which last decades. For all these reasons energy systems themself may be highly path dependent – future economic possibilities depend on previous decisions and patterns of investment. According to Neuhoff [2005] the above mentioned properties is the theoretical justification for many of the renewable energy policy measures that have been in use the latest 25 years. Up-front capital subsidies or investment tax deductions provides public financial support for the initial investment which otherwise will not be undertaken since investor´s discount rates are too high for renewable energy projects to break even. Contracts ensuring stable energy-prices guaranteed at the level of retail

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[1] Lock-in is closely related to path dependence. See for example Arthur et al. [1987] or David [2001] for a detailed explanation of the concept.

tariffs (feed-in tariffs) will also remove or alleviate some of the same uncertainty bias. Public funding or subsidizing also mitigates the disproportionately high transaction costs for risk management tools that results from the small-scale properties that often signify renewable energy projects. Neuhoff [2005] also emphasizes that as technologies improve and the scale of deployment increases, it is of importance to support actual power produced rather than investments, in order to reward performance instead of just installed capacity.

Different categories of implemented policies have been identified, e.g., general framework policies, direct short-term investment subsidies or R&D support. Some are designed to target renewable energy in general while others are aimed specifically for bioenergy. Empirically there are only a few studies that have analyzed the impact of energy and climate policies on the innovative performance for renewable energy [e.g., Johnstone et al. 2010; Rübbelke and Weiss 2011]. The general finding is that certain policies are more effective than others depending on energy technology. Targeted subsidies such as feed-in tariffs are more efficient in stimulating innovations in newly emerged and less developed technologies with high operating costs, while more general policies such as quota obligations with tradable green certificates will stimulate innovations in mature technologies that already have been subject to innovation and learning-by-doing cost improvements. The latter since producers always seek to comply with a regulation in the cheapest possible way. Since bioenergy comprehends many different technologies with various degrees of maturity, it could be argued that both feed-in tariffs as well as quotas might be determinants of innovation for this energy field.

Feed-in tariffs

Feed-in tariffs in this study are defined similar to Sijm [2002] as *"the regulatory, minimum guaranteed price per kWh that an electricity utility has to pay to a private, independent producer of renewable power fed into the grid"*[2]. The extra cost of the guaranteed price is in most policy regimes passed on to consumers via the electricity bill. Figure 2 depicts the development of the average feed-in tariff for the sample countries and for the time period 1978-2010. The first feed-in tariff was introduced 1991 in Germany, Switzerland and the UK and had an average value of 0.021 USD per kWh (in 2005 prices). By 2010, the average feed-in tariff had risen by 319 percent to 0.088 USD per kWh (in 2005 prices).

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[2] The levels of feed-in tariffs are sometimes based on avoided costs of using non-renewable power when generating electricity and sometimes the feed-in tariffs may be fixed without any direct relation to the avoided costs. Feed-in tariffs may be guaranteed for certain time periods and are sometimes differentiated with respect to renewable energy technologies such as solar PV, biomass and wind [Campoccia et al. 2009; Sijm 2002]. Moreover, sometimes the tariffs may also be differentiated on the basis of when (time or season) the electricity is fed into the grid.

Two countries where feed-in tariffs have been used intensively are Germany and Spain. These countries are also representative for the different ways of implementing feed-in tariffs. In Germany, the *fixed price tariff* has mainly been used. Under this design the renewable energy producer is guaranteed a settled remuneration per kWh fed into the grid. The fixed tariffs could be inflation adjusted or have a fixed nominal value. The latter suggest that the value of the tariff will be reduced over time. This property could be further increased by a yearly discount of the tariffs, the so called *front-end loaded tariff*, which is the system that was used in Germany between 2000 and 2009. In Spain, the *premium price tariff* has been a commonly used mechanism to reward renewable energy production. Under this policy a premium is paid additionally to the market price for electricity. These market-dependent feed-in tariff schemes come with a set of different features. The simplest form is the *premium price model* which offers a constant premium on top of the market price. A more modern tariff construction used in Spain today is the variable premium tariff where the premium varies within certain boundaries according to the market price. The purpose of this construction is to avoid windfall profits in the case of sharply increasing market prices, but also to reduce the risk in the event that market price drops heavily [Couture, Gagnon 2010]. A feed-in tariff does not necessarily mean that the guaranteed payment to a renewable energy producer has to be higher than the prevailing market price at every single moment in time. The first feed-in tariff in Germany, the *electricity feed-in tariff law 1991,* based its level of remuneration on a percentage of the mean market price of electricity for the previous year. Denmark and Spain also used this type of policy construction earlier. Due to the great component of randomness in this remuneration scheme it has today been abandoned in favor of other more up-to-date tariff designs [Couture, Gagnon 2010].

