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Demand-pull and technology-push public support for eco-innovation: The case of the biofuels sector[☆]

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ABSTRACT

The purpose of this paper is to explore the differentiated impact of demand-pull and technology-push policies in shaping technological patterns in the biofuels sector. The empirical analysis is based on a novel and original database (BioPat) containing patents in the field of biofuels selected using appropriate keywords and classified according to the technological content of the invention. Our results generally show that technological capabilities and environmental regulation spur innovative activities in the biofuels sector. Both demand-pull and technology-push factors are found to be important drivers of innovation in the biofuels sector. However, technology exploitation activities in first generation technologies are found to be mainly driven by quantity and price-based demand-pull policies. On the contrary, the pace of technology exploration efforts in advanced generation biofuels is shown to react positively to price-based demand-pull incentives but also to technology-push policy. The clear diversity in the impact of different public support instruments provides new insights which fuel discussion on the optimal policy mix debate and offers new elements for the design of future policy strategies.

1. Introduction

Analysis of environmental innovation is gaining growing interest in the current academic and political debate (Berkhout, 2011; Borghesi et al., 2013; Kemp and Oltra, 2011; Markard et al., 2012; OECD, 2011). Different analytical perspectives have been adopted to investigate the dynamics, characteristics and determinants of eco-innovation and their impact on economic systems and societies as a whole (Arundel and Kemp, 2011; Arundel et al., 2011; Beise and Rennings, 2005; Costantini and Mazzanti, 2012; Jaffe and Palmer, 1997; van den Bergh et al., 2007; Wagner, 2007). In particular, there is a growing consensus on the potential pivotal role played by environmental and innovation public policies which are increasingly jointly investigated in order to understand how to foster the rate of introduction and diffusion of new environmental technologies and ensure the conditions for promoting economic development while protecting the environment (Corradini et al., 2014; Del Río, 2009; Mowery et al., 2010; Newell, 2010).

Relevant policy instruments are conventionally classified in the two broad categories of demand-pull and technology-push instruments (e.g., Horbach et al., 2012; Peters et al., 2012; Rennings,

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2000). Both kinds of instruments have been found to be important in spurring innovation in environmental technologies. However, only recently scholars have focused on the differentiated impact of these instruments on the diverse types of innovative activities such as those related to the introduction of incremental or radical innovations (Nemet, 2009), suggesting that demand-pull policies may benefit mature technologies to a larger extent than less mature technologies (Hoppmann et al., 2013). Moreover, the existing empirical literature usually does not differentiate between different types of demand-pull policies, i.e., price or quantity-based instruments which may have a different ability to spur innovation activities, especially when technologies at different stages of maturity are considered.

With regard to these issues, this paper aims to make two main contributions. First, it provides an econometric analysis of the differentiated effects of demand-pull and technology-push instruments on innovation performances by accounting for technology maturity, exploiting a panel database on a large country sample and a relevant longitudinal structure. Second, it investigates the impact produced by different types of demand-pull policies on innovation activities, taking into account the different stages of development of alternative technologies.

For these purposes, the choice of the biofuels sector appears to be appropriate as it is characterized by a strong pace of technological change and rapid evolution in terms of the emergence of different technological trajectories. A remarkable characteristic of the biofuels sector is in fact represented by the existence of different technology groups at different development stages, i.e., technology generations (Suurs and Hekkert, 2009a, 2009b). According to Janda et al. (2012), biofuels can be classified as conventional biofuels (first generation) which are based on conventional technologies mainly adopted by farmers' organizations, and advanced biofuels (second, third and fourth generations) originating from science-based technologies.

Moreover, since biofuels represent an alternative to fossil fuels with a high pro-environment potential related to greenhouse gas (GHG) emission reductions in the transport sector, a number of specific policies from both demand and supply sides have been implemented worldwide in this sector to create a stable investment environment and allow the commercialization and diffusion of biofuel technologies (Panoutsou et al., 2013).

Previous analyses on the effects of policies on the rate and direction of technological change in environmental sectors have proved to be difficult due to considerable measurement problems related to both eco-innovation and policy dimensions (Del Río 2009; Kemp 2010; Kemp and Pontoglio, 2011; Lanoie et al., 2011). In this respect, the paper specifically addresses measurement issues on both innovation and policy sides by carefully selecting information from relevant patent documents and collecting detailed information on different classes of policy instruments.

The rest of the paper is structured as follows. Section 2 describes the background of the analysis with specific reference to the relevant literature and identifies the research hypotheses to be empirically tested. Section 3 highlights the main characteristics of the sector under scrutiny. Section 4 presents the econometric approach and the dataset, while Section 5 provides empirical results. Section 6 offers some conclusive remarks.

2. Literature background

According to Arundel and Kemp (2011) and Arundel et al. (2011), eco-innovation consists of new or modified processes, techniques, systems and products for avoiding or reducing environmental damage. A large body of literature has contributed to finding out which main forces support eco-innovation, by means of theoretical and empirical models.[1] Such analyses suggest that both technology-push and demand-pull forces are important in shaping the rates of introduction and diffusion of new environmental technologies and that the role played by public policies in this context is particularly significant (Del Río 2009; Horbach, 2008; Kuhlmann et al., 2010; Nemet, 2009).

On the technology-push side, previous evidence has shown that the quality of the stock of knowledge and the level of technological capabilities acquired through research and development (R&D) activities are found to be very important for the production and diffusion of eco-innovation both at the micro and macro levels (Johnstone et al., 2012; Löschel, 2002; Popp et al., 2009, 2011a, 2011b). In parallel, since innovation processes need investments, market incentives are important when creating favorable investment conditions for firms (Schmookler, 1966). In this respect, the extent of market demand and the level of prices have been considered important incentives to eco-innovation (Beise and Rennings, 2005; Johnstone et al., 2010; Newell et al., 1999, 2006; Popp, 2002).

Public policies can act on both the demand and the supply sides to create favorable conditions for eco-innovation (Johnstone et al., 2012; Nemet, 2009), with environmental policies and subsidies to R&D recognized as the most important drivers of eco-innovation.[2] Stringent environmental regulation may induce flows of innovations that facilitate being compliant with the environmental targets by changing relative prices and the relative profitability of alternative technologies (Jaffe and Palmer, 1997; Newell, 2010; Porter and van der Linde, 1995). Moreover, environmental policies can create or enlarge the potential market for specific eco-innovations through the adoption of niche strategies (Kemp et al., 1998; Nill and Kemp, 2009). For instance, in the case of renewable energy technologies, demand-pull instruments aim to restore competitive conditions between fossil fuels and renewable energy sources which cannot reach their optimum performance without policy intervention that favors technological and organizational learning through their diffusion.

On the supply/technology side, the role of public policy in shaping the pace of innovation in environmental technologies is also important (Costantini and Crespi, 2013). A large body of literature has identified substantial market failure in the identification of the correct amount of resources that markets are able to allocate in the generation of technological and scientific knowledge (Arrow, 1962; Nelson, 1959). Moreover, the broader perspective adopted by the innovation systems literature has expanded the range of legitimate justification and scope for public intervention in this field to different types of system failures (Borrás and Edquist, 2013; Edquist, 2005; Fagerberg et al., 2005; Metcalfe, 1995; Nelson, 1993). Following these arguments, significant amounts of public funds are spent on programs that increase the quality of scientific and technological capabilities in innovation systems also through the funding of innovative activities by private firms (OECD, 2013).

Hence, in line with this reasoning, we test the following hypothesis:

HP1. Demand-pull and technology-push policies are relevant drivers of eco-innovation.

The policy instruments designed to enlarge the markets for new environmental technologies can be distinguished between

[1] Even though we are aware of strong differences in definitions, for the sake of simplicity, we will use the terms environmental innovation, eco-innovation, environmental-friendly and green technologies interchangeably in this paper.

[2] In this paper, we use the terms demand-pull policies and deployment policies interchangeably, indicating all instruments that aim to foster market expansion for eco-innovation. We also use the terms technology-push, supply-push or supply side as synonyms since only the effects of technology-push instruments have been considered in the present analysis.

quantity-based (such as quotas and targets) and price-based support policies (such as feed-in-tariffs and tax exemptions). Different studies have highlighted the difficulties in ranking price-based and quantity-based instruments with regard to their effectiveness in spurring eco-innovation (Fischer et al., 2003; Kemp and Pontoglio, 2011; Requate, 2005; Veugelers, 2012). According to Johnstone et al. (2010), several features influence the effectiveness of these policy instruments on innovation dynamics, such as, for instance, the type and strength of quantity-based instrument adopted, the stage of maturity of the targeted technological domain and the nature of the environmental effect. However, according to the relatively limited number of studies devoted to evaluating the performances of different instruments in enhancing eco-innovation, price-based mechanisms are usually considered more capable of creating a constant demand for innovation (Jaffe et al., 1999; Popp, 2003; Richard and Stewart, 1981). For example, tax exemptions turned out to be helpful in overcoming the barriers to creating markets for new environmental friendly products (Suurs and Hekkert, 2009a), whereas quantity-based instruments had minor effects on innovation dynamics since standards and quotas do not provide any incentive to innovate beyond the required level of environmental target (Jaffe et al., 1995, 1999; Menanteau et al., 2003). Hence, although the design elements of price-based instruments may diversely influence the effectiveness of their dynamic impact (Del Río, 2009), they are generally perceived as an incentive system that is more stable and predictable for investors, offering a long run perspective that may favor innovative investments (Schmidt et al., 2012). Moreover, by fixing the price rather than the quantity, price-based instruments allow firms to exploit market dynamics by gaining from increased competitiveness due to reduced production costs and by benefiting from market share expansion (Baumol et al., 1979). Finally, the distributive effects of different demand-pull policy types may also play a role in this respect. According to Finon and Menanteau (2003) who examined the dynamic efficiency of the different incentive schemes for the development of renewable energy sources by comparing quota-based bidding systems with feed-in-tariffs, it has emerged that quota systems (green certificates) increase the surplus gained by consumers who pay lower prices, while with price-based instruments (feed-in-tariffs), the surplus is entirely attributed to the producer who consequently receives greater incentives to eco-innovate.

Building on these analyses, we can therefore formulate the second research hypothesis as follows:

HP2. Price-based instruments display a greater impact on innovation activities than quantity-based instruments.

While the literature has provided substantial evidence on the importance of both demand-pull and technology-push instruments in shaping the dynamics of eco-innovation (see, for instance, Horbach et al., 2012; Newell, 2010; Rennings, 2000), the focus of recent contributions has moved towards an analysis of the balance between the two categories of instruments in the policy mix and an analysis of their differentiated effects with regard to the dynamics of environmental innovation at different stages of technological and commercial maturity, and with regard to the different types of innovative activities (Hoppmann et al., 2013; Nemet, 2009; Sagar and van der Zwaan, 2006). In particular, it has been claimed that public financial resources invested in demand-pull measures that aim to stimulate the deployment of renewable technologies (like those related to photovoltaic and wind energy) largely exceed investments in R&D supply policies (Laleman and Albrecht, 2014). Such an unbalanced structure of public budgets in favor of deployment policies has been criticized since it may impose high costs on the community without producing the expected positive impacts in terms of technological and environmental achievements which could be more fruitfully pursued by directly funding R&D activities (Frondel et al., 2008, 2010).

The importance of improving our understanding of the correct balance between demand-pull and technology-push measures within the policy mix is confirmed by recent studies that have conducted a detailed analysis of the mechanisms lying behind the relationship between deployment policies and technological innovation. In particular, by recognizing that firms face trade-offs between exploitation activities within their existing technological portfolios and exploration activities aimed at the generation of new technological options (March, 1991), we can argue that the growth of markets associated with the implementation of deployment policies may create disincentives for the development of non-incremental innovation which are indeed required for developing cost-efficient environmental technologies. In this respect, Nemet (2009) uses a case study on wind energy to assess the effects of demand-pull policies on non-incremental innovations, showing that in the scrutinized sector major inventions do not positively respond to demand stimuli, but, conversely, appear to be fostered by technology-push forces. Hence, it is suggested that a strong focus on deployment policies may direct innovation activities toward exploitation rather than exploration which may lead to a reduction in the pace of radical innovations and increase the risk that the system gets stuck in technological lock-ins (Arthur, 1989; David, 1985).

These arguments have been further tested by the analysis of Hoppmann et al. (2013) who conducted case studies on a global sample of nine firms producing photovoltaic modules complemented by experts' interviews. This study confirms the importance of carefully looking at the types of innovative incentives deriving from deployment policies and at the mechanisms linking policy inducement effects and firms' technological exploitation and exploration activities. In particular, they do not find support for the hypothesis that deployment policies tend to reduce investment in technological exploration activities. On the contrary, they show that an increase in market size induced by policy actions raises the absolute level of investment in both exploration and exploitation. Moreover, they find that most of the observed companies used part of the earnings generated from the exploitation of more mature technologies to finance exploration of alternative non-incremental technologies. However, deployment policies are found to induce firms that pursue more mature technologies to shift the balance towards exploitation activities. This implies that deployment policies may be very effective in inducing incremental innovation, while, under certain circumstances, they can also run the risk of generating technological lock-in effects.

