Heterogeneous Policies, Heterogeneous Technologies: The Case of Renewable Energy[1]

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Abstract

This paper investigates empirically the effect of market regulation and renewable energy policies on innovation activity in different renewable energy technologies. For the EU countries and the years 1980 to 2007, we built a unique dataset containing information on patent production in eight different technologies, proxies of market regulation and technology-specific renewable energy policies. Our main findings show that lowering entry barriers is a more significant driver of renewable energy innovation than privatisation and unbundling, but its effect varies across technologies, being stronger in technologies characterised by the potential entry of small, independent power producers. Additionally, the inducement effect of renewable energy policies is heterogeneous and more pronounced for wind, which is the only technology that is mature and has high technological potential. Finally, the ratification of the Kyoto protocol – determining a more stable and less uncertain policy framework - amplifies the inducement effect of both energy policy and market liberalisation.

Keywords: renewable energy technology, environmental innovation, heterogeneous policy effect, feed-in tariff, renewable energy certificates, entry barrier.

JEL classification: Q55, Q58, Q42, Q48, O34

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1. Introduction

Innovation is commonly regarded as the best way to sustain current standards of living while overcoming severe environmental concerns. This consideration is especially relevant in the case of energy, where increasing resource scarcity calls for the rapid development of alternative energy sources, notably renewable energy (RE). Although renewable energy cannot currently compete with fossil fuels in terms of production costs, impressive technological progress has paved the way to promising new sources such as biomass and solar energy, among others. Countries have also developed areas of specialisation in specific types of renewable energy sources. For example, Denmark has established a strong technological advantage in wind technologies, whereas Sweden and Germany have specialised in bioenergy, Germany and Spain in solar, and Norway and Austria in hydropower.

In addressing the issue of how technological advantages have emerged for renewable energy, the economic literature emphasises the key role of public policies in fostering environmental innovation. Moving from these premises, assessing the effects of targeted environmental policies and/or energy prices on environmental innovations has been the main goal of most empirical research (Jaffe et al., 2003). The seminal contribution of Johnstone et al. (2010) (henceforth JHP) emphasises how guaranteed price schemes and investment incentives appear to play a major role in the early phases of technological development, whereas for relatively more mature technologies, i.e. wind, obligations and quantity-based instruments appear to be more effective policy tools. More recently, Nesta et al. (2014) found a significant effect of energy market liberalisation on innovation in renewable energy technologies (RETs). This result implies that, given the characteristics of the energy market, in which the core competences of the incumbent are generally tied to fossil fuel plants whereas the production of renewable energy is mainly decentralised in small-sized units, the entry of non-utility generators made possible by market liberalisation has increased the incentives to innovate for specialised suppliers of electric equipment, such as wind turbines or solar cells.

Remarkably less attention has been paid, however, to the heterogeneous effects an equal policy or market stimulus exerts on the different RETs. A first step in this direction can be found in a study by Lee and Lee (2013), who proposed a taxonomy of RETs according to a set of indicators derived from the innovation literature and used it to study the similarities and differences across technologies[4]. Their taxonomy identifies six types of innovation patterns depending on market structure and the degree of technological maturity and potential. They show, for instance, that with the exception of solar photovoltaic (PV) and geothermal energy, the market structure of innovators in RETs tends to be levelled (innovators are close competitors, with similar shares of patents granted), which means, among

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[4] This taxonomy has been created by applying a cluster analysis to energy-technology patents filed at the USPTO over the years 1991-2010.

other things, that late entrants can still gain technological leadership of the market (Lee and Lee, 2013). This result suggests that the aggregate effect of deregulation found in Nesta et al. (2014) can be heterogeneous across technologies. They also show that RETs differ in terms of their technological potential, measured here via patent growth, which can influence the magnitude of the inducement effect a policy exerts on different technologies and, consequently, its overall profitability.

This paper expands on previous research along three directions. First, building on the results of the study by Lee and Lee (2013), we take a step forward and use their taxonomy to study how the effects of the market and policy factors studied in the previous literature differ across the eight different RETs. The importance of this analysis is twofold. On the one hand, it disentangles the heterogeneous factors behind aggregate innovation dynamics in RE. On the other hand, it helps in designing customised policy interventions for each specific technology. In particular, we expect a different degree of technological maturity and technological potential to influence the inducement effect of renewable energy policies (REPs), whereas the increase in competition due to deregulation is expected to experience a positive effect of the innovation performances of levelled manufacturing industries[5] (in which firms tend to innovate to escape competition) and a negative effect of un-levelled industries (in which higher competition reduces the post-innovation rents of laggard firms and consequently decreases innovation (Aghion et al., 2005; Sanyal and Ghosh, 2013)). Moreover, we expect the effect of lowering entry barriers to be stronger in those renewable technologies that are, by nature, more suitable for small-scale generation and are consequently characterised by the entry of small independent power producers after liberalisation, such as the cases of wind and solar energy (Jacobbsson and Bergek, 2004; Lehtonen and Nye, 2009).

Second, we extend JHP by testing for the role of market liberalisation and employing a dynamic specification that accounts for the accumulated stock of past knowledge. At the same time, we expand on the study by Nesta et al. (2014) by allowing for differences in the effect of REPs across technologies and considering the effects of disaggregated policy instruments (we consider in particular the specific effect of Renewable Energy Certificates (RECs), feed-in tariffs, public R&D expenditure and summarised all remaining REPs in a single index. See section 3.2 for more details). Moreover, we split the single index of product market regulation (PMR) used by Nesta et al. (2014) into its three sub-components, namely, ownership, entry barriers and vertical integration, and we test them separately. Energy market liberalisation is, in fact, a long and complex process that involves a wide array of aspects that may exert opposite effects on the development of renewable energy (e.g. Pollitt, 2012). These effects are better captured by using the three sub-indexes than using a single indicator. We expect, in particular, that the increase in competition derived by lowering entry barriers and granting free access

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[5] In accordance with Aghion et al. (2005), by "levelled", we mean here an industry in which innovators are close competitors that retain similar shares of the market.

to the grid to independent power producers, favouring the development of decentralised energy production, should provide a positive incentive for innovation, especially in wind and solar thermal energy. In contrast, privatisation and unbundling can favour the emergence of large players and thus may have an ambiguous effect on innovation in RETs as long as these large players are usually tied to large-scale plants using coal, nuclear or gas as primary energy inputs.

Third, endogeneity is an unresolved issue here because, as empirically shown by Nesta et al. (2014), historic successful innovations in clean energy reinforce the power of green lobbies towards policy makers. Because here we consider different REPs rather than a single REP index, finding good instruments for each endogenous policy is exceedingly difficult. We hence rely on a different strategy and indirectly address the issue of policy endogeneity using the ratification of the Kyoto protocol as an exogenous shock for national-level policies in a difference-in-difference setting. To ensure that the Kyoto effect has been incorporated into the national policy framework, we consider only countries that are members of the European Union, where ratification is enforced by all states. To address these issues, we constructed a cross-country dataset covering eight renewable energy technologies (geothermal, hydroelectric, marine, wind, solar thermal, solar photovoltaic, biofuel and waste) in 19 European countries over the 1980-2007 period.

The paper is organised as follows: the next section defines the main determinants of renewable energy innovations, section 3 describes the data used in the analysis, section 4 presents the empirical strategy, and section 5 discusses the main results. Finally, section 6 concludes.

2. Heterogeneous determinants of renewable energy innovations

The establishment of comparative advantages in a given renewable energy technology depends on a host of factors, which we discuss in this section. More precisely, sub-section 2.1 is concerned with the effect of environmental policies, sub-section 2.2 points to market structure and liberalisation, and sub-section 2.3, starting from the taxonomy proposed by Lee and Lee (2013), outlines the rationale behind the expected heterogeneous effect of policy and market factors on renewable energy innovation.

2.1 Environmental Policies and Innovation

Early theoretical studies on the impact of environmental policies on firms' competitiveness emphasise the static trade-off between firms' competitiveness and compliance with environmental regulation (for a review, see Jaffe et al., 1995). This idea has been criticised by the seminal work of Porter and van der Linde (1995), which, considering explicitly the dynamic effect of regulation on the incentives for innovating and eventually changing consumers' habits, predicts a different effect of environmental regulation on firms' competitiveness. In particular, the so-called Porter hypothesis, in its "weak" version (as defined by Jaffe and Palmer, 1997), argues that environmental regulations foster innovation, while no expectation can be formulated *ex-ante* on the effect of regulation on firm competitiveness[6].

The implications of these works are of particular interest in the case of a growing but still limited sector such as renewables, in which the production costs are generally higher in the absence of a public intervention than those of fossil fuel energy sources. In this particular context, the inducement effect of environmental policies is expected to act through several channels. First, both quota systems and demand subsidies, which increase the market for renewable energy, are expected to stimulate innovation thanks to the higher expected return of R&D investments (Popp et al., 2009). Second, with the innovative activity in the renewable energy sectors characterised by a high degree of uncertainty in all phases of its life cycle, all policies able to reduce this uncertainty are expected to spur innovation.

Finally, as theory suggests, the development of green technologies is subject to two market failures: environmental externality and knowledge externality due to the low appropriability of innovation. In such a context, environmental policies alone, despite being necessary to internalise the social cost of CO_2 production, are not sufficient. Consequently, an optimal policy portfolio should include at least an instrument for each of the abovementioned market failures, such as a tradable permit scheme and subsidies for R&D (Jaffe et. al., 2005; Fischer and Newell, 2008; Acemoglu et al., 2012). The effect of REPs on innovation is the precise aim of the abovementioned work of JHP and Nesta et al. (2014), to which we refer for further reference.