Renewable energy quotas

Quota policies are often deployed in the form of *renewable portfolio standard* (RPS). A quota is set for the amount of renewable energy in the total energy production, which energy distributers are obliged to fulfill. This policy is sometimes combined with a certificate trading regime called *tradable green certificates* (TGC). In a TGC scheme the quota can be fulfilled either through own renewable energy production (if those cases where utilities produce their own energy) or by buying certificates from an external accredited generator. In the same way as with the feed-in tariffs, the cost of certificates (in the instance of non-renewable energy generation) is ultimately born by the electricity consumers. Often a TGC regime guarantees a minimum buy-back price of certificates if an excessive amount of renewable energy would be produced for the regular market.

In fig. 2 the number of countries in the sample using quota policies is presented. Renewable portfolio standards and quota policies were introduced later than feed-in tariffs. They were first implemented in Austria in 2001 and nine years later RPSs had also been implemented in Belgium, Italy, Japan, Sweden and the U.K.

Investment support schemes
Investment support policies could be e.g., grants or low-interest loans provided to cover investment costs of bioenergy production capacity. In some instances, investment support schemes cover the whole investment cost. However, it is more usual that the support only covers a certain percentage of the total investment cost. Investment support programs could also be directed towards research and demonstration facilities with the purpose to help immature technology become commercially viable. These schemes are an older type of subsidy than feed-in tariffs and RPS, which has been quite usual in the bioenergy sector. Investment support programs are not a feature of liberalized energy markets in the same way as feed-in tariffs or RPS policies, even if an investment policy by definition does not excludes a design targeted towards production efficiency instead of pure installation. A distinction between R&D policies and investment support also has to be made. Public subsidies of R&D activities without investments in physical production capital are not defined as investment support policies in this study.

4. Model and data

In order to model innovation, a distinction has to be made between *technological* innovation and economically useful innovations in general [Jaffe et al. 2001]. The latter need not necessarily implicate new technology, but could be new organizational forms or even more efficient societal planning. In this study, the former definition is used when trying to estimate the impact of energy and climate policies on innovation activity. A cornerstone in modern theory of technological change is the trichotomy defined by Schumpeter [1911; 1934] where the process of technological change consists of three stages: (1) Invention which is the actual development of a new product or process and is normally what is intended when the word innovation is used in its more general sense. Some of the inventions may be patented while some are not; (2) Innovation is the commercialization of the new product i.e., it is made available for sale in the market and; (3) Diffusion is when an innovation becomes widely adopted by various economic agents.

In Jaffe et al. [2000], two major strands in the literature are identified concerning the determinants of innovation. One is the evolutionary approach, and the other is the investment-subject-to-market-failure approach. The evolutionary model builds on bounded rationality first formulated by Simon [Simon 1947]. In this paradigm firms base their R&D decisions on rules of thumb and routines rather than on optimization. This behavior results as a consequence of imperfect information [Jaffe et al. 2000; Nelson, Winter 1982; Simon 1947]. A theoretical framework that could be attributed to the latter approach (from now on called the investment approach), and used in this study, is what has been named *price-induced technical change* [Hicks 1932]. In this paradigm, as well as in the investment approach in general, R&D decisions are based on firms` efforts to maximize their profits. Accordingly, changes (or expected changes) in relative prices should stimulate inventions towards reduced use of the more expensive factor of production [Newell et al. 1999; Popp 2002]. The notion of price-induced technical change can further be incorporated into a three-dimensional innovation space, where innovation is a function of what Jaffe [1986] and Popp [2002] call supply and demand-side factors.

