Environmental Policies, Product Market Regulation and Innovation in Renewable Energy

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Abstract

We investigate the effectiveness of policies in favor of innovation in renewable energy under different levels of competition. Using information regarding renewable energy policies, product market regulation and high-quality green patents for OECD countries since the late 1970s, we develop a pre-sample mean count-data econometric specification that also accounts for the endogeneity of policies. We find that renewable energy policies are significantly more effective in fostering green innovation in countries with deregulated energy markets. We also find that public support for renewable energy is crucial only in the generation of high-quality green patents, whereas competition enhances the generation of green patents irrespective of their quality.

Keywords: renewable energy technology; patents; environmental policies; product market regulation; policy complementarity.

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

1 Introduction

Innovation is commonly regarded as the most effective response to sustaining current standards of living while overcoming serious environmental concerns. In the case of energy, increasing resource scarcity calls for the rapid development of new energy sources and, in particular, of renewable energy. As of today, renewable energy cannot compete with fossil fuel in terms of production costs but impressive technological progress has paved the way for promising alternatives, such as biomass, solar and wind energy sources [1]. Nations, too, have developed areas of specialization in specific types of renewable energy sources, such as Denmark in wind technologies, Sweden and Germany in bioenergy, Germany and Spain in solar energy, and Norway and Austria in hydropower.

In addressing the issue of how to foster environmental innovation, the theoretical literature stresses the importance of policy interventions targeted at both knowledge and environmental externalities (Fischer & Newell 2008, Acemoglu et al. 2012, Popp et al. 2009). Along these lines, a vast empirical literature has assessed the extent to

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[1]For example, in the most favored geographical locations, wind has proved to be almost as competitive as other forms of electricity generation, whereas solar energy still costs significantly more than fossil fuel energy sources (see e.g. Pan & Khler 2007, Nemet 2006, IEA 2004).

which environmental policies and/or energy prices are able to spur environmental innovations (Popp 2002, Johnstone et al. 2010). Another line of research in the field of energy economics investigates the effect of market liberalization on the propensity to innovate of electric utilities and specialized suppliers of electrical equipment (Jamasb & Pollitt 2008, Sanyal & Ghosh 2012). While both competition and policies in support of innovation are key drivers of energy technologies (Newell 2011), the interplay of these two factors has yet to be assessed in a rigorous empirical framework.

Our aim is to fill this gap by investigating the effectiveness of policies that encourage innovation in renewable energy under different levels of competition. Our theoretical background is the recent reappraisal of the debate about the relationship between innovation and competition in Schumpeterian growth models (Aghion et al. 2001, 2005). These models have questioned the standard argument that oligopolistic markets enhance innovation *via* two arguments: first, lowering barriers to entry yields greater incentives for incumbents to invest in innovation to escape new entrant competition; second, fostering entry is tantamount to supporting the introduction of new inventions into the market. This should be particularly so for renewable energy technologies that involve decentralized energy generation and a smaller scale of production.

More generally, the positive effect of lowering barriers of entry for innovation is likely to prevail in those sectors in which innovation may be radical and competence destroying, as in the case of centralized energy production. Several studies document the political opposition of large utilities to renewable energy policies and to the key role of new players for renewable energy innovation[2]. The internal resistance of the electricity sector against radical innovation also depends on the cognitive "lock-in" of incumbents that lack the appropriate skills to develop these technologies. In this context, the external stimulus of market liberalization, particularly in the form of free access to the grid for independent power producers, might be essential to foster renewable energy innovation (Makard & Truffer 2006).

Our paper is the first to carry out a cross-country analysis that empirically assesses the complementarity between targeted industrial policies and competition in energy production[3]. We developed a unique dataset that contains cross-country information on renewable energy policies (REPs), product market regulation (PMR) and high-quality renewable energy patents, i.e., where priority is claimed in several countries. In fact, one should expect such complementarities to arise because production of energy is generally more expensive with green technologies; thus, public subsidies are essential to spur demand for renewable energy and to make market entry attractive for new players. It follows that a combination of public policies and product market deregulation is likely to bring about a positive effect on innovation. In particular, one should expect policies to be significantly more effective in liberalized markets because public subsidies attract private R&D investments and may

[2]See, e.g., Neuhoff (2005), Jacobsson & Bergek (2004), Hadjilambrinos (2000), Nilsson et al. (2004) and Lauber & Mez (2004). For cross-country econometric analyses on the effect of the energy lobby on energy intensity, see Fredriksson et al. (2004) and, on renewable energy policies, see Nicolli & Vona (2012).

[3]The contribution of Aghion et al. (2012), addressing similar matters, is both more general in that it pertains to all sectors and more specific because it concentrates on manufacturing firms in China.

trigger a race for leadership in the emerging market for clean energy.

Another distinct feature of our contribution is the econometric specification, which, to our knowledge, is the first to combine three econometric issues into a count-data setting. First, we make use of a dynamic empirical setup that accounts explicitly for the fact that innovation tends to occur in technological domains in which firms have previously developed skills and competencies. Second, we account for unobserved country heterogeneity by means of the pre-sample mean Poisson model with linear feedback suggested by Blundell et al. (2002). The initial conditions, built upon pre-sample information about the dependent variable, are the most convenient way to account for unobserved individual effects, particularly when variables of interest are highly persistent. We choose this model because we have a long string of pre-sample observations for our dependent variable, a key requirement to reduce the bias in the estimated coefficients. Finally, we use the GMM estimator because it provides a flexible mechanism to address the issue of endogeneity for both environmental policies and the index of market competition.

