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BIOENERGY INNOVATIONS AND THEIR DETERMINANTS: A NEGATIVE BINOMINAL COUNT DATA ANALYSIS

The research employed a negative binominal count data model approach to analyse the determinants of bioenergy innovations with a special focus on the effect of energy and climate policies. A panel of 14 OECD countries were analysed using patent counts for the period 1978–2009 as a proxy for innovations. The policies examined were feed-in tariffs, quota obligations and different types of investment support schemes. The study found that feed-in tariffs affected innovation positively but quota obligations did not. The results regarding investment support programs were ambiguous since the dummy variable representing strong investment policies was statistically significant whereas the continuous variable for investment support schemes was not. Another finding was that electricity prices seemed to be an important determinant of innovation and that the accumulated stock of knowledge in the bioenergy sector also had a positive impact on bioenergy innovation.

Keywords: economics, renewable energy, energy policy, innovation, patent, bioenergy

Introduction

The use of bioenergy is not a novelty in global energy production. Wood, or its derivatives, has 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 wake of the oil crises of 1973 and 1979, and lately growing concern about global warming, the need to find alternatives to traditional fossil fuels has become a high priority. In this context, bioenergy is an energy source many countries are becoming increasingly reliant on. The common arguments used for the growing use of bioenergy are rela-

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ted to climate issues, security-of-supply and, in some cases, to rural development [European Parliament 2009]. However, compared to many renewable energy sources, including bioenergy, fossil fuels still have cost advantages due to, for example, economies of scale, path dependencies in energy systems and a 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 the cultivation of perennial crops, but also as by-products from forestry, agriculture and industrial processes. There is also the 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, for example, a country becoming an exporter of bioenergy-related technology. Thus, in addition to 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 a key factor in the development and deployment of bioenergy technology. Lower operating costs by continuous improvements in 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 of these related policy schemes has not explicitly been to stimulate innovation, but rather to achieve goals related to energy self-reliance and the mitigation of carbon emissions. One of the first policy measures introduced was publicly financed research development and demonstration (RD&D) [IEA 2004]. This type of support for research on bioenergy started in the mid to late 1970s and has increased considerably since then. For instance, the total annual sum of bioenergy RD&D in the 14 countries included in this study rose from 75 to 611 million USD between 1978 and 2010 (USD in 2012).

The effect of different policy schemes on innovation has been theoretically and empirically investigated in a number of earlier studies [e.g. Lanjouw, Mody 1996; Jaffe, Palmer 1997; Brunnermeier, Cohen 2003; Walz et al. 2008; Johnstone et al. 2010; Noailly, Batrakova 2010; Rübbelke, Weiss 2011]. The majority of these earlier studies focused on the effect of environmental regulations, i.e., policies designed to increase the cost of economic activities that are deemed environmentally harmful. Another approach investigated commonly used support schemes and modeled the intensity of the implemented support. However, only Johnstone et al. [2010] considered the effect on bioenergy technology in particular. Thus, empirical knowledge on how specific policy schemes affect bioenergy related innovations is lacking. The purpose of this study was therefore to estimate and analyze the determinants of bioenergy innovations with a special focus on the effect of energy and climate policies. This was carried out for a sample of 14 countries and for the period between 1978 and 2009. The study specifically aimed to empirically test the hypothesis that innovation in bioenergy technology can be stimulated by appropriate policies or combinations thereof.

Research methodology

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 scientific personnel employed. According to Rübbelke and Weiss [2011], these two proxies could be assumed to correlate with the level of innovation. 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 given by Griliches [1990] is that innovation could be seen as the change in accumulated knowledge (which is an indiscernible variable) and is proportional to research expenditures and other unobserved influences, such as, for example, random influential scientific discoveries. This accumulated knowledge, i.e., level of technological development, 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 such as capital-deepening and other 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, but if knowledge is growing at a constant rate, patenting should increase at 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 themselves to be the best indicator of the result of the innovation process [OECD 2009; Johnstone et al. 2010].

As with all proxies, patents also have some problematic properties. Popp [2003, 2005], commented 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 found 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 began. This is counterintuitive to 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, therefore patents are not a complete measure of innovation activity. Moreover, patent practices across countries are likely to be heterogeneous and the propensity to patent may differ between countries [Johnstone et al. 2010].