Following this discussion, we can formulate the hypothesis that:

HP3. In mature technologies demand-pull policies have a greater impact on innovation dynamics than technology-push instruments.

In contrast, the reviewed literature has shown that demand stimuli may not be sufficient to stimulate innovation activities in less mature technologies in the absence of adequate technological capabilities, suggesting that:

HP4. In less mature technologies innovation is spurred by both demand-pull and technology-push instruments.

Finally, previous discussion of the different innovation incentives provided by quantity and price-based instruments suggests that the latter are generally perceived by investors as more stable and predictable, thus offering a long run perspective. Hence, considering that exploration activities within less mature technologies usually request a strategic commitment towards long-term investment, we can hypothesize that:

HP5. In less mature technologies price-based instruments are more effective in fostering innovation activities than quantity-based instruments.

In order to test our research hypotheses, the present analysis focuses on a relevant sector in the domain of renewable energies, the biofuels sector, which, as will be highlighted in the next section, offers an appropriate research setting for our purposes since it allows us to study the impact of both technology-push and demand-pull policies on innovation dynamics by accounting for the maturity of different technology generations and for the different role played by price-based and quantity-based instruments.

3. The case of biofuels

Over recent decades, several policy instruments have been progressively adopted, especially at the European Union (EU) and OECD level, in order to reduce GHG emissions, and actions for decarbonising road transport are particular relevant within this strategy (EEA, 2012). In this respect, biofuels are expected to substantially contribute to decreasing emissions, but also to improve the sustainability of the transport sector from an energy security point of view by reducing its oil dependence in a context of high volatility of oil prices and increasing fossil fuel scarcity.

The global production of biofuels – liquid and gaseous fuels derived from biomass – has been growing steadily over the last decade from 16 billion liters in 2000 to more than 100 billion liters in 2011 (IEA, 2012a). Today, biofuels provide around 3% of total road transport fuel globally (on an energy basis) with considerably higher shares achieved in certain countries and, according to IEA projections, biofuels will undergo a huge increase in total production and provide up to 27% of world transportation fuel by 2050 (IEA, 2011a, 2012b).[3] Biofuel production costs vary significantly across the main producing countries. Brazil has the highest competitive advantage for bioethanol and is the only producer, based on the current state of technology, that can compete with fossil fuels without public support. This competitiveness derives directly from the introduction of public policies supporting the Brazilian biofuel market until the early '70s. Brazil is considered to be the biofuel industry leader and serves as a policy model for other countries since its sugarcane ethanol is the most successful alternative fuel to date (Sperling and Gordon, 2009). Since 1976, the government has made it mandatory to blend ethanol with gasoline, increasing the mandate continuously. The introduction by the early '90s of flex fuel vehicles ensured the complementary technology needed to sustain market demand also on the infrastructural side and has created a sustainable biofuel economy, where the biofuel industry is fully competitive with the fossil fuel market.

All other producing countries have to adopt some form of policy intervention and world biofuel production and consumption are therefore, characterized by large and pervasive public subsidies. Such support is justified by the environmental, energy security and socio-economic advantages associated with biofuels, but it is considered a transitional measure to allow for the development of technologies leading to cost competitiveness in the medium term (IEA, 2011b).

Policy instruments for the biofuels sector cover a large set of support and regulatory measures (Costantini et al., 2010). Demand-side policy measures currently provide most of the support for biofuels and consist of both price-based and quantity-based instruments. Most countries support the deployment of domestic production of biofuels through favorable tax regimes that reduce cost differentials with fossil fuels and through tax exemptions or fuel tax rebates for gasoline and diesel, or volumetric tax credits. Quantity-based policies to increase the demand for biofuels by substitution of fossil fuels entail regulatory measures, such as targets and mandatory requirements for fuel blending shares. While some of these do not discriminate between distinguished forms of biofuels, others specifically target bioethanol and biodiesel. On the supply side, public intervention is carried out through technology-push policies that aim to increase the whole quality of innovation systems and support specific R&D activities in order to speed up the sector's technological evolution.

For what concerns the role of technological maturity, Hekkert et al. (2007) and Suurs and Hekkert (2009b) suggest that the biofuels domain offers an interesting example of different technology generations competing for public support and represents a relevant case for studying the effects of the balancing exercise between deployment policies and technology-push instruments. As previously mentioned, biofuels can be classified as conventional biofuels (first generation) which are based on conventional technologies and whose additional inventive activities are mainly confined to incremental innovation and advanced biofuels (second, third and fourth generations) originating from science-based non-incremental technologies (Janda et al., 2012). First generation biofuels are made from food crops rich in sugar, starch or vegetable oil. The most common types of first generation biofuels are bioethanol and biodiesel obtained from coarse grains and sugar cane and from oilseeds, respectively. They have limited performance in terms of emission reduction and have been criticized for causing deforestation and putting pressure on agricultural land needed for food and fodder production.[4] However, they are already in a near-commercial stage of development (Cheng and Timilsina, 2011; IEA, 2013). In contrast, advanced generation biofuels produced from residual non-food parts of current crops, as well as other crops that are not used for food purposes, such as *switch grass* and *jatropha*, or are obtained from algae, are expected to contribute significantly to the future energy supply mix (Balan et al., 2013; Carriquirya et al., 2011; Glithero et al., 2013). They are expected to perform much better in terms of costs, land use and emission reduction (Eisentraut, 2010; Sims et al., 2010). However, they are in a pre-commercial stage of development. For instance, depending on the type of biofuels, the cost of cellulosic bioethanol is found to be two to three times higher than the current price of gasoline on an energy equivalent basis. The average cost of biodiesel produced from microalgae is seven times higher than the current price of diesel.

The justification given to the huge amount of resources invested in deployment policies which favored the diffusion of first generation biofuels rests on the argument that a market must be created even if the actual state of technology is not environmentally and economically sustainable because scale effects will help to discover new (advanced generation) technologies for producing biofuels which are more efficient and less harmful to eco-systems. This means that the policy targets implemented until recently were set independently of the available state of technology since they have been designed with the specific purpose of creating a market without considering the new potential technological evolution from the production process side, but only considering it as a final goal to make final products competitive on the fuel market. This has led to a mainly demand-oriented biofuels policy setting which has been criticized only recently by the international community and whose

[3] Brazil, for instance, met about 23% of its road transport fuel demand in 2009 with biofuels.

[4] According to Cheng and Timilsina (2011), current bioethanol and biodiesel production mainly relies on raw materials which are competing with food and feed production for the limited arable land (FAO, 2010; Zhang et al., 2010).

effects on technological patterns have still not been systematically addressed by the scientific literature (GSI, 2013).

Previous detailed studies on the biofuels sector (in the Netherlands) have highlighted the primary role of deployment policies for advancements in first generation technologies which are increasingly perceived as a stepping stone towards future use of advanced generation technologies (Hekkert et al., 2007; Suurs and Hekkert, 2009a, 2009b). In fact, current exploitation efforts in first generation biofuels on improved conversion technologies, integration of systems, fuel quality and specifications, as well as requirements for blending, distribution, and storage respond to the need to overcome the technical and economic barriers that impede unbounded expansion of the market, whatever technology (first or advanced) is used to obtain the final product (Hoekman, 2009).

However, whether the support for the diffusion of first generation biofuels could indirectly stimulate innovation activities in advanced generation biofuels or favor investment concentration in exploitation activities still remains an open issue. Previous evidence suggests that since advanced generation biofuels originate from science-based technologies and require technological exploration activities, technology-push instruments are of crucial importance to their development (Hoekman, 2009; Panoutsou et al., 2013). However, a pure R&D-driven strategy may be ineffective in the absence of market formation activities because it forms a critical barrier to the development of advanced generation technologies. In this respect, within demand-pull policies, price-based tools are expected to be more effective than quantity-based instruments in supporting innovation in energy technologies whose cost is not close to traditional energy technologies, by offering a longer-term perspective that may favor explorative activities.

4. Description of the empirical study

4.1. The empirical model

In order to identify the drivers of the innovation activity in biofuel-related technologies and test our hypotheses, we collected data for OECD members and some non-OECD countries in the time span 1990–2010.[5] Building on previous contributions that have adopted econometric analysis to study the determinants of eco-innovation with specific attention to the role played by public policies (e.g., Johnstone et al., 2010), we considered a standard model setting in the form:

$$\begin{aligned} Y_{i,t} = {} & \alpha_i + \beta_o + \beta_1(\text{InnSys}_{i,t-p}) + \beta_2(\text{EnvSys}_{i,t-p}) + \beta_3(\text{BiofPol}_{i,t-p}) \\ & + \beta_4(\text{EneSys}_{i,t-p}) + (\text{Controls}_{i,t-p}) + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $Y_{i,t}$ indicates the innovation performance measure in the biofuels sector, $i=1,\ldots,N$ indexes countries, $t=1990,\ldots,2010$ indexes time, α_i are country-specific unobserved effects, p stands for eventual lag structure and $\epsilon_{i,t}$ are stochastic errors. In order to test our hypotheses and account for different factors influencing innovative activities in the sector under scrutiny, four specific groups of variables and an additional controls group have been considered, representing respectively: the national innovation system ($\text{InnSys}_{i,t-p}$), the national environmental system ($\text{EnvSys}_{i,t-p}$), the range of specific public policies in the biofuels sector $\text{BoifPol}_{i,t-p}$, the national energy system ($\text{EneSys}_{i,t-p}$) and finally, further standard controls ($\text{Controls}_{i,t-p}$).

4.2. The dependent variable

Measuring innovation is a challenging task especially when specific technological domains have to be analyzed. Indeed, innovation depends on a variety of activities ranging from formalized R&D to production engineering. Organizational innovations and different forms of soft innovations are also relevant (Archibugi and Pianta, 1996; Sirilli, 1997). Though widespread in the literature, the use of patent data to measure innovation has been subjected to much criticism (Griliches, 1990). While a single patent provides information on relevant aspects of the innovative process, only a limited part of produced innovations is patented and patent data classifications are not organized according to economic principles with an intrinsic variability in patent value (Jaffe and Trajtenberg, 2002).

Nevertheless, the use of patent information often represents the only valuable option when a specific technological domain has to be investigated in absence of alternative statistical sources, such as specific R&D or innovation surveys data. In the case of the biofuels sector, large surveys and information on R&D efforts by private firms were not available and we therefore, chose to rely on a patent-based innovation measure. In this respect, we followed a first attempt to analyze innovation drivers in the biofuels sector working with patent data provided by Karmarkar-Deshmukh and Pray (2009) where, however, only ethanol-related patents subclasses in USPTO were considered.

In order to properly identify relevant patents in the investigated sector and better map the evolution of different generation technologies, innovative activities should be detected and classified according to specific criteria which do not correspond to already existing classification tools. In this respect, the hierarchical International Patents Classification (IPC) aims to classify the innovative content of the patent, whereas economic activities are classified according to the domain of goods they produce. Consequently, standard IPC system is only of limited usefulness when it comes to identify a specific sector which does not fit the criteria used in the classification itself (Narin, 2000). This issue appears to be of particular relevance when analyzing the biofuels sector due to its technological cross-cutting nature since technologies which could be ascribed to this field are heterogeneously diffused throughout a large range of sectors (Suurs and Hekkert, 2009a, 2009b). Yet when the set of relevant technologies is diverse, we may miss relevant patents that, for a variety of reasons, do not fall within the identified classes (Leea et al., 2011). In order to tackle this problem and properly identify relevant patents, the dependent variable in our model is computed using a sector-specific (keyword-based) patent database, hereafter called BioPat which also groups patents according to different technology generations for the production of biofuels and for different final products (Costantini et al., 2014).

More specifically, BioPat consists of a hybrid collection method relying on a combination of a description-based keyword search criterion together with a patent class-based search criterion.[6] The

[5] Countries included in our analyses are: Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Greece, Hong Kong, India, Indonesia, Italy, Japan, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Portugal, Russian Federation, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, United Arab Emirates, United Kingdom and United States of America.

[6] The only available patent class-based criterion applied to the biofuels sector is given by green inventory (GI), developed by the world intellectual property organization (WIPO) for a large set of eco-innovation domains (WIPO, 2011). The amount of patents selected in BioPat is larger than counts deriving from GI methodology since BioPat includes all biofuel-related applications, both with the direct aim of producing biofuels or with an indirect (although declared in the description) effect on the biofuels sector but with a main aim that could be different from processing biofuels. According to the experts' validation of BioPat reported in Costantini et al. (2014), the information contained in this database is more closely linked to innovation in the biofuels sector than that deriving from GI classification. For further details on BioPat methodology, see Appendix B.

hybrid process used for selecting patents in BioPat is extremely valid when it is important to understand how technologies evolve over time, if they are narrowly focused on selected and well-established domains, if they are expanding towards complementary sub-technologies needed to exploit market possibility, or if they are more radically evolving towards a different technological trajectory. This characteristic is clearly a crucial aspect of BioPat, since it helps to analyze the diverse effects of different demand-pull and supply-push policies on the technological dynamics of the biofuels sector.