2.2 Market Structure, Liberalisation and Renewable Energy Innovation

The relationship between innovation and competition has been deeply analysed in a vast body of economic literature on endogenous growth (e.g., Boone, 2000, 2001; Aghion and Howitt, 1998). The usual argument put forward in first-generation models, which claims imperfect competition to enhance the appropriability of R&D investments, has been challenged by a new strand of literature offering a more problematic view of this relationship. Aghion et al. (2001, 2005) developed models in which an escaping competition effect counterbalances the standard appropriability (or Schumpeterian) effect. Following their logic, increased competition may shrink a firm's pre-innovation rents more than it reduces its post-innovation rents, consequently increasing profit from innovation activities and R&D expenditures aimed at escaping competition (Aghion et al., 2005). In their view, whether a traditional Schumpeterian effect or the escaping competition effect prevails mainly depends on the industry

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[6] This effect operates through several channels. First, regulation reduces uncertainty in environmental pollution activities; second, it signals firms about potential technological improvements and potential resource inefficiency; third, it induces cost-saving innovation in order to minimise compliance costs. The Porter hypothesis has been the focus of several studies; a good review can be found in Ambech et al. (2013).

structure of innovators. Incumbents are induced to invest more in R&D if the competitive pressure of new entrants is higher and if they are operating in a levelled industry (where firms are neck-to-neck competitors, using the terminology of Aghion et. al., 2005), whereas the higher pressure of new entrants discourages R&D investments in unlevelled markets in which laggard incumbents have competences that are too distant from those needed to imitate leading-edge technologies.

Recent work of Sanyal & Ghosh (2012) investigates how the electricity deregulation in the U.S. has affected the propensity to patents of upstream equipment manufacturers (i.e. General Electrics), which are recognized to be the key actors of innovation in the electricity sector. They find a negative effect, but their rich dataset allows them to distinguish a positive appropriation effect from a pure Schumpeterian one. The former effect occurs since greater competition in wholesale market increases the bargaining power of upstream specialized suppliers, so as their innovative efforts. The appropriation effect tends to be stronger the more non-utility generation actors enter the wholesale market. These new actors (i.e. farmers, firms, small communities, municipalities, households and even environmental activists) are generally specialized in decentralized energy production such as combined generation, local heating systems and renewable sources. The entry of non-utility generators and the associated appropriation effect is hence expected to be significantly stronger for RETs with respect to general electricity, considering the high lock-in of incumbents to fossil fuel technologies and the orientation of entrants in the energy markets towards RE, generally produced by medium- and small-sized firms, which are often the entrants in the market (David and Wright, 2003; Lehtonen and Nye, 2009).

Among the three components of the PMR index used by Nesta et al. (2014), we expect in particular that lowering the entry barriers will trigger an increase in renewable energy innovation. This prediction is supported by previous anecdotal evidence for wind and solar technologies in which the entry of new actors contributed to the creation and diffusion of new knowledge (Jacobsson and Bergek, 2004). The expected effect of unbundling is, on the contrary, controversial. On the one hand, unbundling that increases the competition in energy markets should spur innovation. On the other hand, the financial resources made available by the sales of vertically integrated assets may provide financial resources for merges, acquisitions and horizontal integration, which can act as an obstacle to the diffusion of decentralised energy production and the entry of new players (Pollitt, 2008), inhibiting RE innovation. Finally, privatisation may not necessarily result in the development of RETs for several reasons. First, private companies might be less willing to internalise the pollution externalities stemming from traditional energy sources through the development of RE. Second, private companies tend to be engaged in short-term research rather than in the fundamental research needed to develop renewable energy technologies[7]. As a result, we expect the market to be characterised by low entry barriers and a certain degree of public ownership to be a more fertile context for the development of renewable energy technologies. We have, on the contrary, no a priori expectations about the role of vertical unbundling.

2.3 Heterogeneous effects

To better understand the evolution of renewable energy technologies, we believe it is important to take a step forward and understand how the two mechanisms highlighted above vary across different RETs. In doing so, we draw inspiration from the taxonomy proposed by Lee and Lee (2013), and we use indicators employed in their analysis to sketch out a set of implications that are testable in a rigorous econometric setup.

First, we expect the effect of lowering the entry barriers to depend on the level of each technology's 'developer intensity', which measures the degree of concentration of innovation between firms[8]. This index can be regarded as a proxy for the upstream electric equipment manufacturers' industry structure. Hence, a low level of the index means innovation activities are spread among firms and that there are no technological leaders, while a high level means the industry is unlevelled, with few leaders and several followers. Consequently, we expect an escape competition effect to prevail in the first 'levelled' case and a Schumpeterian effect to prevail in the second. According to Lee and Lee's (2013) taxonomy, technologies such as solar thermal, waste, and wind are characterised by low developer intensity, while geothermal and photovoltaic technologies have high developer intensity, and the others are in between. Moreover, we expect the magnitude of the appropriation effect described in previous section to differ across technologies, and be stronger in RETs where the renewable energy production is decentralised into small- or medium-sized units. This is the case for wind and solar energy, which already showed a high degree of distributed generation in the 1980s[9]. In these cases, lowering entry barriers is more likely to induce the entry of independent power producers, hence increasing the rents of upstream electric equipment manufacturers. In contrast, we expect the appropriation effect to be weaker or absent for technologies such as hydro energy, which, being generally implemented by large utilities due to the size of plants, is less likely to experience the entry of small-scale producers after liberalisation. This brings us to the first testable hypothesis:

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[7] For this last argument, Jamasb and Pollitt (2008) manifest a general skepticism about the incentives of private companies to engage in R&D projects with a long-term payback horizon.

[8] Measured as the ratio of patents granted by the top five firms that are most active in patenting to all the patents in that technology.

[9] Johnson and Jacobsson (2003), Jacobsson and Bergek (2004) and Nilsson at al. (2004) provide anecdotal evidence of the sustained entry of new small producers of wind turbines in Sweden, the Netherlands, Denmark and Germany in the 1970s and 1980s, before the kick-off of the liberalisation process.

Hypothesis 1: *The effect of lowering entry barriers on innovation activities is expected to be positive for wind, solar thermal and waste technologies, which are characterised by both a lower developer intensity and the entrance of many independent producers.*

Notice that the effect of lowering entry barriers on solar PV is mainly an empirical issue. On the one hand, it should be negative or absent for the presence of few well established leaders. On the other hand, it should be positive provided that PV generation is highly decentralized.

The second issue regards the heterogeneous effect of REPs and has been already investigate by seminal paper of JHP. Standard economic theory leads to the conclusion that economic instruments are generally more efficient at promoting technical change than regulatory mechanisms (Jaffe et al., 2003). Technical change, in fact, allows firms to reduce the cost of complying with emission taxes or other economic instruments, whereas regulation does not provide incentives to reduce emissions via technological change beyond the standards imposed. Moreover, different instruments produce a different effect in terms of how surplus is distributed. Feed-in tariffs, for instance, which increase the energy producer surplus, stimulate the demand for upstream innovation. Conversely, quantity-based systems do not directly generate a surplus for producers, who are consequently not encouraged to demand more innovations from upstream equipment manufacturers (Menanteau et al., 2003). These results have been contested in some recent contributions. Fisher et al. (2003) find that a clear-cut and unique ranking of policy instruments was not feasible because the inducement effect of different policies depends on several industry-specific factors, such as the cost of innovation, the innovators' ability to appropriate other firms' innovation and the number of firms in the market. Bauman, Lee, and Seeley (2008) show that under certain circumstances, command and control policies may induce more innovation than market-based instruments. Applied work such as JHP, however, stresses that in the case of renewable energy, it is not just the distinction between price and quota systems that matters but also the degree of the technological maturity of the different RETs. Quantity-based policies such as renewable energy certificates (RECs) tend to promote more mature and cost-effective technologies, such as wind, geothermal and solar thermal technologies, which guarantee lower short-run compliance costs. However, because firms are very likely to choose technologies close to the market or technologies in which they already have a competitive advantage, the incentive for long-run research in less cost-competitive and emerging technologies (such as solar energy or ocean) will be fairly low. On the other hand, technology-specific policies, such as public R&D, and technology-specific price systems, such as feed-in tariffs, that allow differentiation and the specific pricing of individual technologies might be able to support emerging technologies such as solar PV. Consequently, the second hypothesis is:

Hypothesis 2: *The effect of broad policies is stronger for mature technologies, while emerging technologies are more responsive to technology-specific instruments.*

The magnitude of this last effect can, however, depend on another dimension analysed by Lee and Lee (2013), i.e., the technological potential, which measures the average patent growth rate of a technology (Holger, 2003) and is a rough proxy of its innovative potential. More specifically, this index is constructed as the number of patents in a given field in a given year divided by the number of patents in the same field in the previous year. We expect, in particular, that technologies associated with a high technological potential are highly responsive to market conditions and, consequently, reacted more promptly and positively to an increase in the demand for clean energy, which can be driven by REPs, or to an increase in electricity consumption. In other words, we expect RETs that experience a high patent growth rate, such as wind, solar, marine and biofuel, will be strongly driven by either market factors or policy support. Interestingly, a rejection of this hypothesis would mean, for instance, that some RETs have developed consistently even without strong policy support and may therefore experience even more growth if subjected to a stricter or more specific regulation.

Hypothesis 3: *The magnitude of the policy inducement effect, or more generally, of an increasing size of the energy market, is stronger for technologies with high technological potential such as wind, solar, marine and biofuel technologies and weaker or not present for technologies with low technological potential.*

3. Data, measurement issues and descriptive evidence

The set of variables to be included in the empirical analysis concerns a potentially large host of factors, ranging from innovation measurement to policy types, not mentioning the more traditional macroeconomic characteristics. Table 5 at the end of this paragraph summarises the variables used and presents basic descriptive statistics.

3.1 Innovative activity indicator

We use patent counts as our proxy for innovation performance. This choice is consistent with prior studies on renewable energy innovations such as those by Popp (2011), JHP and Nesta et al. (2014). We refer to patents filed at the European Patent Office (EPO) in the eight sub-fields: wind, marine, solar thermal, solar photovoltaic, biofuels, hydroelectric, fuels from waste, geothermal and marine. We then aggregate these patents into a pooled panel that varies across technologies, time and countries. The choice of adopting patents filed at the EPO is particularly attractive for studying innovative activities among European countries and has three main advantages: first, it avoids home country bias issues[10] (Dernish and Khan, 2004); second, we expect patents filed through the EPO to be

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[10] This effect is due to the fact that inventors almost always file for protection in their home country first, with the consequence that the majority of patents at national offices come from domestic inventors.

generally of high quality and to have homogeneous economic value[11]; and third, it eliminates potential bias due to different legal systems and institutional contexts[12].