As seen in fig. 1, the number of bioenergy patents increased at a slow rate from the late 1970s until the mid-90s, after which patent activity started to increase exponentially. However, the ratio between bioenergy patents and total number of patents is not that encouraging when the development for the first period between 1978 and 1996 is considered, since the share of total number of patents steadily decreased. This can be partly explained by the decline in energy prices that occurred in the 1980s and 1990s, which would have lowered the interest for bioenergy. This 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, showed that the innovative effect of rising energy prices seemed to diminish relatively quickly 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 during the 1990s of energy and climate policies related to renewable energy. Once again rising energy prices could also have played a role in the interest in bioenergy until they collapsed at the beginning of the 2008 crisis.

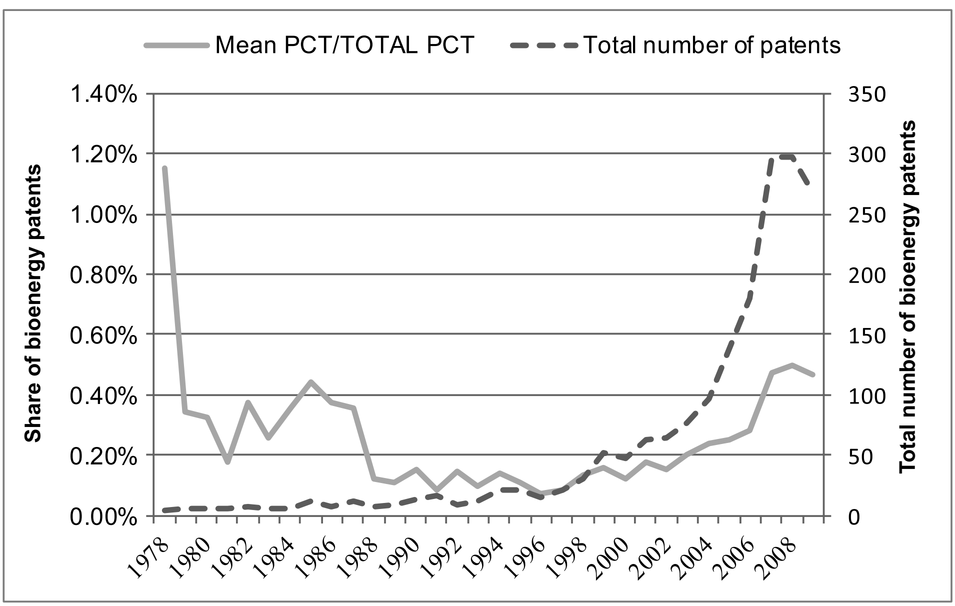

Fig. 1. Total number of patents in bioenergy technologies and its share of total number of patents between 1978 and 2009 for sample countries

Source: OECD [2013]

Determinants of innovation

In Jaffe et al. [2000], two major strands in literature were identified concerning the determinants of innovation. One was the evolutionary approach, and the other the investment-subject-to-market-failure approach. The evolutionary model builds on bounded rationality first formulated by Simon [1947]. In this paradigm, firms base their R&D decisions on rules of thumb and routines rather than on optimization. This behavior arises as a consequence of imperfect information [Simon 1947; Nelson, Winter 1982; Jaffe et al. 2000]. 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 the reduced use of the more expensive factor of production [Newell et al. 1999; Popp 2002]. The notion of price-induced technical change can be further incorporated into a three-dimensional innovation space, where innovation is a function of what Jaffe [1986] and Popp [2002] called supply and demand-side factors.

Supply-side factors in induced innovation were 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.

In a similar way to supply-side factors, Popp used 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 here is to change the relative prices of the output from renewable energy sources with regard to conventional fossil-based energy generation.