In this analysis, we consider that the patent application date closely reflects the timing of inventors' propensity to patent and avoid considering disputes involved in patent grant processes (Griliches, 1990). Moreover, we only consider patents applied to EPO since, as suggested by Johnstone et al. (2010), patents registered in EPO may be more reliable as a data source when patent count models are developed, especially when different OECD countries are compared and several European countries belong to the country sample.[7]

Our dependent variable is broadly defined as a pure count data based on the number of patents applied to EPO which are classified by application date and assigned to the applicant's country. When multiple assignees are present for a single patent, we assigned a proportion of the patent under scrutiny to each country on the basis of the number of assignees for each country. Since econometric count models work with integer values, we then approximated all count data to the closest integer values. We are aware that several studies have tried to analyze innovation dynamics by also controlling for patent quality. In this respect, two general issues should be accounted for. First, given that EPO applications are more expensive than applications to national patent offices, inventors typically apply to EPO if they have strong expectations in terms of economic exploitation of the invention. Hence, for the purpose of this paper, EPO data are superior to data from national patent offices because the difference in costs provides a quality hurdle which eliminates applications for low-value inventions. While the European market is significant, it is still expected that there will be some bias toward applications from European inventors. In the empirical analysis undertaken in this study, this bias is addressed through the inclusion of country fixed effects and a control variable reflecting data on total patent per capita.

Turning to the research hypotheses tested in this paper, in order to test HP1 and HP2, a total patent count variable has been built by considering all patents applied to EPO available in BioPat. Then, with regard to HP3–HP5, we made a distinction in BioPat between patents related to different technology generations according to the classification proposed by Janda et al. (2012). In particular, two dependent variables representing first generation biofuels (here classified as Food and Sugar as the main technological domains available in BioPat) and advanced generation biofuels (here classified as Ligno and Algae as the main technological domains available in BioPat) are considered (see Appendix B for details). The former should reflect innovative activities aimed at the exploitation of technological and market opportunities within the dominant design for producing biofuels for commercial purposes. The latter should capture non-incremental innovation activities deriving from technology exploration efforts within technologies which are still at embryonic production stages, not competing yet with existing biofuel production technologies, but developed for the purpose of exploring new technological and market opportunities in the medium run. Although innovations within advanced generation biofuels could not all be considered radical ones, patents specifically applied for regarding the production process of advanced generation biofuels could be interpreted as a signal of non-incremental research activities since they generally consist of efforts to develop ecologically superior technological alternatives to first generation biofuels with regard to energy balance and food competition issues.

4.3. The independent variables

4.3.1. The innovation system

Let us now describe the set of regressors included in the analysis. The first group of control variables are related to the national innovation system ($\text{InnSys}_{i,t-p}$).[8] In this work, we have included alternatively three measures of the innovative capacity at country level: gross expenditures in R&D (GERD), here expressed as a percentage of GDP taken from the OECD Science, Technology and R&D Statistics (OECD, 2012); the total number of triadic patents by applicants in per capita units taken from World Bank, World Development Indicators (WDI) online database (World Bank, 2013); the stock of accumulated knowledge in the specific biofuels domain taken by BioPat according to the formula:

$$\text{KPAT}_{i,t} = \sum_{s=1}^{t} \text{PAT}_{i,s} e^{[-\mu(t-s)]} \tag{2}$$

where $\text{PAT}_{i,s}$ represents the number of patents in the biofuels sector taken from BioPat applied in country i in year s, where s represents an index of years up to and including year t, whereas μ is the decay rate. Through this knowledge accumulation measure, according to Jaffe et al. (1998), some sector-specific features associated with knowledge cumulativeness can be captured, such as learning by inventing effects which might not be captured by broader country-based measures.

4.3.2. The environmental system

The second group of regressors is included in the model in order to control for the effects that the environmental system ($\text{EnvSys}_{i,t-1}$) at national level may have on the innovation performance of the biofuels sector. For this purpose, previous literature used information on environmental protection expenditure, carbon intensity or proxied environmental stringency through count variables based on the number of policies implemented in a specific field (Brunnermeier and Cohen, 2003; Costantini and Crespi, 2008, 2013; Johnstone et al., 2010; Lanjouw and Mody, 1996).

In view of the fact that expansion of the biofuels sector is strongly related to the objective of reducing the carbon intensity of economic systems, in the proposed empirical analysis, we account for this aspect by including an index of carbon intensity in the model

[7] There are many empirical analyses relying on patents applied to the USPTO instead of EPO. However, in this way, results may overestimate the role of the US compared with other advanced economies since US firms have a higher propensity to apply to USPTO than to other international offices. This is mainly due to the fact that the Patent Cooperation Treaty, which streamlines the filing process in its member country, requires an invention to be novel and involve an inventive step, but states that being non-obvious is sufficient to involve an inventive step. The EPO has a stricter interpretation of this term with respect to USPTO, since European patent application involves an inventive step if it solves a technical problem in a non-obvious way. This introduces two extra requirements: it must solve a problem (no problem solved means no inventive step) and the problem must be technical (solving economic problems means no inventive step). In this respect, patents applied and granted at EPO are judged with greater accuracy in their innovative content than USPTO ones, thus being a more stringent but also a more reliable measure of available technology. By considering only EPO patents, it is implicitly assumed that US firms apply for patent grants only for economically valuable inventions with a potential higher diffusion path since it is much more costly to apply to EPO than to USPTO. Differences in using EPO or USPTO patents at sectoral level are well detected in Bacchiocchi and Montobbio (2010).

[8] For a synthetic view of all variables considered in the analysis, main statistics and correlation matrix, see Appendix A, Tables A1–A3.

specification, built as the ratio between CO_2 emissions (kt) and GDP in PPP (at current international $) taken from the WDI. We adopted CO_2 emissions in equivalent terms, meaning that we include here all GHG emissions expressed in CO_2 terms since we would like to rely on a measure that is quite strongly related to the environmental domain of biofuels and represented exactly by fossil fuels combustion-based emissions. Since the higher the carbon intensity of one country, the lower the domestic efforts in protecting the environment, we expect to find a negative relationship between this index and the innovation performance of the biofuels sector which is consistent with previous evidence (Costantini and Crespi, 2008, 2013; Ghisetti and Quatraro, 2013).

We also controlled for a direct measure of a pro-environmental setting built as the number of policy actions promoting renewable energy sources (solar, wind, geothermal, biomass, biofuels etc.,) by taking information from the IEA/JRC Global Renewable Measures Database which provides data on policies applied in over 100 countries in support of renewable energy from the early 1970s until now. In so doing, we followed the approach proposed in Johnstone et al. (2010) and we constructed a composite policy variable in the form of a count variable given by the annual cumulative number of already existing policies with the aim of fostering renewable energies production, adoption and diffusion in place for each i-th country.[9]

4.3.3. The biofuels policy setting

In the proposed empirical analysis, a specific effort was made to map public policies in the field of biofuels according to a classification criterion that was able to disentangle demand-pull and supply-push policies as well as divide price-based from quantity-based policy tools. In this respect, the case of biofuels is particularly intriguing since information can be collected on several distinguished measures for a broad range of countries in a homogenous way.

On the demand side, we focused our attention on two main tools which have been shown to mostly influence the biofuels sector, namely fuel mandate (here undistinguished between bioethanol and biodiesel) representing a quantity-based instrument, and excise exemptions distinguished by bioethanol and biodiesel as a form of price-based instrument. More specifically, in the third group of variables in Eq. (1) representing public policies applied to the biofuels sector ($\mathrm{BiofPol}_{i,t-p}$), the price-based policy has been built up by looking at tax exemptions obtained by reports provided by the Global Subsidies Initiative (GSI, various years). Based on this information, the variable "excise exemption" is computed for distinguished bioethanol and biodiesel and for biofuels as an aggregate. All tax reductions for distinguished bioethanol and biodiesel were originally expressed in national currencies and current exchange rates with the US dollar were applied to obtain comparable information expressed in US dollars. All excise exemptions were standardized by expressing them in terms of the weight of the exemption on the excise tax applied to gasoline and biodiesel:

$$e^j_{i,t} = \frac{\mathrm{exemption(US\,\$\ per\ litre)}^j_{i,t}}{\mathrm{excise(US\$\ per\ litre)}^j_{i,t}} \times \mathrm{consumption(litres)}^j_{i,t} \qquad (3)$$

where i is the country and j is alternatively given by the couple bioethanol–gasoline or biodiesel–diesel. In this way, we can obtain a measure of support policy which reflects the effective weight of public support for biofuels compared with the cost of standard fossil fuels.[10] Recalling that energy prices related to production costs are quite homogeneous across countries, the specific factor influencing differences in energy prices is given by taxation. This is particularly relevant for transport fuels. This means that the same excise exemption in monetary value may have a different economic impact if the total excise tax paid for gasoline or biodiesel is substantially different across countries. To some extent, this standardization procedure allows the direct effect related to biofuel policies and the inducement effect related to energy prices to be simultaneously accounted for. Moreover, weighting the excise exemption with the corresponding fuel consumption allows us to quantify the real effect of the price-based tool with respect to the market dimension. Finally, the "excise exemption (biofuels)" variable is derived by computing the arithmetic mean of the two fuel-specific variables.

Quantity-based demand-pull policies are here represented by the variable "fuel mandates", including information on mandates for blending targets for bioethanol and biodiesel in gasoline and diesel distributed for final consumption. The corresponding data are also taken from GSI (various years) and are computed as percentage ratios of total fuel consumption. In this specific case, we did not distinguish between bioethanol and biodiesel, since mandates are quite homogenous for the whole country sample analyzed, but more importantly due to the fact that in several countries, the blending mandate is given as a common value that is not distinguished for the two different fuels, thus making it difficult to have separate measures for bioethanol and biodiesel for the whole country sample.

On the supply side, the most specific comparable measure at a cross-country level is public R&D expenditures in the bioenergy domain (IEA, 2011b) here expressed as a percentage of GDP (RD bioenergy), representing a technology-push policy. Since the biofuels sector is complex and strongly interconnected, we adopted the broader category of bioenergy rather than focusing only on liquid biofuels. In addition, data availability for R&D in liquid biofuels is so poor that most of observations in our country sample will disappear.

4.3.4. The energy system and other controls

The fourth group of variables allows us to account for some characteristics of the energy system at country level ($\mathrm{EneSys}_{i,t-p}$), as suggested by Johnstone et al. (2010) and Popp et al. (2011b). For this purpose, we took two measures expressed as total energy consumption and total energy consumption in the transport sector both from the WDI.

Finally, the fifth group of variables refers to further controls to be included in the analysis. In this case, we adopted the level of export flows as a percentage of GDP in order to capture the openness degree of each country as a broad measure of the capacity to compete on the international market (also taken from the WDI). We also included a dummy variable (dummy biodiesel) assuming value 1 if the country is a large producer or consumer of biodiesel. In this way, we can also control for the type of agricultural system which might influence the patterns of innovative activity at country level. For instance, the US, compared with many European countries, is specialized in the production of bioethanol since the agricultural system is highly competitive in producing maize and wheat, whereas in Europe, crop specialization focuses on oilseeds.

[9] We are aware that more specific environmental protection measures would offer a complementary, accurate representation of the environmental setting, but data availability would force us to drop several non-OECD countries such as Argentina, Brazil and China among others whose innovation efforts in biofuels are currently faster than for OECD countries.

[10] We are particularly indebted to an anonymous reviewer for suggestions received regarding the statistical treatment of excise exemption variables.

Lastly, we include year dummies in order to control for cyclical variations in the number of patent counts.[11]

4.4. Econometric methodology

The use of patent data as proxies for innovative activity implies that we have to deal with count variables, that is, variables with non-negative integer values.[12] Econometric models specifically designed for this kind of variable are the Poisson Regression Model (PRM) and the Negative Binomial Regression Model (NBRM). The PRM is the natural starting point for an analysis of count data but it may be biased by an excess in zeros and an overdispersion problem. In many applications, the model underestimates the probability of a zero count and in general of low counts.[13] In addition, the well-known equidispersion assumption of the Poisson model, the equality of the conditional mean and the conditional variance, is commonly violated. Real variables are often overdispersed, that is, the variance exceeds the mean. The major disadvantage with the presence of overdispersion is that estimates are inefficient with the standard errors biased downward, resulting in spuriously large *z*-values and small *p*-values (Cameron and Trivedi, 1986). In these cases, the NBRM, which addresses the failure of the PRM by introducing unobserved heterogeneity across the Poisson means, could be used.

Given that our dependent variables are strongly overdispersed and do not have an excessive number of zeros, a fixed effects NBRM model is used to estimate Eq. (1).[14] The basic model in the context of panel count data was proposed by Hausman et al. (1984). According to their specification, we model the number of patents in one year for each country as a negative binomial process, that is, a Poisson process with distribution parameter randomly distributed in the population and following a gamma distribution $y_{i,t} \sim \text{Poisson}(\gamma_{i,t})$.

Finally, in order to account for unobservable country specific heterogeneity, we rely on the fixed effects estimator by conditioning the probability of the counts for each group on the sum of the counts for the group.[15] The maximum likelihood method is used to estimate the model parameters.[16]

When looking at temporal structure, it is worth mentioning that all explanatory variables are treated with a potential number of lags equal to *p*. This is quite a common choice in the literature, where the dependent variable is represented by an innovation output measure. This modelling choice also reduces potential endogeneity issues related to regressors such as, for instance, the innovation input or the policy variables which may be endogenously linked to the dependent variable.