Figures 1-2 below present patent count trends for the eight RETs from 1980 to 2007. All technologies experienced a visible surge in patenting after the ratification of the Kyoto protocol in 1997, marked with a line in the graphs. This rise was particularly evident in technologies with a high potential such as solar, wind and biofuel technologies, which is coherent with our third research hypothesis. Before this date, patenting activity for biofuel, wind, marine and geothermal appeared relatively flat, while it was slightly steeper for the others, especially solar photovoltaic and waste. The predominance of wind, solar PV and solar thermal technologies, which account for 24%, 25% and 18% of total patenting, respectively, is also confirmed in Table 1. In fourth place is biofuel, with a share of 12%. As expected, the main innovators in Europe are Germany, France, the United Kingdom, Denmark and the Netherlands, which generally show similar technological specialisation with respect to the European average, as highlighted by Tables 1 and 2[13]. There are, however, certain remarkable differences, including the lower share of wind patents in France with respect to the average, the lower share of solar patents in Denmark and the relevant role of patenting in fuel from waste technologies in eastern countries, Finland and Denmark.

[FIGURE 1 & 2 ABOUT HERE]
[]TABLE 1 & 2 ABOUT HERE]

3.2 Environmental policy

Concerning environmental policy data, we refer here to the database on public policies for RE compiled at the International Energy Agency (IEA) and previously used by JHP. This database and the related IEA (2000) publications contain detailed fact sheets at the country level that make it possible to construct adoption dummies reflecting the chronology of policy implementation for most OECD countries. A drawback of this dataset is that it provides information on the year of adoption but does not specify the degree of intensity of the policy adopted. We hence integrate this information using other data sources in all those cases for which policies measured on a continuous scale are available. To the best of our knowledge, this is possible for the following three instruments: public renewable R&D expenditures (R&D), feed-in tariff schemes (FEED-IN) and RECs. Information on the first instrument

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[11] Inventors seeking protection abroad, which is more costly than patenting solely in their home country, generally expect higher returns from their inventions.

[12] For example, until 1988, the Japanese patent system required a single patent application for each separate claim (Ordover 1991), which resulted in a higher number of patent applications from a single invention with respect to the European and American systems.

[13] The shaded areas in Tables 1 and 2 represent the three main specialisations in each country in terms of the share of patents.

is also available in the IEA-OECD dataset, while data for feed-in tariffs have been collected from several specific sources: two reports compiled by the IEA (2004) and Cerveny and Resch (1998) and two websites on renewable energy regulations[14]. Finally, our measure of the stringency of RECs is the variable constructed by JHP, which reflects the share of electricity that must be generated by renewables or covered by RECs.

In this work, we particularly consider the following policy instruments:

1) **Government research and development expenditures** specific to each RET.
2) **Incentive tariffs (feed-in)**, i.e., guaranteed prices above market tariffs for a certain number of years subsidised by the government. The tariffs vary across technologies.
3) **Investment incentives**, i.e., capital grants and all other measures aimed at reducing the capital cost of adopting renewable energy technologies, generally provided by State budgets.
4) **Tax measures** used either to encourage production or discourage consumption (e.g., tax credits or property tax exemptions).
5) **Voluntary programs** adopted at the country level by different stakeholders, i.e., the government, public utilities and energy suppliers that agree to buy energy generated from renewable sources.
6) **Obligations**, which place a requirement on suppliers to provide a share of their energy supply from renewable energy;
7) **Renewable Energy Certificates**, which are tradable certificates generally used to track or document compliance with the quota system.

In the analysis, we include continuous variables for policies for which information is available (RECs, feed-in tariffs and Public R&D support[15]). For all of the other policies, as in JHP, we set the variable "OTHER POL" equal to 1 if any of them are presented in a given country in a given year. Finally, we construct a dummy variable equal to 1 after the signing of the Kyoto protocol in 1997 and zero before (KYOTO), which captures country expectations about both the future policy context for climate change mitigation and the market size for renewables (Popp et al., 2011).

In all European countries, policy support for RE follows a similar path of development. The first wave of policy support dates back to the end of the 1970s and the beginning of the 1980s and was most likely in response to the two oil crises. The main instruments developed at that time were public R&D and investment incentives (included in our OTHER POL variable), as evident from Table 3. During the 1990s, a second wave of policies emerged, composed mainly of feed-in tariffs and tax measures, while the last decade was characterised by the development of quota systems and RECs,

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[14] http://www.ren21.net/ and http://www.res-legal.de.

[15] It must be noted that due to data constraints, the data on both feed-in tariffs and R&D do not vary between solar PV and solar thermal. In both cases, the available data generally refer to solar energy.

which were highly supported by EU Directive 2001/77/EC[16]. Moreover, it has to be noted that the overall stringency of policy support increases over time (see Table 3), while the ranking across technologies remains unchanged. Table 4 shows that for feed-in tariffs, the two solar technologies and wind are those that received the greatest support, while public subsidies for R&D have always been stronger for biofuels and solar technologies.

[TABLE 3 & 4 ABOUT HERE]

3.3 Market liberalisation

To measure market competition, we choose the index for Product Market Regulation used by the OECD (PMR AGGREGATE), which combines information on barriers to entrepreneurship and administrative regulation (e.g., licenses and permits, administrative burdens, and legal barriers), state control (e.g., price control and ownership), and barriers to trade and foreign direct investment (e.g., tariffs and ownership barriers). For the purpose of this paper, the sector of interest is electricity (ISIC 4010) and, to a lesser extent, Gas (ISIC 4020). The PMR index for electricity and gas essentially combines three sub-indexes ranging from 0 to 6 (maximum anticompetitive regulation). The first is ownership (PMR PUB OWN), which assumes five values: private (0), mostly private (1.5), mixed (3), mostly public (4.5) and public (6). The second is an index of entry barriers (PMR ENTRY) that combines information on third-party access to the grid (regulated (0), negotiated (3), no access (6)) and minimum consumer size to freely choose their suppliers (from 'no threshold' (0) to 'no choice' (6)). The third component is vertical integration (PMR VERT INT), ranging from unbundling (0) to full integration (6).

Figure 3 below shows the patterns of PMR for selected countries and makes evident the widespread reduction of market regulation, especially in the 1990s. Entry barriers nearly vanished in all countries at the end of the analysed period, while vertical unbundling is still not completed in the EU countries. Privatisation, in contrast, is not a smooth process and involves important cross-country differences. Figure 3 below, for instance, highlights the fact that in the 1970s, countries such as Germany and Spain were already characterised by a certain degree of privatisation, while in countries such as France and Denmark, state ownership is still widespread (Pollitt, 2005, 2012).

[FIGURE 3 ABOUT HERE]

3.4 Other variables

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[16] Which established the first shared framework for the promotion of electricity from renewable sources at the European level and encouraged the development of RECs.

Popp (2002) emphasises the importance of accounting for the dynamics of knowledge stock in policy inducement studies. This result is reinforced by Aghion et al. (2012), who show that past knowledge, creating a lock-in effect, influences the choice between clean and dirty technologies and partially inhibits policy inducement. To account for this effect, we include in our specification a patent stock that varies across countries, technologies and time (KNOW-STOCK). We construct this variable following Popp et. al. (2011)[17]. In addition to the core variables, we add a consolidated set of controls, which include per capita income levels (GDP_pc) and electricity consumption (ELECT CONS). The first is a proxy for the willingness to pay for a clean environment (Diekmann and Franzen, 1999)[18], and the second captures a simple market size effect (JHP). We expect both variables to have a positive effect on innovation. We further control for electricity prices (ELECT PRICE) that, in line with the literature on induced innovation (Popp, 2002; Newell et al., 1999), we expect to be positively correlated with innovation incentives[19]. Finally, we introduce a dummy reflecting EU enlargement history that takes a value equal to one from the year in which a new country became part of the EU (ENLARG) and controls for structural heterogeneity and the different policy settings of new entrant countries.

[TABLE 5 ABOUT HERE]

4. Empirical Strategy

Our econometric analysis is carried out for 19 EU countries[20] over the years 1980–2007. The choice of referring to EU countries guarantees a highly homogenous political and institutional framework, reducing the possibility that unobservable institutional and political variables bias our estimated effects. Our main analysis is based on specification 1 below, which is applied to the eight different technologies. We take the logarithmic transformations of all variables in the analysis to mitigate for potential outliers and provide coefficients that are easier to interpret. Compared to JHP[21], we decided to disaggregate patents into more subfields to better capture the specificity of each technology.

The benchmark specification for each technology k is:

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[17] Following previous work on patent data (Popp et. Al, 2011; Lovely and Popp 2011), we measure the knowledge capital of country *i* at time *t* for each technology *k* based on the following equation: $K\ Stock_{i,k,t} = \sum_{s=0}^{\infty} e^{-\beta 1(s)}\left(1-e^{-\beta 2(s+1)}\right)PAT_{i,j,t-s}$. We set the rate of knowledge obsolescence to 0.1 (β_1=0.1) and the rate of knowledge diffusion to 0.25 (β_2=0.25). As a result, we obtain a knowledge stock that varies by country, year and technology.

[18] Recent empirical evidence at the micro level suggests that the willingness to pay higher prices for green energy appears, in fact, to be positively related to per-capita income and education (Roe et al. 2001; Wiser 2007).

[19] Following JHP, we argue that because RE represents only a small portion of total electricity generation, the price of electricity can be considered exogenous.

[20] Finland, Greece, Italy, Luxembourg, Sweden, the United Kingdom, Austria, the Czech Rep., France, Hungary, the Netherlands, Portugal, Belgium, Denmark, Germany, Ireland, Spain, Poland, and the Slovak republic.