Energy and climate policy determinants

The policy areas of renewable energy and climate change are relatively new, even though interest in the latter was originally awakened after the oil crisis in the 1970s. In order to understand the fundamentals of 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] argued that network externalities are one of the major obstacles to 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 are also using the same type of technology. The necessary technological support and infrastructure will be more widespread as a consequence. Energy systems also exhibit a strong characteristic of lock-in[1] to established technologies, caused by factors such 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 themselves may be highly path dependent – future economic possibilities depend on previous decisions and patterns of investment. According to Neuhoff [2005], the abovementioned properties are the theoretical justification for many of the renewable energy policy measures that have been in use in the last 25 years. Up-front capital subsidies or investment tax deductions provide public financial support for the initial investment which otherwise would not be undertaken since investors discount rates are too high for renewable energy projects to break even. Contracts ensuring stable energy prices guaranteed at the level of retail tariffs (feed-in tariffs) also remove or alleviate some uncertainty bias. Public funding or subsidizing also mitigate the disproportionately high transaction costs for risk management tools which result from small-scale properties that often signify renewable energy projects. Neuhoff [2005] also emphasized that as technologies improve and the scale of deployment increases, it is of importance to support the actual power produced rather than the investments, in order to reward performance instead of simply 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 at bioenergy. Empirically, there are only a few studies that have analysed the impact of energy and climate policies on the innovative performance of renewable energy [e.g. Walz et al. 2008; Johnstone et al. 2010; Noailly, Batrakova 2010; Rübbelke, 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 stimulate innovations in mature technologies that have already been subject to innovation and learning-by-doing cost improvements [Johnstone et al. 2010] – the latter in particular as producers always seek to comply with a regulation in the cheapest possible way. Since bio-

[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.

energy comprises many different technologies with varying 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 (FIT) in this study were defined as they were by 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. Fig. 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 in 1991 in Germany, Switzerland and the UK, and had an average value of 0.021 USD per kWh (at 2005 prices). By 2010, the average feed-in tariff had risen by 319% to 0.088 USD per kWh (at 2005 prices) [Cerveny, Resch 1998; IEA 2011, 2013].

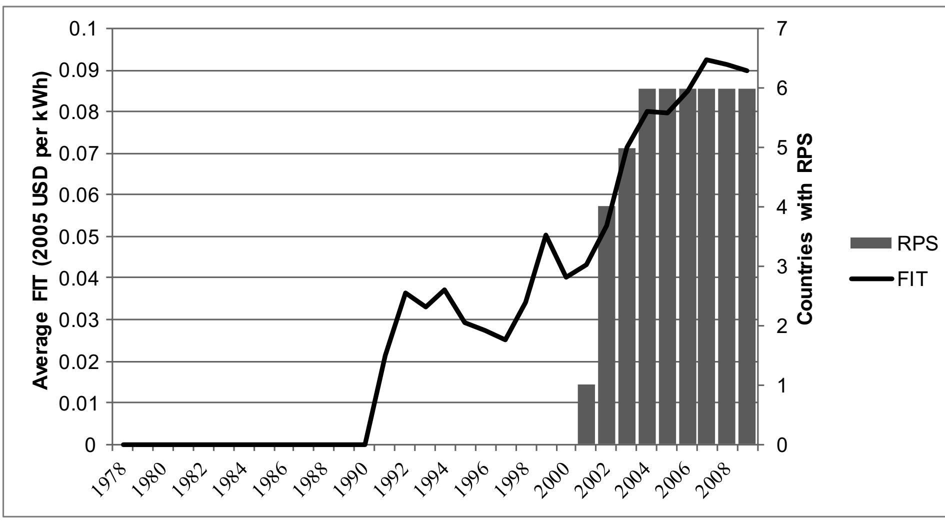

Fig. 2. Average feed-in tariffs and countries with RPS schemes between 1978 and 2009 for sample countries

Source: IEA [2011]

Two countries where feed-in tariffs have been used intensively are Germany and Spain. These countries are also representative of the different ways to im-

[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 photovoltaic, biomass and wind [Sijm 2002; Campoccia et al. 2009]. Moreover, sometimes the tariffs may also be differentiated on the basis of when (time or season) the electricity is fed into the grid.

plement 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. Fixed tariffs can be adjusted to inflation or have a fixed nominal value. The latter suggests that the value of the tariff will be reduced over time. This diminution could be further increased by an annual discount off the tariffs, the so-called front-end loaded tariff, which is the system that was used in Germany between 2000 and 2009 [Busch et al. 2010; Couture, Gagnon 2010; IEA 2011, 2013]. In Spain, the premium price tariff has been a commonly used mechanism to reward renewable energy production. Under this policy, a premium is paid in addition 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 risk in the event that the 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 element of randomness in this remuneration scheme, it has today been abandoned in favor of other more up-to-date tariff designs [Couture, Gagnon 2010].