Supply-side factors in induced innovation are defined by Popp [2002] as those factors that constitute the technological opportunity for innovators to succeed in creating new knowledge. Technological change is not only seen as a function of changes in relative prices for inputs, but also of previous investment in R&D and the accumulated knowledge stock. This serves as a proxy for earlier scientific advancements, making further discoveries easier (in absolute numbers). An early formulation of the concept was made by Scherer [1965] and Schmookler [1966]. Early R&D policies in the 1970s were designed using this understanding.

Analogously to supply-side factors, Popp uses the concept of *demand-side* factors, or market variables, to represent factors that will induce innovation by increasing the value of new innovations [Popp 2002]. Thus, price-induced innovation is embraced by this definition of input prices and market demand of output. The role of policy is here to change the relative prices of the output from renewable energy sources relatively to conventional fossil fuel based energy generation.

Model specification

The model specification, represented by eq. (1), includes three vectors of different types of determinants, quantified either as discrete or continuous:

$$I_{i,t} = f\,(\mathbf{A}_{i,t}, \mathbf{D}_{i,t}, \mathbf{P}_{i,t}) \qquad (1)$$

The specification stipulates that the count of bioenergy patents (I) in country i and time period t can be explained by a vector of policy variables (**A**), vector of supply-side R&D variables related to technical opportunity (**D**) and a vector containing the demand-side market variables (**P**).

The policy vector (**A**) includes four major policy groups: Feed-in-tariffs (FIT), renewable portfolio standards (RPS) (i.e. renewable energy quotas), investment subsidies and renewable energy purchase obligations for grid operators. Tax policies are not explicitly included in the specification even though it is a fairly common policy instrument. The reason for that is the lack of reliable disaggregated data on tax policies used in the sample countries. The vector of R&D variables (**D**) includes two variables controlling for the propensity to patent and the technical opportunity for bioenergy innovation. The vector of market variables (**P**) contains total energy consumption, the market price of electricity and the relative price between biomass and light fuel oil.

For proper estimation of the number of occurrences of an event, count data models such as the Poisson or negative binomial model have been suggested [Cameron, Trivedi 1998]. An event count is formally defined as a realization of a non-negative integer-valued random variable. In this model, an event count is the number of patent applications for each country respectively each year. It is assumed that the patents counts ($I_{i,t}$) follow a negative binomial distribution. Since it is quite likely that the countries investigated will differ substantially in their country-specific characteristics, the negative binomial fixed effects-model suggested by Allison and Waterman [2002] is used. That is, a negative binomial model with country fixed effects is used for the estimation of eq. (1). The downside is that it is not ruled out that the estimates will suffer from an incidental parameters problem[3]. The alternative is to use the fixed effects-model by Hausman, Hall and Griliches [1984], but since the conditional mean function is still homogenous in that model, we would instead have what Greene [2007] names a “left out variable problem”.

Data

14 countries in total are included in the sample (Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland and United Kingdom) constituting an unbalanced panel data set for the time period 1978-2009.

Patents filed under the Patent Cooperation Treaty (PCT)[4] are used. The PCT does not have the same problems of home bias as pure counts of applications made at the national patents offices respectively. Furthermore it does not have the same problems with weak timeliness, i.e., a very long delay between

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[3] The incidental parameters problem arises in cases where the number of parameters increases with the number of observations, e.g. in short panels and *n* is increased by adding more cross-sectional units using individual fixed effects. This could make the estimator inconsistent [Neyman, Scott 1948].

[4] An alternative filing is the Triadic patent families.

application and publishing that could prevail under other filings [OECD 2009]. The PCT also contains longer time-series without structural breaks than other comparable filings. Patents under PCT are defined as applications sorted by inventor's country of residence and priority date (earliest date in the application process). This chosen definition of included patents is based on recommendations made by OECD [2009]. The patent sample consists of biofuel- and fuel from waste technologies given by the ECLA-classification system created by the European patent office (ECLA Y02E50/10 up to Y02E50/346 classes) and has been obtained from the OECD Statistics database [2013]. In cases where total patents for a country and year have been reported as a fraction (when several countries share the credit for a patent) it has been rounded to the nearest integer.