In order to test the validity of alternative lag structures, we performed a Bayesian information criterion (BIC) applied to model in Eq. (1) testing for *p* assuming value 1, 2, 3. Since the penalty term for the number of parameters in the model is larger in BIC than in AIC, the first one is to be preferred as a more stringent overfitting model test. Results on BIC for alternative lag structures are reported at the end of Table 2 which includes the highest number of regressors, thus being characterized by the highest probability of overfitting.[17] The resulting temporal structure from BIC values is characterized by one year lag. This empirical result is consistent with existing contributions (see Johnstone et al., 2010 among others). Moreover, from a conceptual point of view, environmental policy variables over this short horizon (five to eight years, since public policies supporting biofuels were implemented in a systematic way by the early 2000s) are rather stable or growing slightly (in terms of fuel mandates or excise exemptions) because they respond to a long run commitment in policy design and therefore it is difficult to estimate complicated lag structures.[18]

Since there are some concerns at theoretical level about potential mutual causality where technological progress may lead to a perception of comparative advantage in this specific technological domain which may be a catalyst for deciding to adopt pro-biofuel policies in order to exploit the already achieved profitable conditions, treating policy variables with temporal lags may not be enough to mitigate potential endogeneity. To this purpose, we also carried out robustness checks and estimated Eq. (1) by implementing a GMM estimator for count variables with endogeneous regressors (Windmeijer, 2006, 2008).

Nonetheless, from a conceptual point of view, we have to remember that biofuels policies are reasonably standardized among the countries considered in our panel and they have mainly responded in the past to energy security and emission reduction criteria, as has been emphasized in Section 3 which describes the biofuels sector as a whole. This means that countries setting policies supporting biofuels have designed policy instruments without specific considerations about existing best available technologies and related competitive advantages, but with the main purpose of creating a market for well-established – but over costly – technologies that already exist.

5. Results

The empirical results are presented to reflect the research hypotheses outlined in Section 2. As a first step, we propose different specifications for a baseline model to select relevant control variables accounting for the level of technological capabilities within the national innovation system, the energy and environmental setting as well as other factors. Table 1 reports results obtained by performing an NBRM applied to patent count data, where the dependent variable is represented by a count of all

[11] Except for the dummy variable for countries specialized in biodiesel production and consumption, all the other explanatory variables have been log transformed so that coefficients can be interpreted as elasticities. For the former variable, the coefficients can be interpreted as semi-elasticities as usual.

[12] Further research could be devoted to the exploitation of patent data using continuous variables, for example, by computing the ratio of biofuels-related patents to total patents or GDP. Clearly, in such cases, the econometric estimation would have more flexibility since several more approaches could be used than for count variables.

[13] Alternative methods are designed for variables with excessive zeros (Zero-inflated negative binomial regression, Hurdle model, etc.). See Cameron and Trivedi (2009) for a more comprehensive discussion.

[14] If the likelihood-ratio test on the overdispersion parameter provides strong evidence of overdispersion, then the NBRM is preferred to the PRM. See the Appendix for descriptive statistics of the dependent variables and graphical representations of the observed and predicted probability assuming a Poisson and a negative binomial univariate distribution for the dependent variables (Fig. A1).

[15] The Hausman test points out that the fixed effects estimator is more appropriate than the random effects estimator.

[16] The maximum likelihood negative binomial mean-dispersion estimator is not consistent if the variance specification is incorrect. As an alternative estimation strategy, we estimated our basic equation with the PRM using the pseudo maximum likelihood approach. This approach only requires the conditional mean function to be correctly specified and allows consistent estimate of the coefficients even if the count variable is not Poisson distributed (Wooldridge, 1999) and results do not change substantially. Thus, in the following, we simply report those based on the NBRM which, in the absence of significant changes in the estimated coefficients, remain the most efficient estimation method. All results based on the pseudo maximum likelihood approach are available upon request from the authors.

[17] It is worth mentioning that BIC tests could be carried over models with the same number of observations, hence for each model in Table 2, the three alternative lag structures have been tested over the same sample, resulting in fewer observations than those reported for time structure with one lag (which is that reported in full detail in Table 2).

[18] This is also valid for the other explanatory variables, especially those related to innovation capabilities (Hall et al., 1986).

Table 1
Baseline model (dependent variable: total patents in BioPat).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GERD % GDP	1.158***			1.141***					
	(7.57)			(7.77)					
Total patents per capita		0.245***			0.269***		0.284***	0.272***	0.286***
		(5.07)			(5.59)		(5.83)	(5.56)	(5.77)
Patent stock in BioPat			0.629***			0.603***			
			(10.5)			(12.24)			
Export % GDP	0.878***	1.084***	0.833***	0.789***	0.896***	0.881***	0.855***	0.850***	0.809***
	(4.54)	(6.63)	(5.43)	(4.93)	(5.8)	(6.32)	(5.48)	(5.27)	(4.95)
Energy consumption	0.106	0.369***	(0.081)						
	(0.73)	(2.96)	(−0.70)						
Road energy consumption				0.376	0.623**	0.024	0.597**	0.586**	0.557**
				(1.26)	(2.46)	(0.11)	(2.31)	(2.23)	(2.08)
Carbon intensity							−0.697*		−0.668*
							(−1.77)		(−1.68)
Policy count in renewables								−0.095	−0.093
								(−1.55)	(−1.52)
Country specialization dummy in biodiesel	0.767**	0.986***	−0.375	0.789**	0.745**	−0.241	0.646**	0.735**	0.642**
	(2.25)	(3.07)	(−1.08)	(2.47)	(2.42)	(−0.81)	(2.04)	(2.34)	(1.99)
N	407	549	601	407	549	601	548	531	530
ll	−1282	−1516	−1593	−1281	−1517	−1593	−1511	−1507	−1501
χ^2	362	410	568	350	387	570	392	395	398
BIC	2511	2541	2466	2510	2539	2468	2544	2544	2549
Condition number	8.64	8.36	9.04	5.72	5.72	5.61	8.02	7.6	9.16
Mean VIF	1.42	1.4	1.56	1.06	1.01	1.07	1.03	1.07	1.09
Wald test carbon intensity (χ^2)							3.14*		2.83*

z statistics in parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

Table 2
The role of biofuel public policies (dependent variable: total patents in BioPat).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total patents per capita$_{(t-1)}$	0.487***	0.490***	0.493***	0.486***	0.480***	0.468***	0.511***	0.471***
	(6.10)	(5.94)	(6.19)	(6.09)	(6.03)	(5.68)	(6.28)	(5.61)
Carbon intensity$_{(t-1)}$	−1.269***		−1.257***	−1.253***	−1.313***	−1.090**	−1.084**	−1.094**
	(−3.01)		(−2.98)	(−2.97)	(−3.14)	(−2.45)	(−2.42)	(−2.49)
Policy count in renewables$_{(t-1)}$		-0.074	-0.070					
		(-1.20)	(-1.15)					
Excise exemption (biofuels)$_{(t-1)}$	0.567***	0.644***	0.579***				0.528***	0.527***
	(3.14)	(3.53)	(3.22)				(2.91)	(2.94)
Excise exemption (bioethanol)$_{(t-1)}$				0.497***				
				(3.08)				
Excise exemption (biodiesel)$_{(t-1)}$					0.576***			
					(2.95)			
Fuel mandate$_{(t-1)}$						7.038	5.022	5.380
						(1.63)	(1.22)	(1.31)
Public R&D (bioenergy)$_{(t-1)}$								0.067**
								(2.42)
Export % GDP$_{(t-1)}$	0.994***	1.008***	0.941***	0.956***	1.036***	0.984***	1.001***	1.104***
	(5.74)	(5.62)	(5.22)	(5.50)	(5.92)	(5.61)	(5.96)	(6.51)
Road energy consumption$_{(t-1)}$	2.744***	1.026***	0.923***	0.982***	0.910***	0.863***	0.928***	1.025***
	(5.42)	(3.21)	(2.77)	(2.94)	(2.72)	(2.57)	(2.81)	(3.12)
Country dummy in biodiesel	1.141**	1.404***	1.142**	1.140**	1.123**	1.225**	1.286***	1.261***
	(2.40)	(3.15)	(2.42)	(2.38)	(2.38)	(2.54)	(2.67)	(2.63)
N	323	324	323	323	323	323	323	323
ll	−1128	−1136	−1127	−1128	−1129	−1131	−1128	−1125
χ^2	305	309	310	304	301	289	320	332
BIC	2395	2402	2400	2395	2396	2402	2400	2400
Condition number	9.56	10.09	11.17	9.55	9.54	9.69	16.20	16.20
Mean VIF	1.33	1.38	1.49	1.33	1.33	1.33	1.77	1.77
Wald test carbon intensity (χ^2)	9.08***	–	8.87***	8.85***	9.84***	5.98**	5.86**	6.20**
BIC for lag 1	2005	2024	2011	2007	2005	2018	2008	2010
BIC for lag 2	2021	2039	2032	2022	2031	2027	2027	2029
BIC for lag 3	2034	2056	2050	2035	2051	2043	2046	2054
N obs. for BIC in lags	278	278	278	278	278	278	278	278

z statistics in parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

patents available in BioPat related to EPO applications which have direct and indirect use in the investigated sector.[19]

This first round of econometric estimates confirms the importance of technological capabilities in shaping the rate of patenting activities in the biofuels sector. By comparing results for the three alternative variables used to describe the national innovation system, it is worth noting that whatever innovation measure we adopt, innovation performance in the biofuels sector is positively and significantly influenced by the available scientific and technological capabilities.[20]

In the baseline model, we also control for the dimension and the quality of the energy sector and transport sector. As expected, the two variables enter the model with positive and significant coefficients when total patents per capita variable is considered as a technology capacity measure (Columns 2 and 5). Considering the importance of the role of the energy system and the fact that all innovation system related variables are statistically significant, we chose the total patents per capita as a proxy for technological capabilities in the next specifications. This variable also has the advantage of allowing us to control for the general propensity to patent at country level (Johnstone et al., 2010). Moreover, since the two variables associated with the energy system are almost equivalent in terms of robustness, the model fitting (BIC value) of Column 5 is slightly better than in Column 2 and, most importantly, the energy consumption for road transport variable is more directly linked with the biofuel market as reflected by the higher coefficient, we chose the model specification as in Column 5.

Building on this result, we finally include the effect of the environmental setting as defined in the previous Section (Columns 7–9). The first variable under scrutiny is carbon intensity as broadly reflecting the potential contribution of biofuels to decarbonising the transport sector. The sign of the estimated coefficient is coherent with our expectations since carbon intensity is found to be inversely related to patenting activity. This result should reflect the work of an inducement mechanism so that the lower the carbon intensity of one country, the higher the domestic pressure from decarbonization policies and, hence, the faster the pace of innovation in biofuel-related technologies.

The second variable associated with the environmental policy framework here tested refers to a policy count measure. As a matter of fact, this dimension seems to have no impact on the propensity to innovate in biofuels, when considering it both as the only measure for the environmental setting or combining it with carbon intensity. Although when including carbon intensity the model fitting worsens slightly (see BIC values in Columns 5 and 7), we opt to keep carbon intensity as a valuable covariate since the Wald test for omitted variables applied to carbon intensity reveals that this is an omitted variable. This result is strongly confirmed when the full model considering specific biofuels policies is estimated (Table 2).[21]

With regard to other controls included in the analysis, the employed measure of market openness and international competitiveness of the overall economic system results in a quite robust and significant regressor. Finally, in order to control for the influence of specialization on the production of one or the other type of biofuels, a dummy variable for countries that are specialized in biodiesel production or whose consumption patterns are more oriented towards biodiesel is introduced.[22]

The selection of relevant control variables allows us to specifically test the validity of the research hypotheses outlined in Section 2. The results reported in Table 2 refer to HP1 and HP2 and consider the total patent count built on all patents in BioPat as a dependent variable. The econometric estimates support HP1 since both demand-pull and technology-push policies are simultaneously important for shaping the dynamic patterns of technical change in the biofuels domain. Hence, although demand-side policies are dominant in the biofuels sector, other complementary technology-push supports are needed to increase the availability of scientific and technological capabilities and foster the pace of innovation in this domain.[23]

Price-based policies here modelled as an excise exemption for biofuels as a whole, and distinguished by bioethanol and biodiesel, are shown to play a strong positive inducement effect, fostering innovation dynamics in the investigated field with stable and statistically robust coefficients. On the contrary, patenting activity turns out to be non-responsive to quantity-based tools as represented by fuel mandates. This result is confirmed when both types of instruments are jointly introduced in the model (Column 7).[24] This finding is consistent with HP2 but, considering that as mentioned in Section 2, the relative effectiveness of the two types of demand-pull instruments may be influenced by several factors including the stage of the evolution of different technologies, the evidenced neutrality of the quantity-based instrument on innovation activities may reflect the use of the dependent variable referring to the biofuels patenting activity as a whole.