[21] Which only considered 5 technologies, pooling biomass and waste together as well as the two solar technologies.

$$\text{EPO\_PAT}_{it} = f(\beta_1 \text{ K STOCK}_{it-1} + \beta_2 \text{ PMR ENTRY}_{it} + \beta_3 \text{ PMR VERT INT}_{it} + \beta_4 \text{ PMR PUB OWN}_{it} + \beta_5 \text{ Log R\&D}_{it} + \beta_6 \text{ Log FEED-IN}_{it} + \beta_7 \text{ KYOTO}_{it} + \beta_8 \text{ Log RECs}_{it} + \beta_9 \text{ OTHER POL}_{it} + \beta_{10} \text{ Log ELECT PRICE}_{it} + \beta_{11} \text{ Log ELECT CONS}_{it} + \beta_{12} \text{ Log GDP\_pc}_{it} + \beta_{13} \text{ ENLARG}_{it} + \beta_i + \beta_t),$$

where EPO_PAT_{it} stands for the number of patent applications filed at the EPO for country *i* at time *t* in the eight renewable energy technologies analysed. Fixed effects are calculated on the country unit *i*. Time-fixed effects are included in all the specifications to control for common time shocks. As highlighted by Popp et al. (2011), time trends or year-fixed effects rule out the possibility that the knowledge stock (K STOCK), which grows by construction through time, only picks up other tendencies for investment to increase over time. Following Aghion et al. (2012), we lagged the knowledge stock by one year in the analysis to account for possible contemporaneous feedback effects and delayed effects. Overall, this specification enriches previous work by JHP, accounting for the dynamics of past innovation stock and reflecting the degree of market liberalisation through the inclusion of the PMR variables.

The wide array of controls added to the main specifications along with country-fixed effects should eliminate several time-varying sources of unobservable heterogeneity that might bias the estimations of the effect of PMR and REPs on innovation. Reverse causality and measurement error can, however, induce a bias in the estimated coefficient. First, there is a mutual reinforcement effect, initially recognised by Downing and White (1986), that may generate reverse causality: if innovation in environmental technologies follows the implementation of an effective policy support and the liberalisation of the energy market, progress in the generation of renewable energy will, in turn, reinforce the lobbying power of innovating firms and the associations of RE producers asking for further policy support and more liberalisation. Moreover, a negative feedback effect may emerge, as policy-induced technological change can also influence the dynamics of policy support through different channels. In the German case, for instance, the unexpectedly high rate of development of solar PV energy driven by a decrease in the marginal cost of production led policy-makers to underestimate the social costs of the feed-in tariff scheme and to adapt the design of the policy accordingly (Hoppmann et. al., 2014). Second, the specific design of REPs is heterogeneous across countries, and our variable, which mainly accounts for stringency, cannot fully account for these characteristics. Hence, an omitted variable bias could plague the estimated relationship between policy and innovation. Third, some renewable energy policies are measured with substantial error, which can generate a bias in the regression estimates (Wooldridge, 2003). For most policies, in fact, especially those in place since the 1970s and the 1980s (summarised in the variable OTHER POL), a lack of detailed information allows only for policy dummies, which at best are only rough proxies subject to measurement error.

However, considering that the focus of this work is on the heterogeneous effect of different renewable energy policies, an IV strategy is not feasible, given the high number of potentially endogenous regressors. We therefore test the robustness of our results to endogeneity indirectly using the ratification of Kyoto as a quasi-natural experiment or exogenous policy shock. The shortcut for giving a causal interpretation to the Kyoto shock is that each single country in Europe had a small influence on the ratification decision. Obviously, this is only partially true, as large countries have more influence over common EU decisions than smaller ones. Because it is difficult to mitigate concerns for endogeneity in the presence of multiple endogenous regressors, we consider this additional exercise as a robustness check rather than an ideal specification. Technically, we augmented the pooled specification by the inclusion of an interaction between the Kyoto dummy and the pre-Kyoto mean (1990-1996) of the potential endogenous regressors (END_POL(it)), i.e., RECs, FEED-IN, OTHER POL, R&D, and PMR. Specification 2 became:

$$\text{EPO\_PAT}_{ijt}=f(\beta_1\ \text{K STOCK}_{ijt-1} + \beta_2\ \text{PMR ENTRY}_{it} + \beta_3\ \text{PMR VERT INT}_{it} + \beta_4\ \text{PMR PUB OWN}_{it} + \beta_5\ \text{Log R\&D}_{ijt} + \beta_6\ \text{Log FEED-IN}_{ijt} + \beta_7\ \text{KYOTO}_{it} + \beta_8\ \text{Log RECs}_{it} + \beta_9\ \text{OTHER POL}_{it} + \beta_{10}\ \text{Log ELECT PRICE}_{it} + \beta_{11}\ \text{Log ELECT CONS}_{it} + \beta_{12}\ \text{Log GDP\_pc}_{it} + \beta_{13}\ \text{ENLARG}_{it} + \beta_{14}\ \text{KYOTO*Log END\_POL}_{ijt}\ \beta_i + \beta_t),$$

where all technologies *j* have been pooled into a single panel in which fixed effects are calculated on the country unit *i* and the technology unit *j*. The term β_{12} is the coefficient of the interaction effect between Kyoto and the 1990-1996 values of the selected possible endogenous regressors.

5. Results

Table 6 displays the regression results obtained using specification 1 for eight different RETs. For each technology, we present the results for the PMR index split into its three subcomponents (in the main table) and the results for the aggregate index (in the last row)[22]. Given the count nature of the dependent variable, a negative binomial model was employed to estimate the regression coefficients, as in JHP. The differences in the total number of observations across specifications are due to the elimination of some countries for all zero outcomes in the dependent variable, an issue that is particularly severe in emerging technologies. To address this issue, we conducted a robustness check

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[22] For the sake of brevity, we only present the coefficient of PMR AGGREGATE in Table 6. Other covariates' coefficients remain substantially unchanged using PMR AGGREGATE instead of its three sub-components in the analysis.

using a zero-inflated negative binomial estimator, not presented here for the sake of brevity, which produced very similar results. Finally, it should be noted that, given the dynamic specification employed here, the results should be interpret as a short-term effect.

Overall, policy support, the stock of past knowledge, the degree of entry barriers and electricity prices appear to be the main drivers of patenting in RETs, more than the size of the energy markets and consumer preferences towards green goods, proxied here by ELEC CONS and GDP_pc, respectively.

The effect of the PMR AGGREGATE indicator (in the bottom line of Table 6), despite always showing the expected negative coefficient, is statistically significant only for wind, solar thermal and waste energy technologies. Interestingly, the low significance of deregulation on overall RE innovation found by Nesta et al. (2014) hides a significant heterogeneity across RETs, as highlighted by these results[23]. Notice that these heterogeneous effects are broadly consistent with Lee and Lee (2013) taxonomy, as adapted in our hypothesis 1. Moving a step forward, Table 6 also shows that among the three subcomponents of PMR, only PMR ENTRY drives the aggregate result, as it is statistically significant in the case of wind and solar thermal. Across the other technologies, the coefficient of PMR ENTRY has the expected negative coefficient except in the case of hydro and waste, and it is nearly significant in geothermal and solar PV technologies. These results are consistent with the idea that deregulation, favouring the entry of non-utility and independent power producers, generally oriented towards green energy, increases the incentives of electric equipment manufacturers to innovate. Consistent with Hypothesis 1, this result is driven by wind and solar thermal technologies, which are characterised by a low level of concentration in innovative activities across innovators and by the entry of several independent power producers after liberalisation. Moving to the other components of market regulation, PMR PUB OWN present the expected positive sign in five over eight technologies, but the related coefficients are never statistically significant, suggesting a low impact of the type of ownership on RE innovation. Similarly, the contrasting effects exert by unbundling on innovation described in section 2.2, are reflected in the non-significance of the coefficient of PMR VERT INT in most specifications (except for SOLAR_PV, in which unbundling has a negative effect on innovation, but significant at the 10% only).

Moving to policy variables, in line with Hypothesis 2, technology-specific policies like FEED-IN and R&D, appear to play a major role in the early phases of technological development, such as in the case of solar PV or marine energy, whereas for relatively more mature technologies, e.g., wind and solar thermal, quota systems are more effective policy tools. R&D, in particular, is a significant determinant of innovation for several RETs, such as wind, marine, biofuel and geothermal. Interestingly, this

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[23] We refer in particular to results found in Nesta et al. (2014) when restricting the analysis to high-quality patents only (as in our case).

evidence confirms the results found by JHP that remain robust even in our dynamic specification which account for the stock of past knowledge. The only meaningful difference is the insignificant coefficient of R&D for the two solar technologies found in our analysis. Empirically, this difference is partially due to our choice of splitting solar energy in two different categories with respect to JHP, and partially to the absence of countries like US and Japan, which being positive outliers in the distribution of R&D might have partially driven previous result. The insignificant effect of R&D on solar PV is counterbalanced by a positive effect of FEED-IN, the policy instrument designed to directly promote decentralized energy production[24]. Notice that, as in JHP, FEED-IN has no significant effect on other technologies when controlling for other policies. In contrast, RECs have a significant effect on patenting in wind and solar thermal, which being mature technologies are able to capitalised on quota system in order to strengthen their role in the market. Their low significance in all other instances reinforces the idea that when policies leave firms freedom to choose how to meet renewable targets, firms will choose the least costly option. Future policy expectations as proxied by the KYOTO protocol dummy exert a significant and positive effect for wind, solar PV, marine and biofuel technologies, and OTHER POL, controlling for all these policy instruments for which continuous information is not available, shows an expected positive and significant effect for solar PV, marine and biofuels. Interestingly, and in line with H 3, this last set of policy instruments exerts a positive effect only on technologies with an high technological potential.

Among basic controls, ELEC PRICE is associated with a more robust outcome, as it is positive and statistically significant in five of the eight technologies analysed, while the size of the energy market, proxied by ELEC CONS, is significant only for the two solar energy technologies[25]. GDP_pc, reflecting consumer preferences for clean energy, shows the expected positive sign in four of the eight technologies. The effect of ENLARG should be regarded as a control for the differences in the political environment derived by the annexing of a new country to the EU, which cannot be captured by a time-varying country-fixed effect. Its coefficient is significant and negative for wind and solar thermal, suggesting a general lower level of patenting in new EU countries. Finally, the K STOCK, accounting for the dynamics of past Knowledge, is statistically significant and associated with a positive coefficient in wind, solar thermal and waste energy. The stronger persistency of past innovation in more mature renewable energy sources reinforces the relevance of finding the right mix of instruments that are capable of redirecting technical change toward emerging RETs to avoid the risk of a lock-in to more profitable and close to the market technologies like wind energy.