Moore and Ihle [1999] state that a program for financial assistance must remain stable for at least ten years, therefore two feed-in tariff variables is constructed for this study, one for contracts of minimum 10 years or longer and another for contracts shorter than 10 years. The feed-in-tariffs are measured as continuous variables defined as USD per kWh (2005 value). The FIT variables are defined as annual level each year respectively after an enactment or change in level. In instances when a policy has not been in use at the beginning of the year when it was first enacted, it has been considered as enabled the following year, this is based on the assumption that inventors react to sharp policies actually in use. In order to construct the FIT variables in a symmetric manner, policies abolished before the end of a given year will still be counted as in use for that year. In most countries there is no uniform tariff level even within the same technology group. For instance, remuneration levels differ depending on the biofuel technology type and on the size of plant and policy design in use a certain year. To account for this, the feed-in tariffs have been calculated as a weighted average of the different relevant and comparable tariffs in use each year. If the technology base eligible for support is broadened or narrowed over time, in a sense that would change the mean level of tariffs to a non-comparable measurement unit, these specific technologies have not been included. An example of this is the British *Non-fossil fuel obligation* scheme (NFFO) where the fuel base eligible for support has been redefined several times during the existence of the program. Similarly to Rübbelke and Weiss [2011], tariff levels have also been discounted with the stated yearly percentage if tariffs are constructed as descending by the regulator (e.g., in Germany).

The RPS variable is continuous, defined as the percentage of obliged renewable energy in total energy production while a RPS policy was active. The RPS has been counted as active if they were in use before the 1th of July a given year.

Investment subsidies are measured as annual total funding (2005 USD value) of a specific program. In the instances where data on annual budget has not been available, it is assumed that the total initial funding of a certain program is exhausted within five years. The reason for choosing a 5-year limit is that when time limits are explicitly mentioned in policy descriptions, five years is usually the timeframe used. There are policies which due to lack of information have not been possible to include in the continuous investment variable, these policies are taken into account by a cardinal interval variable which measures the total number of investment support policies in use for a specific year and country. Since these programs can target different sectors of the economy and could be more or less effective, it has been divided into three separate variables; strong policies, weak policies and policies directly aimed at the household or residential sector. Cardinal investment policies have been assessed as strong if they are targeted directly towards renewable energy production, either in power generation or production of bioenergy. On the other hand, if a policy only provides little amount of support, e.g., soft loans to renewable energy projects but with risk-adjusted high rents close to what should have been the level if negotiated in the open market, it has been categorized as weak. Furthermore, if it has been unclear whether an explicit renewable energy policy has been relevant at all for bioenergy, it has also been classified as weak. The latter also applies to policies otherwise categorized as residential sector policies. When an investment policy overlaps two categories, it has then been recorded as a fraction for each group.

The data used in the construction of the policy vector is collected from IEA [2004, 2011, 2013] and Cerveny and Resch [1998]. Moreover, various international governmental organizations and websites have been consulted to extend and control the accuracy of the data used to construct the policy vector.

In the RD&D vector (**D**) the propensity to patent is measured by the total number of patents counts under the PCT, aggregated over all technological areas. Thus bioenergy patent is related to the overall trend in patenting in a given country. It also controls for differences in size and research capacity of the countries. This variable is expected to have a positive sign in the regression. Technological opportunity is approximated by the accumulated knowledge stock constructed using a country`s aggregated (public) RD&D expenditures on bioenergy technology. RD&D expenditures are measured in 2012 USD and retrieved from OECD [2013]. The accumulated knowledge stock is built similarly to the work by Söderholm and Klaasen [2007] and is defined as:

$$STOCK_{\mathrm{i,t}} = (1-\delta)STOCK_{\mathrm{i,t-1}} + RD\&D_{i,t-x} \qquad (2)$$

where *STOCK* represents the accumulated knowledge stock, δ is the rate of depreciation and x is the time lag before R&D expenditures is added to the knowledge stock. According to Klaasen [2005] a time lag of two years (x=2) and a depreciation rate of three percent (δ=0.03) is reasonable.