The statistical robustness of these results has been further investigated with respect to the lag structure, the goodness of fit and potential endogeneity problems. With regard to the first issue, the temporal structure with one year lag is here decided on the basis of BIC values computed on three alternative lag structures, namely one, two or three year lags. BIC values for one lag structure are the highest ones. This result is in line with a large part of the empirical contributions reviewed in Section 2 addressing policy inducement effects in other eco-innovation domains. In addition, BIC values also reveal that by including policy variables, the overall goodness of model estimation is not negatively affected by the number of parameters estimated. In this respect, mean VIF and Condition

[19] It should be noted in Table 1 and the others that the number of observations does not correspond to the total given for the examined years and the countries investigated. This is due to the fact that not all the explanatory variables are available for each country in the sample for the same years.

[20] The regressor adopted for the specific stock here is computed by applying a decay rate equal to 0.15 as suggested by Hall (1990). As a robustness check, we have tested how much the decay rate may influence results by computing a patent stock measure by using decay rates equal to 0.05, 0.10, 0.15, 0.20, 0.30 alternatively. Results obtained with alternative decay rates remain unchanged and are available upon request from the authors.

[21] No collinearity bias arises in the nine models since Mean VIF and Condition number values are below the threshold levels of 5 and 30, respectively.

[22] The count of forward citations has been acknowledged to be a good proxy for the technological importance and economic value of patents. Hence, as a control, we test our model on a count indicator based on forward citations received by the BioPat patents in the five years after their publication using the information contained in the OECD EPO Indicators Database (Squicciarini et al., 2013). Results are largely confirmed but we prefer to keep models based on patent counts since results based on forward citation measures can be biased due to the truncation problem. For the sake of simplicity, we have only reported results for the simple patent count variables in the text, but all results based on citation patent counts are available upon request from the authors.

[23] In order to control for the potential influence of the chosen innovation measure here adopted, as a robustness check we estimated all models in Table 2 by including GERD as % of GDP and alternatively specific patent stock, as represented in Tables A4a and A4b in the Appendix A. Results are fully consistent with those reported in Table 2.

[24] Coefficients of excise exemption for bioethanol and biodiesel differ slightly, the one for bioethanol being somewhat lower than the other. The specific way the exemption variables are built allows us to exclude potential bias related to diverse energy prices in different countries. Since energy prices for final consumption consist of production costs which are fairly homogeneous among all OECD countries and tax rates which are fairly heterogeneous among countries, by standardizing exemption for bioethanol and biodiesel with excise amounts for gasoline and diesel respectively, we almost eliminate the impact of energy price differences.

Table 3
The role of biofuel public policies: first and advanced generation biofuel related patents.

	First generation			Second generation		
	(1)	(2)	(3)	(4)	(5)	(6)
Total patents per capita$_{(t-1)}$	0.535***	0.544***	0.597***	0.340**	0.315**	0.360**
	(5.38)	(5.26)	(5.79)	(2.30)	(2.11)	(2.44)
Carbon intensity$_{(t-1)}$	−1.445***	−1.291**	−1.132**	−1.611*	−1.510*	−1.297
	(−2.57)	(−2.29)	(−1.96)	(−1.79)	(−1.68)	(−1.42)
Excise exemption (biofuels)$_{(t-1)}$	0.789***		0.701***	0.769**		0.697*
	(3.17)		(2.83)	(2.01)		(1.81)
Fuel mandate$_{(t-1)}$		14.160**	11.407**		10.492	8.202
		(2.56)	(2.13)		(1.41)	(1.12)
Public R&D (bioenergy)$_{(t-1)}$	0.020	0.018	0.020	0.137**	0.128**	0.134**
	(0.50)	(0.46)	(0.53)	(2.14)	(2.05)	(2.10)
Export % GDP$_{(t-1)}$	0.861***	0.833***	0.922***	0.213	0.173	0.253
	(3.50)	(3.50)	(3.97)	(0.70)	(0.58)	(0.86)
Road energy consumption$_{(t-1)}$	0.015	−0.244	−0.102	1.653**	1.555**	1.607**
	(0.03)	(−0.51)	(−0.22)	(2.21)	(2.07)	(2.18)
Country dummy in biodiesel	0.426	0.496	0.550	1.186	1.468*	1.408*
	(0.85)	(1.02)	(1.12)	(1.34)	(1.83)	(1.74)
N	323	323	323	323	323	323
ll	−1059	−734	−1058	−732	−733	−733
χ^2	221	216	243	215	211	218
BIC	2264	2267	2265	1608	1611	1617
Condition number	16.20	16.11	16.90	16.20	16.11	16.89
Mean VIF	1.77	1.73	1.87	1.77	1.73	1.87

z statistics in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

number also confirm that by including policy variables the models are not affected by multicollinearity problems.

Finally, as already mentioned in Section 4, as a robustness check, the same models in Table 2 have been estimated by using a GMM estimator for count variables, revealing that all results obtained for policy variables are not biased by potential endogeneity (see the Appendix A, Table A4c).[25]

We now turn to testing more specific hypotheses (HP3–HP5) on the potential different role demand-pull and technology-push policies may have on innovation activities in technologies characterized by different technology maturity by disentangling our dependent variable according to different biofuels generations.

Consistently with HP3, the empirical results reported in Table 3 (Columns 1–3) show that deployment policies play a prominent role in shaping the pace of innovation within first generation technologies for the production of biofuels. Moreover, in this case, both price-based and quantity-based instruments play a positive and significant role in triggering patenting activities, confirming the importance of accounting for the stage of maturity of technologies in evaluating the relative effectiveness of different types of demand-pull policies.

In contrast, the role of technology-push instruments appears to be negligible since the coefficient associated with the specific public R&D variable is not statistically significant.

In parallel, when analysing the drivers of innovation activities in advanced generation biofuels, results show that these are found to be sustained by technology-push forces leveraged through specific R&D policies along with demand-pull policies, as claimed in HP4. In addition, consistently with HP5, while price-based mechanisms seem to positively affect the development of innovations in the domain of advanced biofuels, quantity-based instruments appear to have no impact in pulling technology exploration activities.

These results show that different types of policy instruments may have differentiated effects on technology exploration and exploitation activities, and hence on the dynamics of innovation in different technological trajectories. With regard to the case under scrutiny, such evidence confirms concerns raised by the international community (IEA, 2011a) which has suggested that an unbalanced policy mix mainly based on pervasive public support tools directed toward market exploitation may potentially lead to reducing the propensity to engage in exploration activities, thus favouring the emergence of a technological lock-in. However, results also show that technology exploration activities leading to the generation of innovations in advanced biofuels cannot rely only on technology-push policies, but that the expectations on the growth of demand induced by deployment policies tend to increase the incentives towards exploratory innovative investments. Here, the dynamic incentives related to the adoption of price-based mechanisms are found to be effective in favouring technology exploration by creating a constant demand for innovation.

6. Conclusions

In this paper we have analysed the role of demand-pull and technology-push policy instruments in shaping innovation activities in the biofuels sector. More specifically, the analysis builds upon recent contributions to the differentiated effects of these two categories of instruments on the dynamics of environmental innovation at different stages of technological maturity. In this respect, the present paper offers a systematic study based on an econometric analysis focused on the biofuels domain, a sector which is expected to substantially contribute to decreasing GHG emissions and improve the sustainability of the transport sector and which is

[25] In Table A4c the coefficient associated with the variable "total patents per capita" loses its statistical significance though endogeneity issues are not expected to be relevant for this variable. This is probably due to the differences in estimation methods' structure between GMM and NBRM. We believe that NBRM generally provides the most reliable estimates given the structure of our data. However, in order to test that the overall robustness of our results on policy variables is not affected by the choice of the innovation system variable, we ran the same regressions in Tables A4a and A4b by applying the GMM estimator. In these cases, both policy and innovation variables turned out to be robust and statistically significant. All results are available upon request from the authors.

characterized by a pervasive role of public policies, in particular on the demand side.

The role of different policy instruments has been analysed by considering the diverse stages of maturity of biofuel technologies. In addition, the differentiated effects of demand-pull policies have been addressed by distinguishing between price-based and quantity-based instruments.

The empirical investigation relies on an original source of information that gathers international patents in the biofuels sector collected using a keyword-based methodology and organized in order to distinguish between different technology generations. Such information has been matched with a wide range of country-level public policies specifically designed to sustain the biofuels sector either by quantity and price-based deployment instruments and technology-push instruments.

The econometric analysis has been designed to test five specific research hypotheses grounded on previous relevant literature. Our results can be summarized as follows. First, by looking at the general innovation performance in the biofuels sector, we find that both demand-pull and technology-push instruments are relevant in shaping the speed of technological change, revealing that the combination of both types of policy support is required to start a positive dynamic evolution of the technological trajectory in the biofuels sector.

Second, we find that at a general level price-based deployment instruments display a greater impact on innovation activities with regard to quantity-based instruments, providing a robust empirical evidence for the ongoing debate about the choice of the correct deployment policies to be implemented. In this respect, the paper makes a step beyond the current debate when the impact of different policy types is scrutinized by accounting for the different degree of maturity of alternative technologies. When we distinguish between first and advanced technological generations within the biofuels domain, we find that in the former case innovation activities mainly respond to demand-pull instruments, both price and quantity-based. On the contrary, in the case of (less-mature) advanced generation technologies, these are found to be influenced by both demand-pull and technology-push public supports, with price-based instruments displaying a greater innovation inducement effect than quantity-based tools.

These results appear to have relevant analytical and policy implications. Public policies seem to be effective in shaping the dynamics of eco-innovation and a well-designed policy framework therefore has the potential to allow innovation and energy systems to escape carbon lock-in. Moreover, our study provides new insights into the importance of carrying out detailed analyses of the mechanisms linking demand-pull and technology-push policies with the rate, type and direction of innovation activities in environmental technologies. Indeed, the effects of these instruments may be significantly influenced by the specificities of sectors and the different degree of maturity of technological options.

More specifically, these results perfectly fit the current debate on the reform of policy incentive to renewable energies and in particular to biofuels occurring both in EU and the US. For instance, according to the proposal for a new Directive for renewable energy debated by the European Commission (EU, 2014), the key points to be discussed in the near future regarding the biofuels support policy setting concern both demand-pull and technology-push instruments that aim to: (i) encourage the transition to advanced biofuels, by inviting member states to promote the consumption of such biofuels and requiring them to set specific national targets favoring advanced biofuels; (ii) increase R&D investments in advanced biofuels in order to speed up the transition from first to second and third generation technologies.

The empirical results provided in this paper may fuel such policy debate by confirming that both demand-pull and technology-push policies are valid support for stimulating innovation, but also by suggesting that if advanced generation technologies are the main policy objective, tax exemptions or other price-based mechanisms should be preferred to targets and blending mandates. In addition, the proposed analysis confirms the idea that public R&D efforts are crucial when new technologies for advanced generation biofuels have to be promoted in order to reduce the potential risks of technological lock-in within first generation technologies.

With regard to future research directions, our study contributes to highlighting the importance of working on the design of policy mix in order to foster sustainable transition by providing appropriate incentives that favour technology exploration activities and avoid the system being locked-in within the dominant technology design. In this regard, further research is certainly needed to study how policy instruments, both on the demand and the supply side, interact and affect the intensity and the direction of technical change in environmental domains. Finally, considering the potential strong interrelations between different policy tools, complementarities and coordination at the national and supra-national levels emerge as important aspects to be studied for policy design. In this context, an important issue which is still poorly investigated is represented by the role of international policy spillovers. On the one hand, these may influence the domestic propensity to innovate since environmental and energy policies implemented by foreign countries may foster the conditions for the generation and diffusion of new technologies also in the domestic context; on the other hand, technology-push policies adopted by foreign countries may shape domestic technological capabilities, due to knowledge spillover effects.

Appendix A.

Data description and main statistics.

Table A1 Variable definition and data sources.

Variable name	Definition	Source
	Dependent variables	
Patent count BioPat	Patent count selected by keywords or technological domain in BioPat	EPO via Thompson Innovation
	Regressors	
GERD % GDP	Gross domestic expenditure on R&D as % of GDP	OECD (2012)
Total patents per capita	Total number of patent application by applicant per 1000 inhabitants	World Development Indicators (WDI) Online database (World Bank,2013)

Specific patent stock	Stock of past applied patents (calculated on past values of the dependent variable as Eq. (5), decay rate = 0.15 (Table 1))	EPO via Thompson Innovation
Carbon intensity	Ratio between CO_2 emissions (kt) and GDP in PPP (current international $)	WDI
Energy consumption	Total energy used including petroleum products, natural gas, electricity and combustible renewable and waste as % of GDP in PPP (current international $)	WDI
Road energy consumption	Total energy used in the road sector including petroleum products, natural gas, electricity and combustible renewable and waste as % of GDP in PPP (current international $)	WDI
Export % GDP	Total export value as % of GDP in PPP (current international $)	WDI
Excise exemption (biofuels)	Average ratio between value of excise tax reductions for bioethanol and biodiesel (US $ per litre) and energy tax (US $ per litre) weighted by specific fuel consumption	International Institute for Sustainable Development's Global Subsidies Initiative (GSI, 2008), IEA (energy taxes), OECD (fuel consumption)
Excise exemption (bioethanol)	Ratio between value of excise tax reductions for bioethanol (US $ per litre) and energy tax (US $ per litre) weighted by total gasoline consumption	GSI, IEA (2011b), OECD
Excise exemption (biodiesel)	Ratio between value of excise tax reductions for biodiesel (US $ per litre) and energy tax (US $ per litre) weighted by total diesel consumption	GSI, IEA, OECD
Fuel mandate	Mandates for blending targets for ethanol and biodiesel consumption on gasoline and diesel (% of total fuel consumption)	GSI
Policy count in renewables	Number of already existing policies with the aim of fostering renewable energies production, adoption and diffusion	IEA Policies and measures database for renewable energy (IRENA)
RD bioenergy	Public R&D expenditures in Bioenergy as % of GDP	IEA RD&D Online data service

Table A2 Descriptive statistics (variables in natural logarithm except for count and dummy variables).