Quota policies are often deployed in the form of renewable portfolio standards (RPS). A quota is set for the amount of renewable energy within the total energy production, which energy distributors 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 renewable energy production (in cases where utilities produce their own energy) or by buying certificates from an external accredited generator [IEA 2004]. 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 the certificates if an excessive amount of renewable energy were to be produced for the regular market. In fig. 2 the number of countries within 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 were also implemented in Belgium, Italy, Japan, Sweden and the UK [IEA 2011].

Investment support policies could for example be grants or low-interest loans provided to cover the 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 [IEA 2004, 2011]. Investment support programs could also be directed towards research and demonstration facilities with the purpose of helping immature technology become commercially viable. These schemes are an older type of subsidy than feed-in tariffs and RPS, and are quite common 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 exclude a design targeted towards production efficiency instead of pure installation. A distinction between R&D policies and investment support should also be made. Public subsidies of R&D activities without investment in physical production capital were not defined as investment support policies in this study. The first investment policies were implemented (among the sample countries) in Denmark with its Act on support for the utilization of renewable energy sources starting in 1981, and shortly after in Italy in 1982 with the 308/82 law (1982–1989). The Italian 308/82 law enabled public investment of 113 million USD in 295 different renewable energy projects between 1982 and 1989. The support scheme did not have a big impact on renewable energy markets due to the modest scale of the financial resources and the highly bureaucratic management of the programs [IEA 2004]. Germany started its Support of the federal states scheme in 1985. This program is managed by the federal states (Länder) in Germany and regional differences could be large. Regional support in Germany is often sector specific, e.g. it could be targeted towards the agricultural sector or a specific industry. Solar PV and biogas systems have been prioritized technologies in these regional support programs [IEA 2011]. By the late 90s, different support schemes were in use in most of the sample countries. Until the middle of the first decade of the 2000s, countries such as Canada and Finland relied entirely on investment support schemes for the bioenergy sector [IEA 2004]. In Canada, a prominent support scheme for bioenergy is the ecoEnergy program and in Finland the Biorefine technology programme for new biomass products. The Canadian ecoEnergy program is a compilation of various support schemes, targeted towards different types of bioenergy such as biomass use in power generation or biofuels for the transportation sector. The Finnish Biorefine technology programme for new biomass products was introduced in 2007 and supports pilot and demonstration plants, the development of innovative new products and cooperation between companies from different industrial clusters for innovation in biomass technology [IEA 2011].

Empirically, investment support schemes have not shown any significant impact on innovation in bioenergy but were a significant determinant for waste-to-energy technology in the study by Johnstone et al. [2010], a technological field which to some extent is included in the definition of bioenergy in this study by the inclusion of e.g. landfill gas-technology.

Model specification

In order to model innovation, a distinction has to be made between technological innovation and economically useful innovations in general [Jaffe et al. 2000]. The latter need not necessarily implicate new technology, but could be new organisational forms or even more efficient societal planning. In this study, the former definition was used.

A cornerstone of the modern theory of technological change is the trichotomy defined by Schumpeter [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 on the market and; (3) Diffusion is when an innovation becomes widely adopted by various economic agents.

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

$$I_{i,t} = f\,(A_{i,t}, D_{i,t}, P_{i,t}) \tag{1}$$

The specification stipulated that the count of bioenergy patents (I) in country i and time period t could 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) included three major policy groups: feed-in tariffs (FIT), renewable portfolio standards (RPS) (i.e. renewable energy quotas) and investment subsidies. Tax policies were not explicitly included in the specification even though they are a fairly common policy instrument. The reason for that was the lack of reliable disaggregated data on tax policies used in the sample countries. The vector of RD&D variables (D) included two variables checking for the propensity to patent and the technical opportunity for bioenergy innovation. The vector of market variables (P) contained total energy consumption, the market price of electricity and the relative price between roundwood and light fuel oil.

For a 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 patent counts ($I_{i,t}$) follow a negative binomial distribution. Since it was quite likely that the countries investigated would differ substantially in their country-specific characteristics, the fixed-effects negative binomial model sug gested by Allison and Waterman [2002] was used in this study. That is, a negative binomial model with country-fixed effects was used for an estimation of equation (1). The downside was that it was not ruled out that the estimates would suffer from an incidental parameters problem[3]. The alternative was to use the fixed effects-model by Hausman et al. [1984], but since the conditional mean function would still be homogeneous in that model, instead there would have been what Greene [2007] names a "left-out variable problem".