The demand-side factors, the market price vector (**P**), contains the electricity prices and the relative price between roundwood and light fuel oil. This price ratio serves as a proxy for the relative price between biomass and other important fossil fuel prices. Moreover, a variable on total energy consumption is included to control for the energy market size, higher energy consumption means that there is greater potential sales for energy technology and therefore larger incentives to innovate. The electricity and coal prices are retrieved from IEA [2013] and are expressed in USD per kWh and USD per ton (2005 value). Total energy consumption is measured in TWh and originates from the OECD Statistics Database [2013]. In order to take the earlier discussed heterogeneity amongst the sample countries 13 dummy variables[5] is added to the regression equation. This is in line with the methodology of the Allison and Waterman [2002] fixed effects model.

Finally, in 1994 the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) was negotiated which is expected to have had an impact on the patenting behaviour in countries included in the sample. An additional dummy is included in the regression to distinguish between pre- and post-TRIPS patenting activity. This dummy takes the value of 1 from 1995 onwards.

The data for national RD&D expenditures have a few missing observations which cannot be omitted since it would make the construction of the knowledge stock impossible, in those instances the methodology of linear interpolation employed in Jaunky [2009] using the mean of the observations before and after the missing observation have been used to complete the series.

Results

Theoretically it is possible that patenting is affected with a time lag, therefore several model specifications containing lagged independent variables have been tested in order to decide upon a feasible first specification of the model. One variable does improve the model when it is lagged; the relative price between roundwood and light fuel oil. To test if the binomial count model is appropriate, a dispersion test is conducted. The test indicates that the data is overdispersed, and accordingly the negative binomial model is appropriate. The regressions have been conducted using bootstrapping since normal robust sandwich standard errors could be unreliable in the presence of outliers, moreover these are more likely to influence the standard errors in smaller samples. [Cameron, Trivedi 1998].

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[5] The dummy for Austria is excluded to avoid perfect multicollinearity

The results regarding the policy variables are diverse. Both variants of feed-in tariffs are statistically significant, with a positive impact on innovation. In addition, the cardinal variable for the strong investment policies is statistically significant with a positive sign. The other policy variables such as quota obligations (RPS) or other different measures of investment support schemes are not statistically significant.

The demand-side variables; total energy consumption, electricity prices and the relative prices for roundwood versus light fuel oil are all statistically significant. Both supply-side variables measuring total research capacity, propensity to patent and technological opportunity for innovation is statistically significant with an expected positive sign. The time period after the negotiation of the Trips agreement has also had a significant impact on patenting in biofuel technology, indicating that it could lead to biased conclusions regarding policies if this variable is omitted. A variety of interaction variables controlling for interaction effects between the independent variables are also tested, none of them are statistically significant.

The correlation between the independent variables is also inspected in order to control for multicollinearity. In the first specification the correlation between the weak investment policies variable and total PCTs is 0.63 and therefore a regression is estimated where it is omitted, but the significance and sign of the other independent variables remain robust.

However, the assumption that the various investment support programs contained in the three cardinal interval variables have the same impact on innovation could be questioned. Therefore a set of binary dummy variables for each of the three cardinal investment support variables is constructed and substituted for the cardinal variables. This represents other relevant investment policy support but which is not possible to quantify in the continuous variable. The results from that regression coincide with those of the first specification. Finally, a single dummy variable is constructed substituting all the cardinal variables. The dummy is significant with a positive sign and once again the same results are obtained regarding the other independent variables. Arguably, this confirms the robustness of the result from the first specification.