Variable name	No Obs.	Max	Min	Mean	St. Dev.	% of zero
Patent count total Biofuels (BioPat)	735	1958	0	74.48	233.27	22%
Patent count first gen (BioPat)	735	1226	0	47.15	155.19	30%
Patent count advanced gen (BioPat)	735	283	0	10.15	30.80	47%
GERD % GDP	461	1.42	−1.61	0.42	0.60	
Total Patents per capita	607	8.02	−1.87	4.45	1.92	
Specific patent stock (15% decay rate)	735	9.21	0	3.48	2.31	
Export % GDP	685	5.45	1.88	3.51	0.71	
Energy consumption	688	14.66	8.01	11.34	1.39	
Road energy consumption	665	1.97	−0.69	0.97	0.37	
Carbon intensity	629	1.41	−0.02	0.85	0.26	
Excise exemption (biofuels)	399	1.16	0	0.08	0.14	
Excise exemption (bioethanol)	399	1.14	0	0.08	0.15	
Excise exemption (biodiesel)	399	1.18	0	0.08	0.14	
Fuel mandate	398	0.10	0	0.01	0.01	
Total policy count	714	14.00	0	0.65	1.46	
RD bioenergy	406	7.70	−4.34	2.83	1.77	

Note: All variables including zeros as valuable information when transformed logs were treated as value + 1 in order to retain all useful information.

Table A3 Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Patent count total biofuels (BioPat)	1															
(2) Patent count first gen (BioPat)	0.99	1														
(3) Patent count advanced gen (BioPat)	0.94	0.95	1													
(4) GERD % GDP	0.38	0.38	0.37	1												
(5) Total patents per capita	0.60	0.60	0.59	0.84	1											
(6) Specific patent stock (15% decay rate)	0.70	0.69	0.68	0.59	0.65	1										
(7) Export % GDP	−0.64	−0.63	−0.53	0.01	−0.30	−0.40	1									
(8) Energy consumption	0.60	0.58	0.56	0.36	0.47	0.82	−0.66	1								
(9) Road energy consumption	0.04	0.03	-0.05	0.11	−0.05	0.11	−0.35	0.47	1							
(10) Carbon intensity	0.19	0.19	0.20	−0.42	−0.16	0.10	−0.32	0.16	0.07	1						
(11) Excise exemption (biofuels)	−0.05	−0.03	0.06	0.14	0.02	0.18	0.14	0.07	−0.03	−0.17	1					
(12) Excise exemption (bioethanol)	−0.03	−0.01	0.07	0.16	0.04	0.20	0.13	0.12	0.00	−0.19	0.97	1				
(13) Excise exemption (biodiesel)	−0.07	−0.06	0.04	0.11	0.01	0.14	0.14	0.01	−0.07	−0.13	0.97	0.88	1			
(14) Fuel mandate	−0.09	−0.07	0.04	0.09	−0.05	0.11	0.16	0.02	−0.02	−0.16	0.69	0.62	0.72	1		
(15) Total policy count	0.20	0.20	0.22	0.28	0.24	0.41	−0.34	0.57	0.45	0.08	0.38	0.39	0.34	0.35	1	
(16) RD bioenergy	0.58	0.57	0.60	0.58	0.69	0.78	−0.41	0.71	0.15	0.13	0.24	0.27	0.19	0.16	0.52	1

Table A4a
Robustness check for alternative innovation measures in Table 2 – GERD.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GERD % GDP$_{(t-1)}$	1.397***	1.354***	1.390***	1.412***	1.360***	1.328***	1.400***	1.391***
	(8.50)	(8.29)	(8.43)	(8.54)	(8.29)	(7.90)	(8.49)	(8.46)
Carbon intensity$_{(t-1)}$	−0.614		−0.557	−0.610	−0.772	−0.863*	−0.566	−0.845
	(−1.20)		(−1.07)	(−1.19)	(−1.54)	(−1.68)	(−1.06)	(−1.60)
Policy count in renewables$_{(t-1)}$		−0.055	−0.041					
		(−0.92)	(−0.68)					
Excise exemption (biofuels) $_{(t-1)}$	0.797***	0.888***	0.805***				0.781***	0.807***
	(3.65)	(4.18)	(3.69)				(3.50)	(3.73)
Excise exemption (bioethanol)$_{(t-1)}$				0.712***				
				(3.96)				
Excise exemption (biodiesel)$_{(t-1)}$					0.659***			
					(2.72)			
Fuel mandate$_{(t-1)}$						4.321	1.322	1.097
						(1.01)	(0.32)	(0.27)
Public R&D (bioenergy)$_{(t-1)}$								0.065**
								(2.41)
Export % GDP$_{(t-1)}$	0.599***	0.638***	0.572***	0.541***	0.634***	0.524***	0.595***	0.688***
	(3.29)	(3.45)	(3.04)	(2.98)	(3.35)	(2.71)	(3.28)	(3.84)
Road energy consumption$_{(t-1)}$	0.230	0.126	0.224	0.281	0.192	0.238	0.221	0.315
	(0.69)	(0.38)	(0.67)	(0.85)	(0.57)	(0.69)	(0.66)	(0.95)
Country specialization dummy in biodiesel	0.637	0.608	0.662	0.645	0.634	0.765	0.680	0.672
	(1.31)	(1.32)	(1.37)	(1.30)	(1.33)	(1.54)	(1.36)	(1.35)
N	294	294	294	294	294	294	294	294
ll	−1035	−1035	−1043	−1034	−1038	−1041	−1036	−1033
χ^2	285	279	287	291	268	255	287	302

z statistics in parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

Table A4b
Robustness check for alternative innovation measures in Table 2 – specific patent stock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent stock in BioPat(15%)$_{(t-1)}$	0.696***	0.668***	0.711***	0.704***	0.679***	0.678***	0.699***	0.685***
	(10.52)	(10.62)	(10.46)	(10.71)	(10.26)	(10.23)	(10.59)	(10.34)
Carbon intensity$_{(t-1)}$	−0.909**		−0.953**	−0.893**	−1.021***	−0.981**	−0.822*	−0.932**
	(−2.27)		(−2.37)	(−2.24)	(−2.59)	(−2.36)	(−1.93)	(−2.20)
Policy count in renewables$_{(t-1)}$		0.031	0.052					
		(0.56)	(0.96)					
Excise exemption (biofuels)$_{(t-1)}$	0.524***	0.644***	0.511***				0.489***	0.503***
	(3.20)	(4.00)	(3.12)				(2.82)	(2.97)
Excise exemption (bioethanol)$_{(t-1)}$				0.512***				
				(3.68)				
Excise exemption (biodiesel)$_{(t-1)}$					0.400**			
					(2.26)			
Fuel mandate$_{(t-1)}$						5.232	2.083	2.109
						(1.57)	(0.61)	(0.62)
Public R&D (bioenergy)$_{(t-1)}$								0.054**
								(2.32)
Export % GDP$_{(t-1)}$	0.680***	0.811***	0.717***	0.645***	0.698***	0.654***	0.684***	0.782***
	(4.49)	(5.03)	(4.68)	(4.36)	(4.40)	(4.21)	(4.58)	(5.14)
Road energy consumption$_{(t-1)}$	0.263	0.280	0.316	0.308	0.214	0.139	0.233	0.321
	(0.91)	(0.96)	(1.08)	(1.07)	(0.72)	(0.46)	(0.80)	(1.09)
Country specialization dummy in biodiesel	0.197	0.414	0.178	0.164	0.209	0.321	0.283	0.208
	(0.42)	(0.98)	(0.38)	(0.35)	(0.46)	(0.68)	(0.59)	(0.43)
N	341	342	341	341	341	341	341	341
ll	−1165	−1165	−1174	−1164	−1168	−1169	−1165	−1163
χ^2	434	414	432	447	418	417	436	454

z statistics in parentheses
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

Table A4c
Robustness check for endogeneity of policy variables in Table 2 (GMM estimator for count variables).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total patents per capita$_{(t-1)}$	−0.189	−0.246	−0.135	−0.154	−0.206	−0.231	−0.174	−0.209
	(−0.59)	(−0.76)	(−0.41)	(−0.50)	(−0.66)	(−0.86)	(−0.61)	(−0.77)
Carbon intensity$_{(t-1)}$	−1.90**		−1.819**	−1.791**	−2.242***	−2.234***	−1.988***	−1.910**
	(−2.29)		(−2.24)	(−2.19)	(−2.67)	(−2.85)	(−2.63)	(-2.32)
Policy count in renewables$_{(t-1)}$		−0.053	−0.038					
		(−1.44)	(−1.07)					
Excise exemption (biofuels)$_{(t-1)}$	0.782*	1.053***	0.825**				0.830**	0.904***
	(1.95)	(2.58)	(2.23)				(2.85)	(2.58)
Excise exemption (bioethanol)$_{(t-1)}$				0.834***				
				(2.84)				
Excise exemption (biodiesel)$_{(t-1)}$					0.436			
					(0.81)			
Fuel mandate$_{(t-1)}$						4.466	−1.672	−1.463
						(0.50)	(−0.26)	(−0.24)
Public R&D (bioenergy)$_{(t-1)}$								0.108***
								(2.57)
Export % GDP$_{(t-1)}$	1.543***	1.605***	1.529***	1.505***	1.469***	1.414***	1.519***	1.596***
	(4.31)	(3.70)	(4.17)	(4.85)	(3.37)	(3.35)	(4.04)	(4.22)
Road energy consumption$_{(t-1)}$	2.744***	2.568***	2.562***	2.876***	2.527***	2.380***	2.769***	2.771***
	(5.42)	(5.54)	(4.95)	(5.97)	(4.52)	(4.37)	(5.60)	(5.85)
N	323	324	323	323	323	323	323	323

z statistics in parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

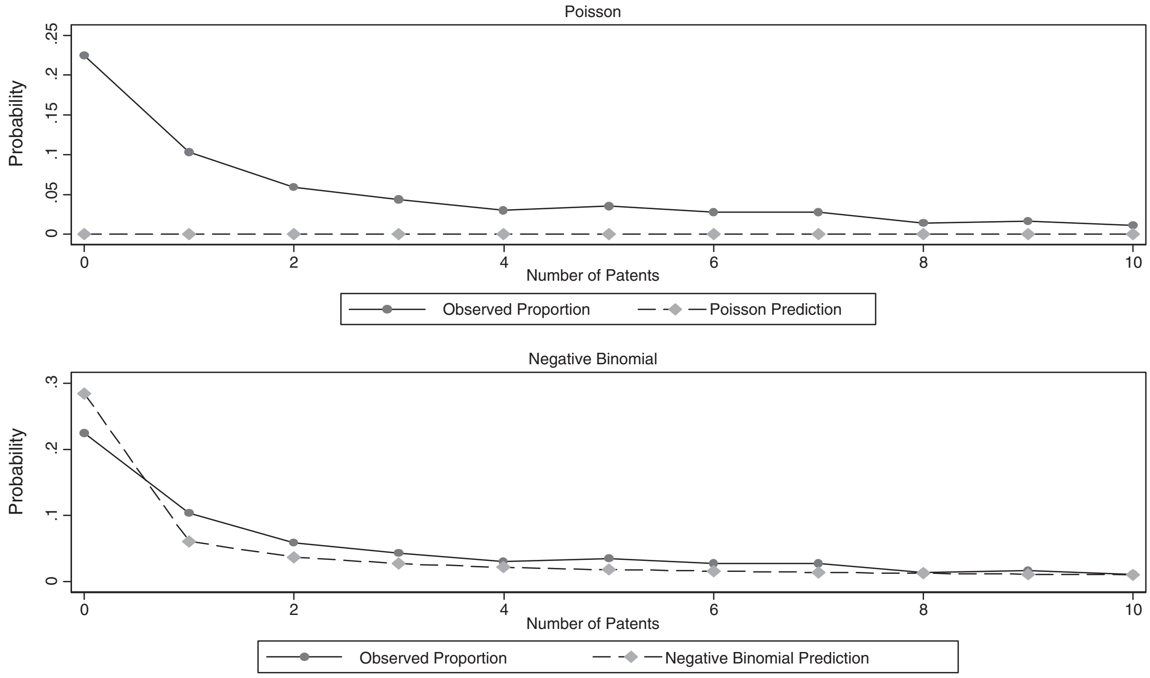

Fig. A1. Robustness check for dependent variable patent count BioPat: observed and predicted probability assuming a Poisson and a negative binomial univariate distribution.

Appendix B.

Synthetic description of BioPat.