The specification of the negative binominal model is given by equation (2) and (3). $E(I_{it})$ was the expected value (i.e. the mean) of the patent counts and β was a vector of coefficients. A, D and P were the vectors of determinants of innovation in the model and C was the country-fixed effects.

$$E(I_{it}) = u exp(\mathrm{x}'_{it}\beta) \tag{2}$$

where:

$$\mathrm{x}'_{it}\beta = \alpha + \beta_1 A_{it} + \beta_2 D_{it} + \beta_3 P_{it} + \delta C_i \tag{3}$$

The error term $u = \exp(\varepsilon_{it})$ was assumed to be gamma distributed.

Data

Fourteen countries in total were included in the sample (Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland and the United Kingdom) constituting an unbalanced panel dataset for the time period 1978–2009. The data on patents and the control variables was obtained from the OECD. The data used in the construction of the policy vector was collected from IEA [2004, 2011, 2013] and Cerveny and Resch [1998]. Moreover, various international governmental organizations and websites were consulted to extend and control the accuracy of the data used to construct the policy vector. Information on feed-in tariff levels and renewable energy quotas for specific years and countries was gathered from the latter sources in the case of missing information in the IEA database.

Patents filed under the Patent Cooperation Treaty (PCT)[4] were used as the PCT does not have the same problem of home bias as a simple count of applications made at the national patent offices might have. Furthermore, it does not have the same problems with weak timeliness, i.e., a very long delay between 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 filed under the PCT are defined as applications sorted according to

[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.

the 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 consisted 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 was obtained from the OECD Statistics database [2013]. In cases where total patents for a country and year were reported as a fraction (when several countries share the credit for a patent), it was rounded off to the nearest integer.

Following Moore and Ihle [1999], that a program for financial assistance must remain stable for at least ten years, two feed-in tariff variables were therefore constructed for this study: one for contracts of a minimum of 10 years or longer, and another for contracts shorter than 10 years. The feed-in tariffs were measured as continuous variables defined as USD per kWh (2005 value). The FIT variables were defined annually after an enactment or change in level. In instances when a policy was in use at the beginning of the year that it was first enacted, it was considered enabled the following year. This was based on the assumption that inventors react to active policies actually in use. In order to construct the FIT variables in a symmetric manner, policies abolished before the end of a given year were still counted as in use for that year. In most countries there was no uniform tariff level even within the same technology group. For instance, remuneration levels differed depending on the biofuel technology type and on the size of plant and policy design in use in a certain year. To account for this, the feed-in tariffs were calculated as a weighted average of the different relevant and comparable tariffs in use in each year. If the technology base eligible for support was 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 were not included. An example of this was the British NonFossil Fuel Obligation scheme (NFFO) where the fuel base eligible for support has been redefined several times during the existence of the program. As in the research by Rübbelke and Weiss [2011], tariff levels were also discounted with the stated yearly percentage if tariffs were constructed as descending by the regulator (e.g., in Germany).

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

Investment subsidies were measured as annual total funding (2005 USD value) of a specific program. In the instances where the data on the annual budget was not available, it was assumed that the total initial funding of a certain program was exhausted within five years. The reason for choosing a 5-year limit was that when time limits are explicitly mentioned in policy descriptions, five years is usually the timeframe used [IEA 2011]. Due to a lack of information, it was not possible to include some policies in the continuous investment variable, however these policies were taken into account by a cardinal interval variable which measured the total number of investment support policies in use for a specific year and country. Since these programs could target different sectors of the economy and could be more or less effective, they were divided into three separate variables; strong policies, weak policies and policies directly aimed at the household or residential sector. Cardinal investment policies were assessed as strong if they were directly targeted towards renewable energy production, either in power generation or the production of bioenergy. On the other hand, if a policy only provided a little 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 on the open market, it was categorized as weak. Furthermore, if it was unclear whether an explicit renewable energy policy was relevant at all for bioenergy, it was also classified as weak. The latter also applied to policies otherwise categorized as residential sector policies. When an investment policy overlapped two categories, it was then recorded as a fraction for each group. Table 1 summarizes the process in which the policy variables were constructed.