It is possible that the ambiguous effect of the investment support schemes could be a result of the method used in the quantification of the investment support variable. The continuous variable consists of many different types of investment support programs such as measures aimed directly at bioenergy investments, but also to renewables in general. Therefore a further disaggregated continuous investment support variable is constructed in order to investigate whether a smaller subset of the policies have had an impact on innovation in bioenergy. The new categories are; bioenergy investment support (mainly in power and large scale heat generation), investment support against renewables in general and support to renewable energy in the household and residential sector.

It should be mentioned that the categorization is not analogous to the classification of the cardinal interval variable for the investment support programs not possible to quantify continuously. However, in the regressions using these new classifications it is found that none of them is statistically significant and therefore the result from the first specification is unchanged.

Another reason why RPS schemes and investment support programs do not show any significant effect could be the somewhat broad definition of the dependent variable; bioenergy is a fairly diversified energy field and consists of many types of technology. Some of the policy programs might have affected innovation in a narrow field of bioenergy technology, but the patents classes used in the study are too diversified to enable the detection of such effect in the regressions. The information on the policies in the IEA database is also in some cases quite vague, something which makes it harder to assess the relevance of the investment support schemes than in the case of the levels of feed-in tariffs. The investment support variable may therefore possibly contain a higher share of noise than the other policy variables.

The strongest impact on patenting in biofuel technology is given by total energy consumption with an elasticity of 2.39, which means that if energy consumption rises by 1 %, patenting will increase by 2.39 %. Other demand-side factors like the electricity price and the lagged relative price between roundwood and light fuel oil have an elasticity of 0.87 and -0.33 respectively. Regarding supply-side factors the accumulated knowledge stock has a quite strong effect with an elasticity of 0.44. The feed-in tariffs have an elasticity of 0.17 and 0.072 respectively. The tariff associated with longer contractual agreement than 10 years has an impact more than twice the impact of the feed-in tariff negotiated on shorter terms, something that is in line with the theoretical assumptions regarding the feed-in tariffs. The elasticity for the strong investment policies is 0.127, the finding that only the strong investment support variable is statistically significant supports the division of the cardinal investment variable into several variables of different relevance. The result of the regression is given in table 1.

The results are to some extent contradictory to the earlier assessments by Johnstone et al. [2010] who did not find any effect of feed-in tariffs on innovation in the bioenergy field. Investment support schemes have a significant impact in their study but the support is only measured as a binary dummy which is consistent with the statistically significant and positive effect of the strong investment policies in this study. Quota obligations do not have a statistically significant effect in either of the studies.

6 Conclusions

This study investigates the effect of climate and energy policies on innovation in bioenergy technology in a sample of 14 countries during the time period between 1978 and 2009. Innovation is approximated by patent counts, and a vector of different disaggregated policy measures has been included together with a set of market and R&D variables in order to assess their impact on innovation. An inspection of the development of the number of patents and the amount of support targeted towards renewable energy during the investigated time period, suggests that these programs have played an important role for technological change in the biofuel sector.

The econometric results indicate that policies such as feed-in tariffs and investment support programs have a statistically significant and positive impact on innovation in bioenergy technology. Renewable energy quotas fail to have a significant effect on innovation in this study. Market variables such as total energy consumption, electricity prices and the relative price between roundwood and light fuel oil have also had a significant, positive effect on innovation. The variables representing technological opportunity for innovators and over-all research capacity of a given country (measured by accumulated RD&D expenses on biofuel technology and total patent counts over all technology groups), do show to have a positive and significant effect on innovation as well which is in line with the theoretic assumptions of the model.

The economically most noteworthy result of the study relevant for policy-makers is that innovation is significantly driven by electricity prices. Policy measures as feed-in tariffs and certain investment support schemes also play a role for the development of bioenergy technology. Thus, these findings motivate a combination of measures imposed to internalize negative external effects of power production and properly designed support programs in order to further increase the rate of innovation in biofuels, something which hopefully will make bioenergy a fully cost-competitive substitute for traditional fossil fuels.

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Acknowledgements

We thank Bio4Energy, a strategic research environment appointed by the Swedish government, for their financial support. We would also like to thank Kristoffer Bäckström and Vishal Jaunky for their help.