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[24] The negative coefficient of FEED-IN for wind is an unexpected result already found in JHP. As in their case, we believe this is an empirical issue due to the potential presence of endogeneity and collinearity with other policy variables. Interestingly, if we run specification two on wind patent only, to mitigate the potential endogeneity, result change and the marginal effect of FEED-IN becomes positive.

[25] These results are generally consistent with JHS. The differences are due to our decision to split renewable technologies into more subsamples with respect to their study and our dynamic specification.

In order to test H3, and to have a proper quantifications of different effects, Table 8 below presents short-term marginal effects, computed as the change in the expected number of patent relative to the mean resulting from an inter-quartile change in variable Xi, holding all variables at their observed value (as in Nesta et al., 2014). PMR ENTRY exerts a sizable effect on both wind and solar thermal energy, being associated with an increase in patents filed at the EPO of respectively the 43 and 36 per cent. The size of the effect is in line with Nesta et al. (2014). Moving to the policy variable, the quantification confirms H 3, showing a stronger effect of policy and market effects on technologies with a n high technological potential (wind, solar, marine and biofuel). The effects of KYOTO and OTHER POL are particularly striking in the case of marine energy (resp. 216% and 172%), and biofuel (resp. 110% and 29%). On the contrary, the effect of R&D is stronger for wind and geothermal energy. Interestingly, policy variables are never significant for hydro and waste, two technologies that are not directly accounted for in the work by JHP. Concerning hydropower, this result most likely occurs because it is a mature and consolidated technology with a low opportunity for technological improvement (Popp et al., 2011) and is close to full capacity in several EU countries (IEA, 2010). For waste energy, it is most likely still too early to judge its response to policy stimulus, as it is a new and emerging technology with low technological potential (Lee and Lee, 2013) representing only a small portion of the renewable electricity portfolio. Finally, also market stimulus given by an increase of ELEC PRICE show stronger effect on solar thermal, PV, marine and geothermal energy (resp. 15%, 14%, 130% and 280%), while ELEC CONS is the only significant exception having a big effect on waste energy (52%), but contextually showing a strong effect also on the two solar technologies (resp. 38 and 28%).

Column 1 of Table 7 presents the results for the pooled specifications with country- and technology-specific fixed effects in which the coefficients are not constrained to vary across technologies but represent an average effect. The aggregate result confirms previous evidence. The controls and the K STOCK are associated with the expected coefficients, while among the three components of PMR, only entry barriers constitute a statistically significant driver of innovation. It should be noted here that the aggregate results are mainly driven by wind and the two solar technologies, which represent approximately 70% of the total patenting in RE. The effect of FEED-IN is never significant in the pooled specification of column 1, whereas KYOTO and R&D show the expected positive coefficient. RECs, in contrast, are not statistically significant, a result that reflects their heterogeneous effect across technologies, as also shown in Table 6. On the other hand, the more homogeneous results for PMR ENTRY, R&D, KYOTO and OTHER POL are reflected here by a coefficient that is statistically significant and in line with our expectations. Columns 2-6 of Table 7 present a robustness check in which we interacted the Kyoto protocol with the 1990-1996 levels of the five different policy variables. The regression results mainly confirm previous evidence, while the interaction is significant for FEED_IN, R&D and PMR ENTRY. An exogenous policy shock such as the ratification of the Kyoto protocol amplified, on aggregate, the inducement effect of FEED-IN and R&D subsidies. In particular FEED-IN, which were never significant except in the case of solar PV and wind, became significant after Kyoto, probably thanks to the less uncertain policy environment caused by the ratification of the international protocol. Similarly, column 6, shows as KYOTO also amplify the effect of energy market liberalisation, corroborating Nesta et al. (2014) result that the effect of REPs is stronger in more competitive markets. It is surprising, on the contrary, the insignificant effect of RECs, which were highly supported by the Kyoto protocol. This result is probably due by the heterogeneous effect that quota systems exert on different technologies, as shown in Table 6.

[TABLE 6 - 8 ABOUT HERE]

6. Conclusions

This paper contributes to the growing literature on environmental innovations in several ways. First, we test the qualitative implications of the work by Lee and Lee (2014) and use them to disentangle the aggregate evidence found in previous studies on the determinants of RE innovation, accounting for the intrinsic characteristics of eight different renewable technologies and for dynamics in the innovation equation. As a result, we find that the aggregate effect of market liberalisation found in the previous literature is driven by technologies with a lower development intensity (i.e., with less concentrated patenting activity across firms) and more subjected to the entry of independent power producers, such as wind and solar thermal energy. Similarly, the effect of REPs is heterogeneous across technologies and depends on their different degrees of maturity. In line with previous work (JHP), mature technologies are more responsive to quota systems, ensuring lower compliance costs for the producer, while emerging technologies benefit largely from demand subsidies and public support for R&D. Contrary to our expectations, FEED-IN are statistically significant and associated with a positive coefficient only in the case of solar PV, but their aggregate effect turn out strongly significant after the ratification of the Kyoto protocol, when the policy framework becomes more stable and less uncertain. Moreover, we try to synthesise previous contradicting empirical evidence. If from the one hand, in fact, JHP found a significant effect for several policies, on the other hand Nesta et al. (2014), found an insignificant effect of their aggregate REPs indicators when controlling for its potential endogeneity and for the dynamics of past knowledge. These two analyses are, however, difficult to compare given their completely different empirical settings. In the present work we fill this gap, showing as even partially accounting for endogeneity thanks to the KYOTO interactions and including a K STOCK, REPs still play a relevant inducement effect. This result, in a way, reconciles previous evidence, and stress the relevance of accounting for the intrinsic heterogeneity of both policy support and renewable energy technologies. Second, the analysis show as the magnitude of these effects also depend on the degree of technological potential of different RETs, and is consequently stronger for wind, solar, marine and biofuel energy. This result suggests that additional specific policy support in these technologies could represent a profitable investment for countries with suitable natural conditions. Third, we further develop the idea put forward by Nesta et al. (2014) and provide a careful evaluation of the impact of energy market liberalisation on renewable energy technologies. In particular, we show that lowering entry barriers has a significant positive impact on renewable energy technologies, while the degree of vertical integration and the types of ownership are non-influential factors. Moreover, KYOTO amplifies this effect, confirming the complementarity hypothesis, put forward by Nesta et al. (2014), that environmental policies are more effective in competitive markets. For the future, a major concern is the recent trends of market integration in EU countries that have brought about excessive concentration with few large players dominating the market, e.g., EDF, ENI, E-ON, and Vattenfall. This process may undermine the entry of new innovative players and the development of the DG paradigm.

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Table 1. Total count of patent by country and share of each technology on total Renewable Energy patenting. Solar PV, wind, solar thermal and biofuel. Shaded area represent the three main country specialization (in terms of share of patents).

Country	**Total Patent**	**Solar photovoltaic**		**Wind**		**Solar thermal**		**Biofuel**	
		Count	**Share of Total Patent**	**Count**	**Share of Total Patent**	**Count**	**Share of Total Patent**	**Count**	**Share of Total Patent**
Germany	2985	**912**	**0.31**	**745**	**0.25**	**602**	**0.20**	205	0.07
France	767	**244**	**0.32**	89	0.12	**147**	**0.19**	**103**	**0.13**
United Kingdom	655	**140**	**0.21**	**112**	**0.17**	73	0.11	**101**	**0.15**
Denmark	503	6	0.01	**299**	**0.59**	26	0.05	**112**	**0.22**
Netherlands	459	**157**	**0.34**	68	0.15	**69**	**0.15**	**69**	**0.15**
Italy	383	**88**	**0.23**	**59**	**0.15**	**90**	**0.24**	56	0.15
Spain	307	**43**	**0.14**	**135**	**0.44**	**73**	**0.24**	16	0.05
Austria	266	**42**	**0.16**	25	0.09	**64**	**0.24**	26	0.10
Sweden	245	23	0.09	**70**	**0.29**	**42**	**0.17**	**34**	**0.14**
Belgium	197	**63**	**0.32**	**38**	**0.19**	22	0.11	**36**	**0.18**
Finland	134	20	0.15	**21**	**0.16**	10	0.07	**41**	**0.31**
Ireland	68	6	0.09	5	0.07	9	0.13	**10**	**0.14**
Greece	48	**9**	**0.18**	**11**	**0.23**	**9**	**0.18**	8	0.17
Luxembourg	40	6	0.14	**7**	**0.18**	**14**	**0.34**	3	0.08
Portugal	37	3	0.08	**7**	**0.19**	**8**	**0.22**	**7**	**0.19**
Hungary	32	2	0.06	3	0.09	**12**	**0.37**	3	0.08
Czech Republic	20	0	0.00	1	0.05	2	0.10	**8**	**0.40**
Poland	17	0	0.00	1	0.06	**3**	**0.18**	**4**	**0.24**
Slovak Republic	12	0	0.00	1	0.09	**3**	**0.26**	1	0.09
Total	7172	1762	0.25	1695	0.24	1276	0.18	839	0.12

Table 2. Total count of patent by country and share of each technology on total Renewable Energy patenting. Waste, hydro, marine and geothermal. Shaded area represent the three main country specialization (in terms of share of patents).

Country	**Total Patent**	**Waste**		**Hydro**		**Marine**		**Geothermal**	
		Count	**Share of Total Patent**	**Count**	**Share of Total Patent**	**Count**	**Share of Total Patent**	**Count**	**Share of Total Patent**
Germany	2985	303	0.10	135	0.05	19	0.01	65	0.02
France	767	94	0.12	70	0.09	16	0.02	6	0.01
United Kingdom	655	62	0.09	94	0.14	70	0.11	6	0.01
Denmark	503	**33**	**0.07**	12	0.02	16	0.03	0	0.00
Netherlands	459	55	0.12	25	0.05	8	0.02	10	0.02
Italy	383	36	0.09	29	0.08	17	0.04	9	0.02
Spain	307	9	0.03	12	0.04	18	0.06	2	0.01
Austria	266	37	0.14	**58**	**0.22**	3	0.01	11	0.04
Sweden	245	21	0.09	25	0.10	20	0.08	10	0.04
Belgium	197	20	0.10	13	0.07	1	0.01	5	0.03
Finland	134	**26**	**0.19**	7	0.05	7	0.05	2	0.01
Ireland	68	8	0.12	**17**	**0.25**	**13**	**0.19**	0	0.00
Greece	48	3	0.06	5	0.10	4	0.08	0	0.00
Luxembourg	40	**8**	**0.19**	3	0.08	0	0.00	0	0.00
Portugal	37	4	0.11	6	0.16	2	0.05	0	0.00
Hungary	32	**4**	**0.12**	2	0.06	2	0.06	**5**	**0.15**
Czech Republic	20	**6**	**0.28**	**3**	**0.12**	0	0.00	1	0.05
Poland	17	**6**	**0.35**	0	0.00	0	0.00	**3**	**0.18**
Slovak Republic	12	**3**	**0.26**	**3**	**0.22**	1	0.09	0	0.00
Total	7172	735	0.10	516	0.07	215	0.03	135	0.02

Figure 1. Patent trends for solar PV, wind, solar thermal and biofuel. Years 1980-2007.