Table 1. Description and sources of data used

Type of variable	Data	Source	Processing by authors
Dependent variable	Patent data	OECD [2013]	None, compiled at the OECD. Originally data originates from the European Patent Office
Policy variables (independent variables)	Policy description	IEA [2004], IEA IRENA database [2011, 2013]. Cerveny and Resch [1998]. Governmental and bioenergy organizational websites*	Quantification of investment support data and computation of yearly mean feed-in tariff levels made by authors. In some cases (i.e. Japan) computation of effective quota levels for the RPS have also been made by the authors since explicit information regarding these have not been available
Control variables (independent variables)	Prices on energy, biomass and electricity. Total numbers of patents and yearly bioenergy RD&D. Total energy consumption	FAO [2013], OECD [2013]	Accumulated RD&D stock computed by summation of yearly expenses on bioenergy research

* France: FOGIME – http://www.muredatabase.org/
Belgium: Res Regulation – http://www.resregulation.gr/bibliography/
Canada: CBSA – http://www.cbsa-asfc.gc.ca
The Netherlands: SDE – http://www.energy.eu/
Japan: MoE – http://www.meti.go.jp/english/policy/energy_environment/renewable/index.html
General: http://fxtop.com/en/; http://faostat3.fao.org/

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

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

where: *STOCK* – the accumulated knowledge stock,
δ – the rate of depreciation,
x – the time lag before R&D expenditures was added to the knowledge stock.

According to Klaasen et al. [2005] a time lag of two years (x = 2) and a depreciation rate of 3% (δ = 0.03) is reasonable.

The data for national RD&D expenditures had some missing observations which could not be omitted since it would have made 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 was used to complete the series.

The demand-side factors included in vector (P), contained the electricity prices and the relative price between roundwood and light fuel oil. This price ratio served as a proxy for the relative price between biomass and other important fossil fuel prices. The reason for the choice of light fuel oil as proxy and not a broad index on oil prices was due to the limited data availability. Moreover, a variable on total energy consumption was included to check for the size of the energy market – higher energy consumption meant that there were greater potential sales for energy technology and therefore larger incentives to innovate. The electricity price was retrieved from IEA [2013] and was expressed in USD per kWh (2005 value). Total energy consumption was measured in TWh and originated from the OECD Statistics Database [2013]. In order to account for the aforementioned heterogeneity amongst the sample countries, 13 dummy variables[5] were added to the regression equation. This was 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 was expected to have had an impact on the patenting behaviour in the countries included in the sample. With TRIPS, intellectual property law was first introduced to the international trading system

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

and is still the most extensive international agreement on intellectual property so far introduced. An additional dummy was included in the regression to distinguish between pre- and post-TRIPS patenting activity. This dummy took the value of 1 from 1995 onwards.

Results and discussion

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

The econometric results were deemed statistically-reliable and nothing in the chosen estimation technique or model specification warranted further scrutiny. The patent data reliability was, however, harder to validate. This was not in terms of its source, but rather since it was difficult to validate that each patent was exclusively related to bioenergy technologies. The results were applicable to several issues and areas. Since the focus was on the effect energy and climate policies had on bioenergy innovation activity, the foremost area of applicability was in policy formulation. That is, based on the results, policy-makers could better assess different policy options if they desired to stimulate bioenergy innovation in their climate agenda.

The result of the regression is given in table 2. The results regarding the policy variables were diverse. Both variants of feed-in tariffs were statistically significant, with a positive impact on innovation. In addition, the cardinal variable for the strong investment policies was statistically significant with a positive sign. The other policy variables, such as quota obligations (RPS) or other different measures of investment support schemes were not statistically significant.

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

Table 2. Estimated coefficients of the negative binomial model with country fixed effects

Variable	Elasticity	P > z	Elasticity lower bound	Elasticity higher bound
Total PCT	0.150**	0.033	0.012	0.288
Investment support (continous)	0.010	0.494	-0.019	0.039
Strong investment policies	0.127**	0.029	0.013	0.241
Weak investment policies	0.009	0.696	-0.037	0.056
Household investment p.	0.019	0.467	-0.031	0.068
RPS	0.025	0.152	-0.009	0.059
Feed-in tariffs A (longer agreement)	0.172***	0.000	0.101	0.242
Feed-in tariffs B	0.072***	0.003	0.024	0.119
Energy consumption (market size)	2.394***	0.002	0.868	3.921
Accumulated bioenergy knowledge stock	0.439**	0.014	0.087	0.790
Electricity price	0.871***	0.001	0.365	1.378
Lagged relative price: roundwood/ light fuel oil	-0.332***	0.003	-0.549	-0.115
TRIPS	0.284***	0.004	0.089	0.479
Country dummies	14 DV			
Log-likelihood	-619.705			
Chi-squared (prob)	52.40	(0.000)		
n = 373				