The main purpose of BioPat is to gather full information on the technological patterns of the biofuels sector encompassing drawbacks in standard IPC class selection methods. The patents related to biofuels are spread across several IPC classes because the technology that characterizes the sector basically consists of thermo/bio-chemical processes and very common raw materials that can find applications in several fields. For this purpose, a keyword analysis seems to be more appropriate than using IPC codes as given by GI classification (WIPO, 2011) in order to include all biofuel-related technologies. The last decade's literature on keyword analysis basically consists of selections of words from already existing keyword lists or the extraction of keywords from titles and, at least, abstracts of patents and scientific publications.

According to Suurs and Hekkert (2009a, 2009b), the biofuels sector can be defined as an emerging technological domain, meaning that technologies that are already well established in the production process constitute only a small part of the technological options that are under development in the whole sector. As emphasized in Costantini et al. (2014), the rapid dynamics of a biofuels innovation system in terms of increasing technological

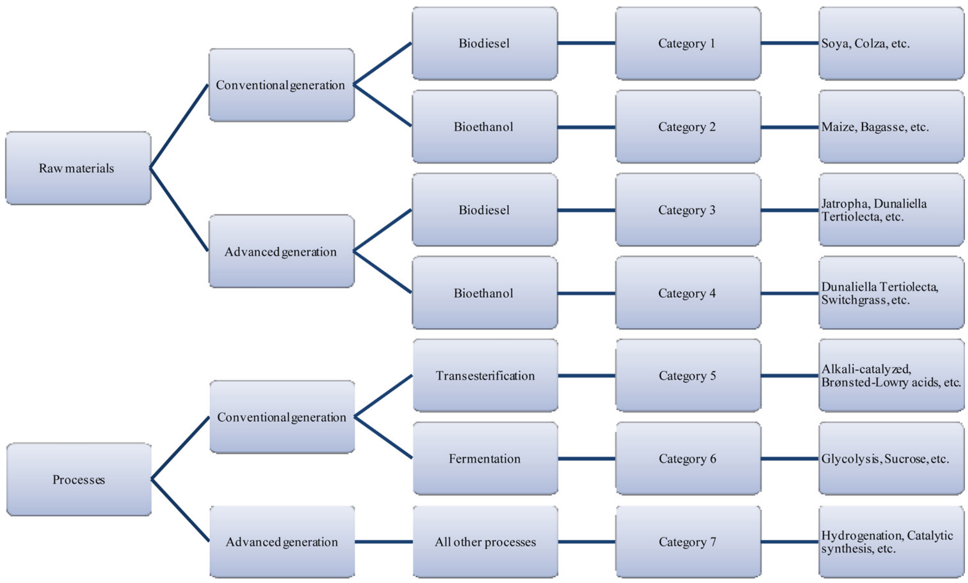

Fig. B1. Alternative structures of database and classifications using keywords in BioPat.

opportunities and exploring new trajectories is well described by the investigation into emerging new IPC classes where patents are classified, revealing that technologies directly or indirectly related to the biofuels sector are rapidly expanding in several directions and consist both of complementary innovations in an established technological domain or more radical inventions related to new emerging technological trajectories.

The first step towards building BioPat was the selection of a keyword list to be used in patent research engines. The search for keywords was divided into two different steps: the first one was dedicated to a search for "raw material" keywords, where a relevant number of technical and scientific papers was analysed in order to pick out the terms describing the biomass used (or potentially used) to produce biofuels. The second step consisted of an accurate description of the "transformation process" currently known in biofuels production, including pre-treatment processes, chemical agents involved in the process and technical instrumentation used in it. Hence, the final selection of keywords comes from an iterative procedure which allows results from scientific articles to be compared with patent results. This first step led to the selection of several keywords which showed positive results both in patents and articles via Scopus. Then, keywords extracted by examining scientific publications and Scopus were validated and completed by technical experts.

Table B1
Validation of BioPat for EPO patents: % of patents related to the biofuels sector.

Type	GI	% of biofuel-related patents	GI filtered by keywords	% of biofuel-related patents
Direct application	5%	28%	15%	40%
Indirect application	14%	72%	23%	60%
Total	19%		38%	

Source: Costantini et al. (2014).

Table B2
Structure and classifications using keywords in BioPat.

Type	Keyword	Bloc	Generation	Biodiesel	Bioethanol	Biogas
Algae	*Chlorella vulgaris*	3–4	2	1	1	0
Algae	Dunaliella tertiolecta	3–4	2	1	1	0
Livestock	Anaerobic digestion	8	1	0	0	1
Crop	Corn	2	1	0	1	0
Crop	Maize	2	1	0	1	0
Crop	Colza	1	1	1	0	0
Crop	Soybean	2	1	0	1	0
Ligno	*Switchgrass*	4	2	0	1	0
Ligno	*Miscanthus*	4	2	0	1	0
Ligno	*Poplars*	4	2	0	1	0
Livestock	Edible tallow	3–5	2	1	0	1
Livestock	Animal manure	3–5	2	1	0	1
Oleaginous	Palm oil	1	1	1	0	0
Oleaginous	Vegetable oil	1	1	1	0	0
Oleaginous	Coconut oil	1	1	1	0	0
Oleaginous	*Jatropha*	3	2	1	0	0
Sugar	Sugarcane	2	1	0	1	0
Sugar	*Sorghum*	2	1	0	1	0
Sugar	Bagasse	2	1	0	1	0

Source: adapted from Costantini et al. (2014).

The patents were downloaded using Thomson innovation. The selection method was applied by searching for keywords in the title, abstract, description and claim fields. According to the IPC terms of reference, patent novelty is usually classifiable following two main principles: a patent can be characterized by engineering content or by bio-chemical content. The latter is true for the biofuels sector and represents an explanation of the cross-cutting shape that it assumes in the IPC classification. In light of this, unlike the standard procedure where only title and abstract field are included, we decided to expand the use of keywords to the “patent descriptions” and “patent claims” fields in order to exploit the possibility of catching all patents that have a hypothetical, and not necessarily direct, function in the biofuels production process.

All process-specific and raw material keywords were used in the Thomson innovation jointly with a more general keyword (such as bio-diesel, bio-ethanol, bio-gas, bio-fuels) in order to exclude patents that share the same raw materials or transformation processes (pharmaceutics and cosmetics are strongly related to the biofuels sector, for example).

All the patents included in BioPat amount to 1,293,197 records, including duplicates (21% EPO, 59% USPTO, 20% WIPO, considering both applications and grants). Patents included in BioPat were compared with those obtained by using IPC codes included in GI, in order to consider to what extent the two classification systems overlap. It is worth mentioning that a large amount of patents included in green inventory (GI) is also present in BioPat, hence resulting in the possibility of applying a hybrid method where keywords used for BioPat could be used as searching criteria in GI output. According to Costantini et al. (2014), the validation process of the patents included in GI and patents in GI filtered by BioPat keywords shows that this second criterion is helpful in selecting patents whose main object is closely related to the biofuels sector, allowing those patents included in GI but out of the biofuels sector to be dropped.

More specifically, a group of experts was interviewed in order to distinguish between patents with a direct application in the biofuel production process and an indirect one. We downloaded the description field of the whole universe of patents belonging to GI classes from which we randomly selected a 1% sample. Experts were then asked to validate the same GI classes filtered with keywords. The sample was built as follows: from the EPO patents in BioPat database, the patents that showed at least one IPC class belonging to GI were selected, the duplicates eliminated and 1% of the selected patents randomly extracted.

The results of the validation are summarized in Table B1 which shows that the keywords selection method applied to GI classes doubled the percentage of patents related to the sector. Moreover, the results of the validation procedure also showed that the share of patents directly related to the investigated sector increases when GI classes are filtered by the selected keywords.

As a mere example of how data in BioPat can be classified, Fig. B1 and Table B2 represent the disaggregation between raw materials and processes which in turn can be divided into conventional and advanced generation biofuels and further subdivided into the final product, bioethanol or biodiesel.

The database structure allows the building of several alternative statistics on patent count according to the topic under investigation. For the purpose of the current work, we used block classification, for instance, referring to bioethanol vs. biodiesel, summing up blocks referred to the specific final good and after that, dropping all duplicate patents in each sub-domain in order to avoid double counting. It is worth mentioning that in this specific distinction, the same patent could be classified both as bioethanol and biodiesel. Such patents were not dropped from one or the other subdomain since they refer to patents which are valid for producing both liquid biofuels.

Source: adapted from Costantini et al. (2014)

References

Archibugi, D., Pianta, M., 1996. Measuring technological through patents and innovation surveys. Technovation 16 (9), 451–468.

Arrow, K., 1962. Economic Welfare and the Allocation of Resources for Invention, In: The Rate and Direction of Inventive Activity: Economic and Social Factors. National Bureau of Economic Research, Inc. 609–626.

Arthur, W.B., 1989. Competing technologies, increasing returns, and lock-in by historical events. Econ. J. 97, 642–665.

Arundel, A., Kemp, R., 2011. Measuring eco-innovation. UNU-MERIT Working Paper Series No. 2009–017, Maastricht, The Netherlands.

Arundel, A., Kanerva, M., Kemp, R., 2011. Integrated Innovation Policy for an Integrated Problem: Addressing Climate Change, Resource Scarcity and Demographic Change to 2030. PRO INNO Europe: INNO-Grips II report, Brussels: European Commission, DG Enterprise and Industry.

Bacchiocchi, E., Montobbio, F., 2010. International knowledge diffusion and home-bias effect: do USPTO and EPO patent citations tell the same story? Scand. J. Econ. 112, 441–470.

Balan, V., Chiaramonti, D., Kumar, S., 2013. Review of US and EU initiatives toward development, demonstration, and commercialization of lignocellulosic biofuels. Biofuels Bioprod. Bioref. 7 (6), 732–759.

Beise, M., Rennings, K., 2005. Lead markets and regulation: a framework for analyzing the international diffusion of environmental innovations. Ecol. Econ. 52, 5–17.

Baumol, W.J., Oates, W.E., Batey Blackman, S.A., 1979. Economics, Environmental Policy, and the Quality of Life. Prentice-Hall, Englewood Cliffs.

Berkhout, F., 2011. Eco-innovation: reflections on an evolving research agenda. Int. J. Technol. Policy Manage. 11, 191–197.

Borghesi, S., Costantini, V., Crespi, F., Mazzanti, M., 2013. Environmental innovation and socio-economic dynamics in institutional and policy contexts. J. Evol. Econ. 23 (2), 241–245.

Borrás, S., Edquist, E., 2013. The choice of innovation policy instruments. Technol. Forecasting Social Change 80 (8), 1513–1522.

Brunnermeier, S.B., Cohen, M.A., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manage. 45, 278–293.

Cameron, A.C., Trivedi, P.K., 2009. Microeconometrics Using Stata. Stata Press, Texas.

Cameron, A.C., Trivedi, P.K., 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. J. Appl. Econom. 1, 29–53.

Carriquirya, M.A., Dub, X., Timilsinac, G.R., 2011. Second generation biofuels: economics and policies. Energy Policy 39, 4222–4234.

Cheng, J.J., Timilsina, G.R., 2011. Status and barriers of advanced biofuel technologies: a review. Renew. Energy 36 (12), 3541–3549.

Costantini, V., Crespi, F., 2013. Public policies for a sustainable energy sector: regulation, diversity and fostering of innovation. J. Evol. Econ. 23, 401–429.

Costantini, V., Crespi, F., 2008. Environmental regulation and the export dynamics of energy technologies. Ecol. Econ. 66, 447–460.

Costantini, V., Mazzanti, M., 2012. On the green and innovative side of trade competitiveness? The impact of environmental policies and innovation on EU exports. Res. Policy 41, 132–153.

Corradini, M., Costantini, V., Mancinelli, M., Mazzanti, M., 2014. Unveiling the dynamic relation between R&D and emission abatement. National and sectoral innovation perspectives from the EU. Ecol. Econ. 102, 48–59.

Costantini, V., Crespi, F., Curci, Y., 2014. A keyword selection method for mapping technological knowledge in specific sectors through patent data: the case of biofuels sector. In: Economics of Innovation and New Technologies., http://dx.doi.org/10.1080/10438599.2014.942583.

Costantini, V., Crespi, F., Zezza, A., 2010. Biofuels public support and technological specialisation in the energy sector. In: Mazzanti, M., Montini, A. (Eds.), Environmental Efficiency, Economic Performances and Environmental Policy. Routledge, London, pp. 190–212.

David, P.A., 1985. Clio and the economics of QWERTY. Am. Econ. Rev. 75 (2), 332–337.

Del Río, P., 2009. The empirical analysis of the determinants for environmental technological change: a research agenda. Ecol. Econ. 68, 861–878.

Edquist, C., 2005. Systems of innovation: perspectives and challenges. In: Fagerberg, J., Mowery, D., Nelson, R. (Eds.), Oxford Handbook of Innovation. Oxford University Press, Oxford, pp. 181–208.

Eisentraut, A., 2010. Sustainable Production of Second-Generation biofuels. Potential and perspectives in major economies and developing countries, IEA Information Paper, International Energy Agency, OECD-IEA Pbl. Paris, France.

European Environment Agency (EEA), 2012. Environmental indicator report 2012 – Ecosystem resilience and resource efficiency in a green economy in Europe, EEA Copenhagen.