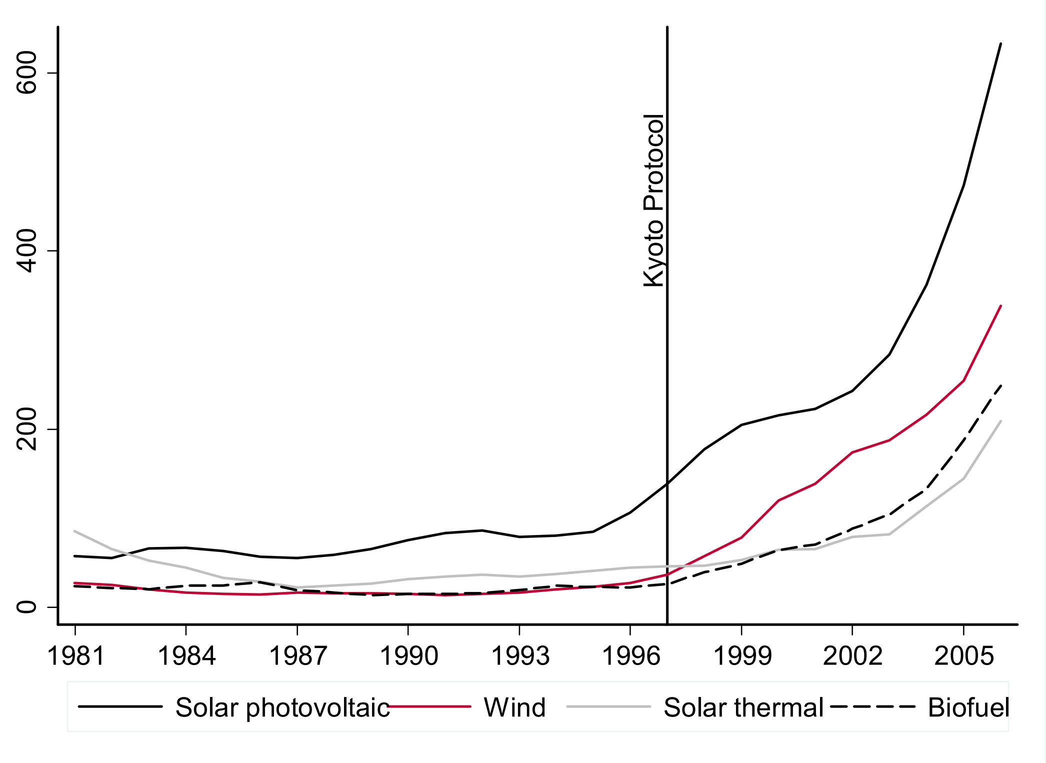


Figure 2. Patent trends for waste, hydro, marine and geothermal. Years 1980-2007.

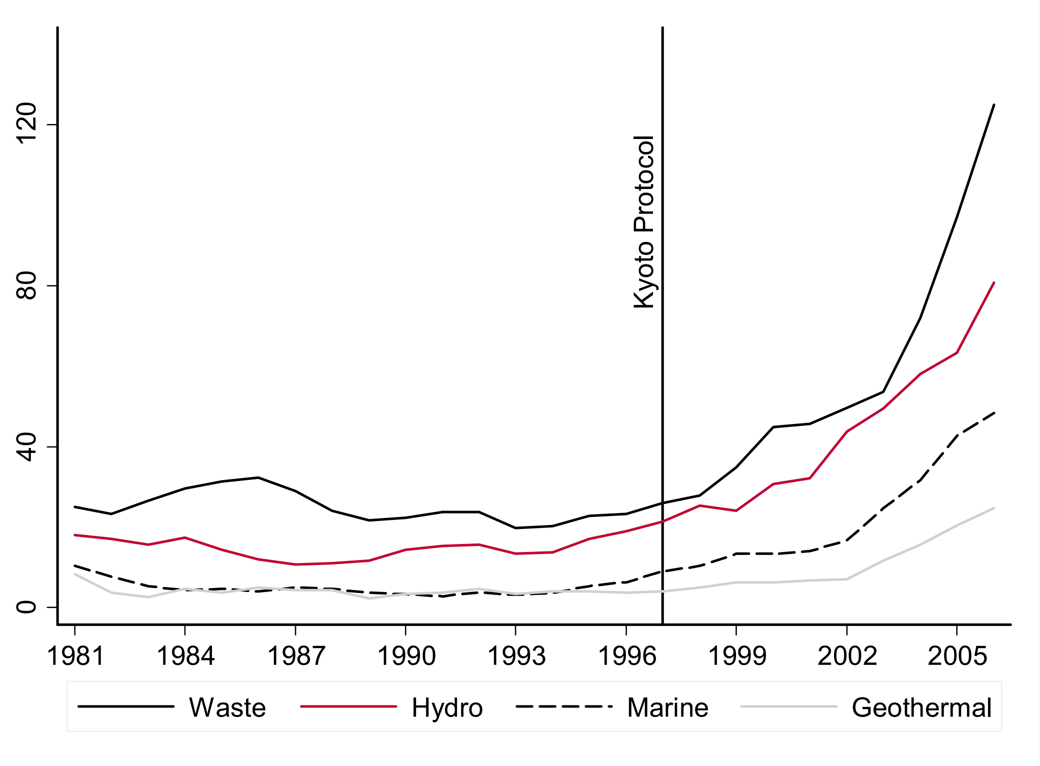


Table 3. Average value (across technologies) of different REPs by Country in the three decades (In Log). Shaded areas highlight positive values.

Country	**FEED-IN**			**RECs**			**R&D**			**OTHER POL**		
	80-89	**90-91**	**00-07**	**80-89**	**90-91**	**00-07**	**80-89**	**90-91**	**00-07**	**80-89**	**90-91**	**00-07**
Austria	0.00	**0.02**	**0.13**	0.00	0.00	**1.92**	**0.58**	**0.63**	**0.87**	0.00	**0.80**	**1.00**
Belgium	0.00	**0.03**	**0.10**	0.00	0.00	**1.01**	**0.85**	**0.31**	**0.80**	0.00	**0.80**	**1.00**
Czech Republic	0.00	0.00	**0.10**	0.00	0.00	0.00	0.00	0.00	**0.13**	0.00	**0.90**	**1.00**
Denmark	0.00	**0.02**	**0.01**	0.00	0.00	**1.90**	**0.42**	**1.00**	**1.06**	**1.00**	**1.00**	**1.00**
Finland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.45**	**0.64**	0.00	**1.00**	**1.00**
France	0.00	**0.00**	**0.03**	0.00	0.00	0.00	**0.53**	**0.71**	**1.61**	**1.00**	**1.00**	**1.00**
Germany	0.00	**0.05**	**0.09**	0.00	0.00	0.00	**1.86**	**1.95**	**2.13**	**0.50**	**1.00**	**1.00**
Greece	0.00	**0.04**	**0.05**	0.00	0.00	0.00	0.00	**0.32**	**0.61**	0.00	0.00	0.00
Hungary	0.00	0.00	**0.08**	0.00	0.00	0.00	0.00	**0.02**	**0.37**	0.00	**0.40**	**1.00**
Ireland	0.00	0.00	**0.01**	0.00	0.00	0.00	**0.00**	**0.08**	**0.30**	**0.60**	**1.00**	**1.00**
Italy	0.00	**0.04**	**0.01**	0.00	**0.11**	**1.14**	**1.64**	**1.44**	**1.34**	**0.80**	**1.00**	**1.00**
Luxembourg	0.00	**0.04**	**0.05**	0.00	0.00	0.00	0.00	**0.03**	**0.13**	0.00	**0.60**	**1.00**
Netherlands	0.00	0.00	**0.03**	0.00	**0.43**	**1.44**	**1.32**	**1.49**	**1.67**	0.00	**1.00**	**1.00**
Poland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Portugal	**0.01**	**0.07**	**0.18**	0.00	0.00	0.00	**0.58**	**0.31**	**0.18**	0.00	**0.50**	**1.00**
Slovak Republic	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00
Spain	0.00	**0.06**	**0.14**	0.00	0.00	0.00	**1.56**	**1.25**	**1.41**	0.00	0.00	**1.00**
Sweden	0.00	**0.00**	**0.01**	0.00	0.00	**1.76**	**1.46**	**0.84**	**1.21**	0.00	**0.60**	**1.00**
United Kingdom	0.00	0.00	0.00	0.00	0.00	**0.84**	**1.51**	**1.10**	**1.35**	0.00	0.00	**1.00**

Note: Values equal to zero mean that the given policy has not been enforced in the respective Country in the considered time period.

Table 4. Average value (across countries) of different REPs by technology in the three decades (In Log).