* 10% significance, ** 5% significance, *** 1% significance

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

However, the assumption that the various investment support programs contained in the three cardinal interval variables had the same impact on innovation could be called into question. Therefore, a set of binary dummy variables for each of the three cardinal investment support variables was constructed and substituted for the cardinal variables. This represented other relevant investment policy support which, however, was impossible to quantify in the continuous variable. The results from that regression coincided with those of the first specification. Finally, a single dummy variable was constructed substituting all the cardinal variables. The dummy was significant with a positive sign and once again the same results were obtained regarding the other independent variables. Arguably, this confirmed the robustness of the result from the first specification.

It was possible that the ambiguous effect of the investment support schemes could have been a result of the method used in the quantification of the investment support variable. The continuous variable consisted of many different types of investment support programs, such as measures aimed directly at bioenergy investment, but also at renewables in general. Therefore, a further disaggregated continuous investment support variable was constructed in order to investigate whether a smaller subset of the policies had an impact on innovation in bioenergy. The new categories were: bioenergy investment support (mainly in power and large-scale heat generation), investment support against renewables in general, and support for renewable energy in the household and residential sector. It should be mentioned that the categorization was not analogous to the classification of the cardinal interval variable for the investment support programs impossible to quantify continuously. However, in the regressions using these new classifications, it was found that none of them was statistically significant and, therefore, the result from the first specification remained unchanged.

Another reason why RPS schemes and investment support programs did not show any significant effect could have been 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 patent classes used in the study were too diversified to enable the detection of such an effect in the regressions. Information on the policies in the IEA database was also in some cases quite vague regarding the scope and magnitude of the support targeted to bioenergy specifically, which made 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 have contained a higher share of noise than the other policy variables.

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

The results were 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 had a significant impact in that study but the support was 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 did not have a statistically significant effect in either of the studies.

In order to test how sensitive the results were to the assumed depreciation rate (3%) and lag structure (2 years) for the knowledge stock variable, a sensitivity analysis was carried out. Table 3 presents the regression results based on 2% and 4% depreciation rate and a one and 3-year lag structure. The sensitivity analysis is presented as a percentage change to the results in table 2. As table 3 indicates, the results were relatively robust to minor changes in the parameters used to construct the knowledge stock variable. No important change in the sign or significance of the variables used was detected.

Table 3. Sensitivity analysis of depreciation rates and lags in the construction of the knowledge capital stock. Change in estimated coefficients compared to the base model in percentage points

Variable	2% depreciation rate	4% depreciation rate	2-year lag	4-year lag
Total PCT	-0.5**	-0.5**	-9.5**	8.6**
Investment support (continous)	-1.2	-1.2	-23.8	14.3
Strong investment policies	0.4**	0.0**	-5.7**	3.1**
Weak investment policies	-5.0	12.7	7.9	4.2
Household investment p.	-6.3	-1.7	-45.1	3.1
RPS	-9.8	13.3	-1.6	7.6
Feed-in tariffs A (longer agreement)	0.1***	0.6***	-1.9***	2.5***
Feed-in tariffs B	2.6***	4.4***	-3.4***	7.4***
Energy consumption (market size)	-3.4***	4.5***	-0.8***	0.3***
Accumulated bioenergy knowledge stock	-4.3**	6.7**	17.3***	-6.1**
Lagged relative price: roundwood/light fuel oil	-0.5***	-0.1***	-5.9***	2.8***
Electricity price	-3.4***	-1.7***	-12.2***	0.6***
TRIPS	-1.7***	0.3***	-1.4***	-1.5***
Country dummies	14 DV	14 DV	14 DV	14 DV

Significance of estimated coefficients: * 10% significance, ** 5% significance, *** 1% significance

Conclusions

This study investigated the determinants of bioenergy innovations with a special focus on the effect of energy and climate policies, within a sample of 14 countries between 1978 and 2009. Innovation was approximated by patent counts, and a vector of different disaggregated policy measures was 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 suggested that these programs played an important role in technological change in the biofuel sector.

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

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

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