EU, 2014. Proposal for a Directive of the European Parliament and of the Council amending Directive 98/70/EC relating to the quality of petrol and diesel fuels and amending Directive 2009/28/EC on the promotion of the use of energy from renewable sources (first reading) – Political agreement, Brussels.

Fagerberg, Mowery, D., Nelson, R., 2005. The Oxford Handbook of Innovation. Oxford University press, Oxford.

FAO, 2010. Bioenergy and food security. Environment and Natural Resources Management, Series No 16. Food and Agricultural Organization, Rome, Italy.

Finon, D., Menanteau, P., 2003. The static and dynamic efficiency of instruments of promotion of renewables. Energy Stud. Rev. 12 (1), 53–82.
Fischer, C., Parry, I.W.H., Pizer, W.A., 2003. Instrument choice for environmental protection when technologicalinnovation is endogenous. J. Environ. Econ. Manage. 45, 523–545.
Frondel, M., Horbach, J., Rennings, K., 2008. What triggers environmental management and innovation? Empirical evidence for Germany. Ecol. Econ. 66 (1), 153–160.
Frondel, M., Ritter, N., Schmidt, C.M., Vance, C., 2010. Economic impacts from the promotion of renewable energy technologies: the German experience. Energy Policy 38 (8), 4048–4056.
Ghisetti, C., Quatraro, F., 2013. Beyond inducement in climate change: does environmental performance spur environmental technologies? A regional analysis of cross-sectoral differences. Ecol. Econ. 96, 99–113.
Glithero, N.J., Ramsden, S.J., Wilson, P., 2013. Barriers and incentives to the production of bioethanol from cereal straw: a farm business perspective. Energy Policy 59, 161–171.
Global Subsidies Initiatives (GSI), 2013. Biofuels – At What Cost? A review of costs and benefits of EU biofuel policies, Global Subsidies Initiative. International Institute for Sustainable Development, www.globalsubsidies.org
Griliches, Z., 1990. Patent statistics as economic indicator: a survey. J. Econ. Lit. 28, 1661–1707.
Hall, B.H., 1990. The manufacturing sector master file: 1959–1987. NBER Working Paper No. 3366.
Hall, B.H., Griliches, Z., Hausman, J.A., 1986. University patents and R and D: is there a lag? Int. Econ. Rev. 27 (2), 265–283.
Hausman, J.A., Hall, B., Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. Econometrica 52, 909–938.
Hekkert, M.P., Suurs, R.A.A., Negro, S.O., Kuhlmann, S., Smits, R.E.H.M., 2007. Functions of innovation systems: a new approach for analyzing technological change. Technol. Forecasting Social Change 74, 413–432.
Hoekman, S.K., 2009. Biofuels in the U.S. – challenges and opportunities. Renew. Energy 34 (1), 14–22.
Hoppmann, J., Peters, M., Schneider, M., Hoffmann, V.H., 2013. The two faces of market support – how deployment policies affect technological exploration and exploitation in the solar photovoltaic industry? Res. Policy 42 (4), 989–1003.
Horbach, J., 2008. Determinants of environmental innovation – new evidence from German panel data sources. Res. Policy 37, 163–173.
Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact – the role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122.
IEA, 2012a. IEA Oil Market Report, August 2012. International Energy Agency, Paris.
IEA, 2012b. World Energy Outlook, 2012. International Energy Agency, Paris.
IEA, 2011a. Technology Roadmap–Biofuels for Transport. International Energy Agency, Paris.
IEA, 2011b. IEA Energy Technology RD&D 2011 Statistics. International Energy Agency, Paris.
Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79, 610–619.
Jaffe, A.B., Fogarty, M., Banks, B., 1998. Evidence from patents and patent citations on the impact of NASA and other federal labs on commercial innovation. J. Ind. Econ. 46, 183–205.
Jaffe, A.B., Newell, R.G., Stavins, R.N., 1999. Technological change and the environment. Resources for the future. Discussion paper 00-47, Washington.
Jaffe, A.B., Peterson, S., Portney, P., Stavins, R., 1995. Environmental regulation and the competitiveness of US manufacturing: what does the evidence tell us? J. Econ. Lit. 33, 132–163.
Jaffe, A., Trajtenberg, M., 2002. Patents, Citations, and Innovations: A Window on the Knowledge Economy. MIT Press, Cambridge, Mass.
Janda, K., Kristoufek, L., Zilberman, D., 2012. Biofuels: policies and impacts. Agric. Econ.: Czech 58, 372–386.
Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45, 133–155.
Johnstone, N., Haščič, I., Poirier, J., Hemar, M., Michel, C., 2012. Environmental policy stringency and technological innovation: evidence from survey data and patent counts. Appl. Econ. 44, 2157–2170.
Karmarkar-Deshmukh, R., Pray, C.E., 2009. Private sector innovation in biofuels in the United States: induced by prices or policies? AgBioForum 12, 141–148.
Kemp, R., 2010. Eco-innovation: definition, measurement and open research issues. Econ. Politica: J. Anal. Inst. Econ. 3, 397–420.
Kemp, R., Oltra, V., 2011. Research insights and challenges on eco-innovation dynamics. Ind. Innov. 18, 249–253.
Kemp, R., Pontoglio, S., 2011. The innovation effects of environmental policy instruments—a typical case of the blind men and the elephant? Ecol. Econ. 72 (C), 28–36.
Kemp, R., Schot, J., Hoogma, R., 1998. Regime shifts to sustainability through processes of niche formation. The approach of strategic niche management. Technol. Anal. Strategic Manage. 10, 175–195.
Kuhlmann, S., Shapira, P., Smits, R., 2010. A systemic perspective: the innovation policy dance. In: Smits, R., Kuhlmann, S., Shapira, P. (Eds.), The Theory and Practice of Innovation Policy. An International Research Handbook. UK (Edward Elgar), Cheltenham, pp. 1–22.
Laleman, R., Albrecht, J., 2014. Comparing push and pull measures for PV and wind in Europe. Renew. Energy 61, 33–37.
Lanjouw, J.O., Mody, A., 1996. Innovation and the international diffusion of environmentally responsive technology. Res. Policy 25, 549–571.
Lanoie, P., Lucchetti, L., Johnstone, N., Ambec, S., 2011. Environmental policy, innovation and performance: new insights on the Porter hypothesis. J. Econ. Manage. Strategy 20, 803–842.
Leea, J., Veloso, F.M., Hounshell, D.A., 2011. Linking induced technological change, and environmental regulation: evidence from patenting in the U.S. auto industry. Res. Policy 40, 1240–1252.
Löschel, A., 2002. Technological change in economic models of environmental policy: a survey. Ecol. Econ. 43, 105–126.
March, J., 1991. 'Exploration and exploitation in organizational learning'. Organ. Sci. 2 (1), 71–87.
Markard, J., Raven, R., Truffer, B., 2012. Sustainability transitions: an emerging field of research and its prospects. Res. Policy 41, 955–967.
Menanteau, P., Finon, D., Lamy, M.L., 2003. Prices versus quantities: choosing policies for promoting the development of renewable energy. Energy Policy 31 (8), 799–812.
Metcalfe, J.S., 1995. Foundations of technology policy – equilibrium and evolutionary perspectives. In: Stoneman, P., Dasgupta, P., Nelson, R. (Eds.), Handbook in the Economics of Innovation. Blackwell.
Mowery, D.C., Nelson, R.R., Martin, B.R., 2010. Technology policy and global warming: why new policy models are needed (or why putting new wine in old bottles won't work). Res. Policy 39, 1011–1023.
Narin, F., 2000. Tech-Line background paper. In: Tidd, J. (Ed.), Measuring Strategic Competence. Imperial College, London.
Nelson, R.R., 1959. The simple economics of basic scientific research. J. Pol. Econ. 67, 297–306.
Nelson, R.R. (Ed.), 1993. National Innovation Systems: A Comparative Analysis. Oxford University Press, New York.
Nemet, G., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38, 700–709.
Newell, R.G., 2010. The role of markets and policies in delivering innovation for climate change mitigation. Oxford Rev. Econ. Policy 26 (2), 253–269.
Newell, R., Jaffe, A.B., Stavins, R., 2006. The effects of economic and policy incentives on carbon mitigation technologies. Energy Econ. 28, 563–578.
Newell, R., Jaffe, A.B., Stavins, R., 1999. The induced innovation hypothesis and energy-saving technological change. Q. J. Econ. 114, 941–975.
Nill, J., Kemp, R., 2009. Evolutionary approaches for sustainable innovation policies: from niche to paradigm. Res. Policy 38, 668–680.
OECD Statistics, 2012. Online database. OECD Publishing, Paris.
OECD Science, Technology and Industry Scoreboard, Innovation for Growth. OECD Publishing, Paris, 2013.
Fostering Innovation for Green Growth, OECD Green Growth Studies. OECD Publishing, Paris, 2011.
Panoutsou, C., Bauen, A., Duffield, J., 2013. Policy regimes and funding schemes to support investment for next-generation biofuels in the USA and the EU27. Biofuels Bioprod. Bioref. 7 (6), 685–701.
Peters, M., Schneider, M., Griesshaber, T., Hoffmann, V.H., 2012. The impact of technology-push and demand-pull policies on technical change – does the locus of policies matter? Res. Policy 41 (8), 1296–1308.
Popp, D., 2002. Induced innovation and energy prices. Am. Econ. Rev. 92, 160–180.
Popp, D., 2003. Pollution control innovations and the Clean Air Act of 1990. J. Policy Anal. Manag. 22 (4), 641–660.
D. Popp, R.G. Newell, A.B. Jaffe, 2009. Energy, the environment, and technological change. NBER Working Paper Series, No 14832.
Popp, D., Hafner, T., Johnstone, N., 2011a. Environmental policy vs. public pressure: innovation and diffusion of alternative bleaching technologies in the pulp industry. Res. Policy 40, 1253–1268.
Popp, D., Haščič, I., Medhi, N., 2011b. Technology and the diffusion of renewable energy. Energy Econ. 33, 648–662.
Porter, M., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9, 118.
Rennings, K., 2000. Redefining innovation–eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32, 319–332.
Requate, T., 2005. Timing and commitment of environmental policy, adoption of new technology, and repercussions on R&D. Environ. Res. Econ. 31 (2), 175–190.
Richard, B., Stewart, R.B., 1981. Regulation, innovation, and administrative law: a conceptual framework, 69 California. Law Rev. 69 (5), 1256–1377.
Sagar, A.D., van der Zwaan, B., 2006. Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. Energy Policy 34 (17), 2601–2608.
Schmidt, T.S., Schneider, M., Rogge, K.S., Schuetz, M.J.A., Hoffmann, V.O., 2012. The effects of climate policy on the rate and direction of innovation: a survey of the EU ETS and the electricity sector. Environ. Innov. Soc. Trans. 2, 23–48.
Schmookler, J., 1966. Invention and Economic Growth. Harvard University Press, Cambridge.
Sims, R.E.H., Mabee, W., Saddler, J.N., Taylor, M., 2010. An overview of second generation biofuel technologies. Bioresour. Technol. 101 (6), 1570–1580.
Sirilli, G., 1997. Science and technology indicators: the state of the art and prospects for the future. In: Antonelli, G., De Liso, N. (Eds.), Economics of Structural and Technological Change. Routledge, London.
Squicciarini, M., Dernis, H., Criscuolo, C., 2013. Measuring Patent Quality: Indicators of Technological and Economic Value. OECD Science, Technology and Industry Working Papers 2013/3. OECD Publishing, Paris.
Sperling, D., Gordon, D., 2009. Two Billion Cars: Driving Toward Sustainability. New York, Oxford University Press.

Suurs, R.A.A., Hekkert, M.P., 2009a. Competition between first and second generation technologies: lessons from the formation of a biofuels innovation system in the Netherlands. Energy 34, 669–679.
Suurs, R.A.A., Hekkert, M.P., 2009b. Cumulative causation in the formation of a technological innovation system: the case of biofuels in the Netherlands. Technol. Forecasting Social Change 76, 1003–1020.
van den Bergh, J.C.J.M., Faber, A., Idenburg, A., Oosterhuis, F., 2007. Evolutionary Economics and Environmental Policy, Survival of the Greenest. Elgar, Cheltenham.
Veugelers, R., 2012. Which policy instruments to induce clean innovating? Res. Policy 41 (10), 1770–1778.
Wagner, M., 2007. On the relationship between environmental management, environmental innovation and patenting: evidence from German manufacturing firms. Res. Policy 36, 1587–1602.
Windmeijer, F.A.G., 2008. GMM for panel count data models. In: Matyas, L., Sivestre, P. (Eds.), The Econometrics of Panel Data. Springer.
Windmeijer, F., 2006. GMM for Panel Count Data Models. Working paper no. 06/591, University of Bristol.
Wooldridge, J.M., 1999. Distribution-free estimation of some nonlinear panel data models. J. Econ. 90, 77–97.
World Bank, 2013. World Development Indicators, WDI online database. The World Bank, Washington DC.
World Intellectual Property Organization (WIPO), 2011. The IPC Green Inventory database. http://www.wipo.int/classifications/ipc/en/est/
Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M., 2010. Food versus fuel: what do prices tell us? Energy Policy 38, 445–451.