Country	**Feed-in**			**R&D**		
	80-89	**90-91**	**00-07**	**80-89**	**90-91**	**00-07**
Biofuel	0.01	0.02	0.05	0.97	1.12	1.51
Geothermal	0.01	0.02	0.03	0.63	0.29	0.37
Hydro	0.01	0.02	0.03	0.01	0.10	0.18
Marine	0.01	0.01	0.02	0.17	0.10	0.20
Solar photovoltaic (PV) energy	0.01	0.03	0.11	1.23	1.23	1.49
Solar thermal energy	0.01	0.03	0.11	1.23	1.23	1.49
Waste	0.01	0.01	0.03	0.00	0.00	0.40
Wind	0.01	0.03	0.05	0.94	0.95	1.01

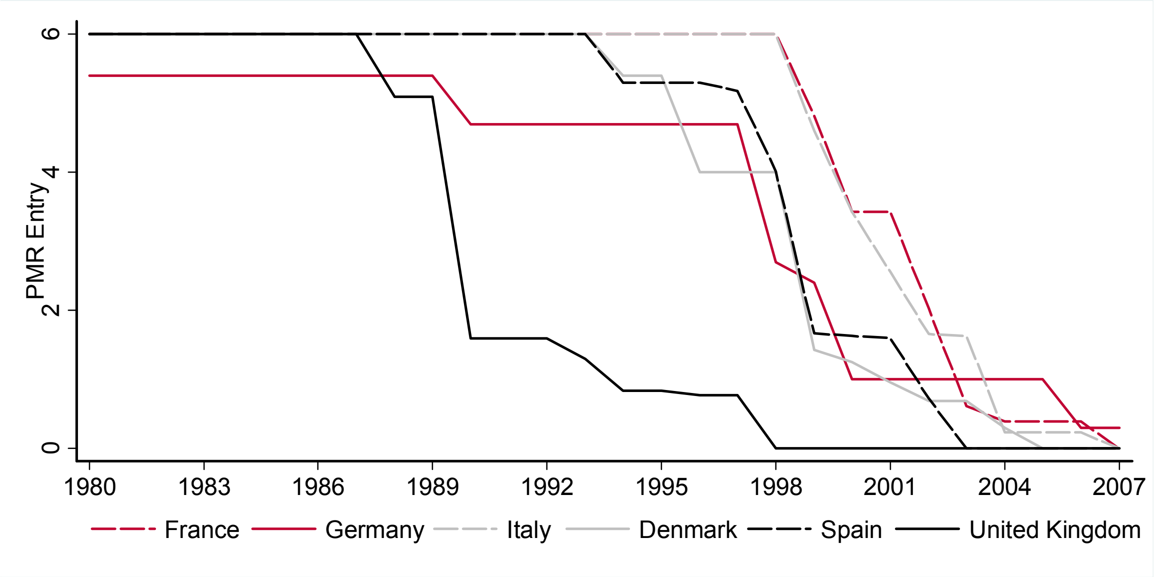
Note: Only technologies specific policies considered

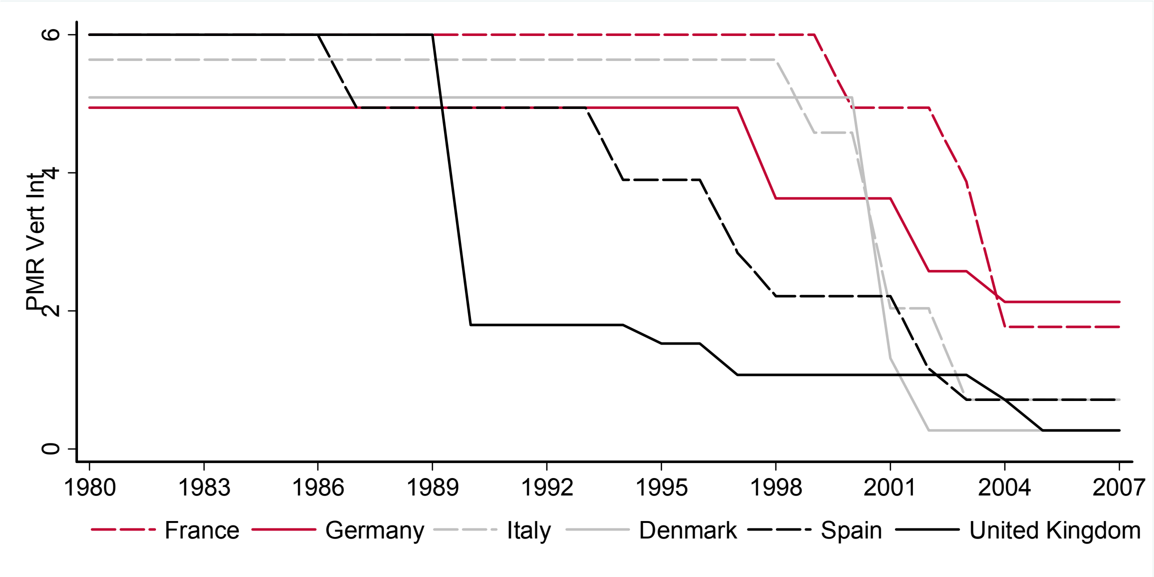
Table 5. Descriptive Statistics

Acronim	**Description**	**Obs**	**Mean**	**St. Dev.**	**Min**	**Max**
Patent at the EPO						
SOLAR_PV	Solar Photovoltaic	532	3.2	11.4	0	153
SOLAR_TH	Solar Thermal	532	2.2	6.2	0	77
WIND	Wind	532	3.1	10.9	0	131
HYDRO	Hydroelectric	532	0.9	2.2	0	27
GEOTHERMAL	Geothermal	532	0.2	1.1	0	15
MARINE	Marine and Ocean	532	0.3	1.1	0	14
BIOFUEL	Biofuel	532	1.5	3.5	0	35
WASTE	Fuel from Waste	532	1.3	3.3	0	39
ELEC PRICE	Average of Housholds and industrial energy end use price, USDppp/unit. (Log).	520	0.09	0.03	0.03	0.18
ELEC CONS	Average of Housholds and industrial electricity consumption, Gwh per capita. (Log)	532	1.5	0.4	0.77	2.6
GDP	Gross domestic Product per capita. USD 2006 prices and PPP. (Log).	515	3.1	0.3	2.1	4.4
PMR AGGREGATE	Product Market Regulation, average electricity and gas Sector.	520	4.3	1.6	0	6
PMR ENTRY	Product Market Regulation, average electricity and gas Sector. Sub-index: Entry Barrier	520	4.1	2.1	0	6
PMR VERT INT	Product Market Regulation, average electricity and gas Sector. Sub-index: Vertical Integration	532	4.4	1.7	0	6
PMR PUB OWN	Product Market Regulation, average electricity and gas Sector. Sub-index: Public Ownership	532	4.3	1.6	0	6
Technology specific Public R&D expenditure. USD 2006 prices and PPP. (Log).						
R&D	SOLAR_PV	532	1.3	1.4	0	5.1
R&D	SOLAR_TH	532	1.3	1.4	0	5
R&D	WIND	532	0.9	1.1	0	4.1
R&D	HYDRO	532	0.1	0.2	0	2.4
R&D	GEOTHERMAL	532	0.4	0.7	0	3.6
R&D	MARINE	532	0.1	0.4	0	3.1
R&D	BIOFUEL	532	1.1	1.1	0	4.2
R&D	WASTE	532	0.1	0.4	0	4.1
Technology specific feed-in tariff. USD 2006 prices and PPP. (Log).						
FEED-IN	SOLAR_PV	532	0.04	0.09	0	0.47
FEED-IN	SOLAR_TH	532	0.04	0.09	0	0.47
FEED-IN	WIND	532	0.02	0.04	0	0.15
FEED-IN	HYDRO	532	0.01	0.03	0	0.11
FEED-IN	GEOTHERMAL	532	0.01	0.03	0	0.17
FEED-IN	MARINE	532	0.01	0.04	0	0.44
FEED-IN	BIOFUEL	532	0.02	0.03	0	0.14

FEED-IN	WASTE	532	0.01	0.02	0	0.11
KYOTO	Kyoto Protocol dummy	532	0.39	0.48	0	1
RECs	Share of electricity covered by a tradable permit. (Log)	532	0.16	0.54	0	3.04
OTHER POL	Adoption Dummy for other REPs	532	0.53	0.49	0	1
Lagged Knowledge Stock						
K STOCK	SOLAR_PV	532	8.7	26.32	0	295.1
K STOCK	SOLAR_TH	532	8.2	18.8	0	164.7
K STOCK	WIND	532	7.5	22.7	0	91
K STOCK	HYDRO	532	3.1	5.1	0	38.4
K STOCK	GEO	532	0.7	1.6	0	17.8
K STOCK	MARINE	532	1.1	2.1	0	24.8
K STOCK	BIOFUEL	532	4.4	7.4	0	63.5
K STOCK	WASTE	532	4.9	9.9	0	91
ENLARG	Dummy for new entrant in the EU	532	0.2	0.4	0	1

Figure 3 Trend in PMR in Selected Countries. (Respectively: Entry, Vertical Integration and Public Ownership). Years 1974-2007.





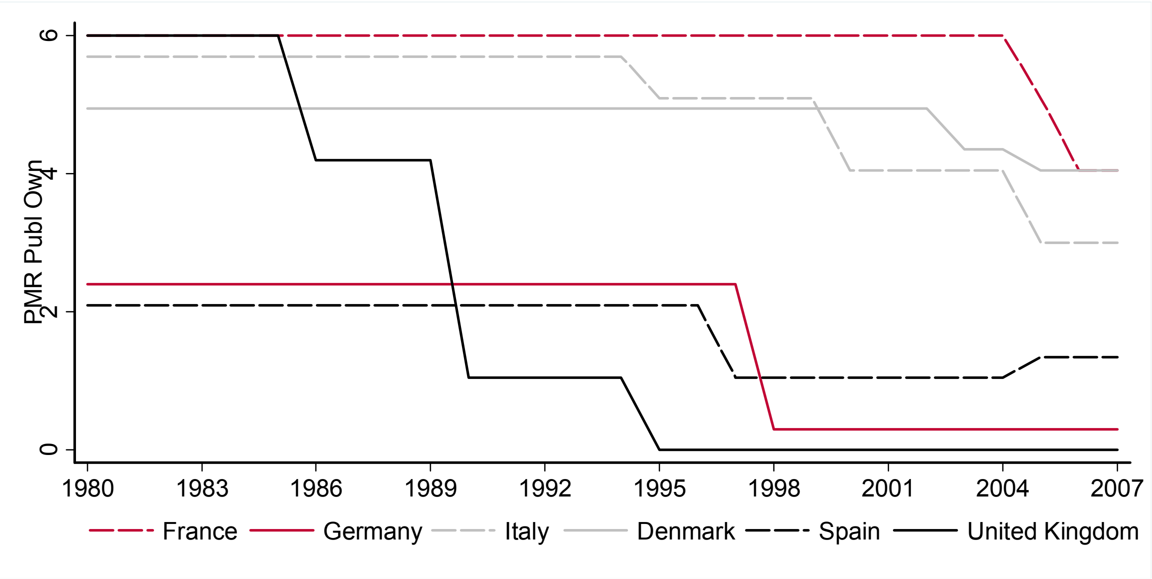

PMR Publ Own
0
2
4
6
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
France
Germany
Italy
Denmark
Spain
United Kingdom

Table 6. Technological Sub-sample.

	Wind	**Solar_th**	**Solar_PV**	**Marine**	**Hydro**	**Biofuel**	**Geothermal**	**Waste**
K STOCK	0.0054***	0.0092**	-0.0036**	-0.0698*	-0.0024	-0.0184*	-0.1207	0.0195***
	(0.0012)	(0.0040)	(0.0018)	(0.0389)	(0.0181)	(0.0103)	(0.1586)	(0.0059)
PMR ENTRY	-0.3218***	-0.1413**	-0.0960	-0.1336	0.0959	-0.0751	-0.2343	0.0129
	(0.0610)	(0.0720)	(0.0606)	(0.1110)	(0.1014)	(0.0766)	(0.1878)	(0.0854)
PMR VERT INT	0.0993	-0.0934	0.1298*	0.0686	-0.1652	-0.0263	-0.1560	-0.0810
	(0.0630)	(0.0869)	(0.0775)	(0.1236)	(0.1213)	(0.0760)	(0.2059)	(0.0956)
PMR PUB OWN	0.0845	0.0207	-0.0503	0.0210	-0.0140	0.0063	0.3362	-0.0564
	(0.0646)	(0.0646)	(0.0602)	(0.1172)	(0.0898)	(0.0751)	(0.2103)	(0.0814)
R&D	0.3926***	0.0054	0.0968	0.6356***	0.3600	0.1666**	0.4160**	-0.0554
	(0.0737)	(0.0766)	(0.0708)	(0.1784)	(0.2741)	(0.0768)	(0.2167)	(0.1050)
FEED-IN	-5.1387***	-0.8592	1.5440***	-11.5346	2.9548	-0.0210	0.4656	2.8425
	(1.7979)	(0.5869)	(0.5780)	(7.1748)	(2.6000)	(2.1857)	(4.2469)	(3.6925)
KYOTO	0.4778**	0.1342	1.9649***	0.8407**	0.7505	1.7038***	-0.0231	0.5473
	(0.2089)	(0.4779)	(0.4749)	(0.3593)	(0.6580)	(0.5929)	(0.6025)	(0.5429)
RECs	0.1526**	0.1938**	-0.0886	-0.2245*	-0.1796	-0.0589	0.0845	0.0080
	(0.0661)	(0.0847)	(0.0845)	(0.1296)	(0.1121)	(0.0774)	(0.2833)	(0.1012)
OTHER POL	0.0636	0.2623	0.4142**	0.6686*	0.1956	0.4505**	-0.4583	0.1827
	(0.1992)	(0.1843)	(0.1863)	(0.3668)	(0.2514)	(0.2053)	(0.5662)	(0.1910)
ELEC PRICE	0.6341	9.1864**	14.3594***	15.9511**	4.4071	15.4684***	20.6210*	3.7185
	(3.7573)	(4.2926)	(3.8492)	(7.5617)	(6.2890)	(4.7205)	(10.6309)	(4.8740)
ELEC CONS	-0.1256	2.0008***	2.0909**	0.5850	-0.7365	1.1801	-1.6209	1.6076*
	(0.5688)	(0.6719)	(0.8967)	(1.3459)	(1.4082)	(1.0308)	(1.6356)	(0.8605)
GDP_pc	1.6397*	1.5128*	-1.2488	1.2114	3.5998***	0.2730	2.6629	2.0857**
	(0.8940)	(0.8581)	(1.0836)	(1.3170)	(1.3068)	(1.0664)	(2.5388)	(0.9636)
ENLARG	-0.5429**	-0.4486*	0.2711	-0.7316	0.2461	-0.3641	-0.6491	0.2570
	(0.2489)	(0.2421)	(0.3834)	(0.4815)	(0.3619)	(0.2662)	(0.6209)	(0.2626)
PMR	-0.2163***	-0.2391***	-0.0163	-0.0712	-0.0945	-0.1060	-0.2174	-0.1313*
AGGREGATE	(0.0672)	(0.0727)	(0.0589)	(0.1019)	(0.0849)	(0.0763)	(0.1815)	(0.0793)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	495	495	448	429	475	495	346	495

Negative binomial estimations. *, **, *** indicate significance at 10%, 5% and 1% levels, respectively. Robust standard error in parenthesis. All regressions include year and country effects.

Table 7. Full Sample & Kyoto Interactions.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
K STOCK	0.0035***	0.0035***	0.0026***	0.0034***	0.0027***	0.0057***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
PMR ENTRY	-0.0920***	-0.0999***	-0.1056***	-0.0881***	-0.0764**	-0.1197***
	(0.0312)	(0.0325)	(0.0312)	(0.0318)	(0.0317)	(0.0277)
PMR VERT INT	0.0023	0.0047	0.0017	-0.0020	-0.0130	-0.0650**
	(0.0346)	(0.0346)	(0.0346)	(0.0353)	(0.0351)	(0.0311)
PMR PUB OWN	0.0011	0.0086	0.0222	-0.0045	0.0166	0.0901***
	(0.0264)	(0.0278)	(0.0269)	(0.0279)	(0.0268)	(0.0276)
R&D	0.0678**	0.0686**	0.0829***	0.0659**	0.0750***	0.1730***
	(0.0290)	(0.0291)	(0.0294)	(0.0292)	(0.0291)	(0.0300)
FEED-IN	-0.1839	-0.1909	-0.4239	-0.1775	-0.2129	-0.0290
	(0.3179)	(0.3177)	(0.3185)	(0.3171)	(0.3137)	(0.3351)
KYOTO	1.0476***	1.0085***	0.8157***	0.9820***	0.8075***	0.5460***
	(0.2083)	(0.2133)	(0.2149)	(0.2341)	(0.2226)	(0.1814)
RECs	-0.0004	0.0046	0.0192	-0.0006	-0.0013	0.0382
	(0.0342)	(0.0345)	(0.0350)	(0.0342)	(0.0344)	(0.0348)
OTHER POL	0.2945***	0.3073***	0.3156***	0.3099***	0.2675***	0.0126
	(0.0825)	(0.0839)	(0.0825)	(0.0864)	(0.0827)	(0.0840)
ELEC PRICE	6.0896***	6.7005***	6.3392***	5.8639***	5.3459***	11.0688***
	(1.9463)	(2.0668)	(1.9407)	(1.9774)	(1.9609)	(1.6900)
ELEC CONS	1.5010***	1.4800***	1.5748***	1.4879***	1.7625***	0.6457**
	(0.3249)	(0.3264)	(0.3371)	(0.3253)	(0.3416)	(0.2673)
GDP_pc	1.1284***	1.1807***	1.2311***	1.1743***	1.1757***	0.7090**
	(0.3923)	(0.3975)	(0.3902)	(0.3985)	(0.3799)	(0.3171)
ENLARG	-0.2063**	-0.2351**	-0.1609	-0.1958*	-0.1075	-0.3605***
	(0.1046)	(0.1098)	(0.1065)	(0.1059)	(0.1103)	(0.1018)
KYOTO*RECs		-0.8580				
		(0.9979)				
KYOTO*FEEDIN			10.1020***			
			(2.3677)			
KYOTO*OT POL				0.0812		
				(0.1346)		
KYOTO*R&D					0.2558***	
					(0.0878)	
KYOTO*PMR ENTRY						-0.0603*
						(0.0334)
*Country*tech FE*	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3678	3678	3678	3678	3678	3678

Negative binomial estimations. *, **, *** indicate significance at 10%, 5% and 1% levels, respectively. Robust standard error in parenthesis. All regressions include year and country effects.

Table 8: Average Marginal Effect

	Wind	Solar_th	Solar_PV	Marine	Hydro	Biofuel	Geothermal	Waste
Mean	3.13	2.24	3.21	0.389	0.928	1.53	0.238	1.34
PMR ENTRY	0.43	0.26	*0.13*	*1.48*	*-0.44*	*0.21*	*4.33*	*-0.04*
PMR VERT INT	*-0.11*	*0.14*	-0.13	*-0.54*	*0.61*	*0.06*	*2.30*	*0.21*
PMR PUB OWN	*-0.07*	*-0.02*	*0.05*	*-0.18*	*0.04*	*-0.01*	*-4.66*	*0.11*
R&D	0.71	*0.01*	*0.08*	0.23	*0.14*	0.24	2.06	*-0.02*
FEED-IN	-0.11	*-0.02*	0.03	*-0.27*	*0.02*	*0.01*	*0.02*	*0.01*
KYOTO	0.15	*0.24*	0.18	2.16	*0.29*	0.25	*-0.10*	*0.01*
RECs	0.07	0.12	*-0.04*	-0.83	*-0.28*	*-0.06*	*0.51*	*0.01*
OTHER POL	*0.02*	*0.12*	0.13	1.72	*0.21*	0.29	*-1.93*	*0.14*
ELEC PRICE	*0.01*	0.15	0.14	1.30	*0.17*	0.36	2.84	*0.10*
ELEC CONS	*-0.02*	0.38	0.28	*0.58*	*-0.30*	*0.33*	*-2.40*	0.52

Italics denote marginal effects derived from non-significant parameters at the 10% level. Each cell displays the change in the expected number of patents relative to the mean. All effects have been calculated based on the discrete changes in the expected number of patents in absolute terms resulting from a change in Xi from the 1st to 3rd quartiles of the distribution, holding all other variables at their observed values. For the three PMR variables, the change is computed from the 3rd to the 1st quartile. For RECs we calculated the marginal effect in the shorter period 1990-2005 given the high rate of zero in the first decade analysed.