Our main findings are the following. First and foremost, we find that REPs are significantly more effective in fostering green innovation in countries with deregulated energy markets. The effect is sizeable; REPs are twice as effective in deregulated energy markets with respect to the average level of regulation in developed countries. Second, energy market deregulation has a positive effect on innovation. This effect is primarily driven by the entry barrier component of the PMR index and becomes weaker when the main variables of interest are instrumented. Third, both public policies and their interaction with PMR have a much larger effect on high-quality triadic patents than on generic ones. Finally, our analysis allows us to reassess the role of other determinants of renewable energy technologies that have been the focus of the existing empirical literature (see e.g. Popp 2002, Johnstone et al. 2010). We conclude that public R&D expenditures play a key role only for high-quality triadic patents, whereas energy prices are not as important as previously thought when controlling for REPs and PMR.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical underpinnings on which our empirical strategy is based in detail. The first part of Section 3 provides details on the methodology used to build our dataset and our main policy indicators, while the second part describes the econometric matters at hand. Section 4 presents the baseline results. Sections 5 and 6 are all robustness checks, the former controlling for the endogeneity of the policy variables, and the latter accounting for patent quality. Section 7 quantifies the marginal effect of the policy variables. Section 8 concludes.

2 Factors affecting renewable energy innovations

The relationship between innovation and competition has been recently reconsidered in Schumpeterian growth models (see e.g. Aghion et al. 2001, 2005). This new class of models incorporates both the classical Schumpeterian effect, in which competition reduces innovative rents and therefore R&D investments, and an escaping competition effect. The latter effect holds that the threat of entry of new firms induces incumbents to increase R&D investments to preserve or enhance their market shares. The theory suggests that the effect of competition on innovation is crucially mediated by initial sectoral characteristics. In particular, a positive effect of competition on innovation prevails in sectors initially characterized by low levels of competition. In the case of energy industries, both the electricity and the gas sector are naturally characterized by a low level of competition at the onset of the liberalization process; therefore, the escaping competition effect is expected to prevail. Nonetheless, country-level studies, mostly limited to the US and the UK, found that R&D expenditures and patent activities declined after market reforms[4]. It is worth noting, however, that this evidence neither applies directly to cross-country comparisons nor seems robust for patent-based analyses, particularly for renewable energy patents(Jamasb & Pollitt 2011).

The literature on innovation regimes provides a slightly different rationale to support the positive effect of competition on radical innovations. Winter (1984) distinguishes between an entrepreneurial innovation regime, in which entry spurs innovation, and a routinized regime, characterized by R&D investments of large firms aimed at improving existing technologies[5]. In a similar vein, Klepper (1996) explains an industry's life cycle in terms of returns on R&D investments, where product innovation is more beneficial to smaller and younger firms, while process innovation yields greater returns for large firms. As a result, during their life cycle, firms modify the type of innovative activities undertaken, gradually shifting towards routinized process R&D activities. As a whole, the positive effect of competition on innovation is expected to strongly dominate in the context of radically innovative technologies and emergent markets.

Renewable energy innovation seems to fit the conditions highlighted in the literature on innovation regimes well. Such innovation is in fact radical and competence destroying for the centralized paradigm of energy production (David & Wright 2006, Lehtonen & Nye 2009). While production of energy from more promising renewable sources is mainly decentralized in small and medium sized units, the skills of incumbents are tied to large scale plants using coal, nuclear materials or gas as primary energy inputs. Thus, there is substantial evidence showing the sustained entry of new firms producing clean energy or with new electric equipment, such as wind turbines, even before the liberalization process began[6]. These new firms are considered key players for innovation in the electricity sector (Jacobsson & Bergek 2004, Sanyal & Cohen 2009). Thus, we expect the effect of deregulation to be positive on innovation in renewable energy (Makard & Truffer 2006).

From an empirical viewpoint, past contributions have previously assessed the effect of liberalization on innovation. Sanyal & Ghosh (2012) show that greater competition in wholesale markets can increase the fraction of innovative rents that are obtained by specialized upstream suppliers, as long as many non-utility generation actors enter the wholesale market. These new actors (such as farmers, small com-

[4]See for the US Dooley (1998), Sanyal (2007), Nemet & Kammen (2007), Sanyal & Cohen (2009), Sanyal & Ghosh (2012) and for the UK Jamasb & Pollitt (2008). Similarly, the negative effects of deregulation on energy R&D were found for electric utilities worldwide by Sterlacchini (2012), Salies (2010).

[5]Empirical evidence that small firms tend to undertake more radical innovation or in general respond to different innovative inputs can be found in Akcigit & Kerr (2010), Scherer (1984), Acs & Audretsch (1988), among others. In particular, Acs & Audretsch (1988) found that lower market concentration increases innovation by small firms by a factor of 2

[6]See, e.g., Jacobsson & Johnson (2000), Jacobsson & Bergek (2004), Nilsson et al. (2004), Lauber & Mez (2004), Hadjilambrinos (2000), Makard & Truffer (2006).

munities, municipalities and households) are generally specialized in decentralized energy production, such as combined generation, local heating systems and renewable sources. In Denmark, for instance, most wind turbines are owned by households, municipalities and small communities, whereas utility-owned wind capacity accounted for only 15% of the total installed wind capacity in 1990 (Hadjilambrinos 2000).

Deregulation of the energy markets has often been designed to favor these small producers. In the US for example, the approval of the Public Utility Regulatory Policies Act (PURPA) mandates that public utilities purchase energy from small-scale power producers, essentially non-utility generators producing from renewable sources (Loiter & Norberg-Bohm 1999). The entry of non-utility generators with their associated positive effect on innovation is therefore expected to be significantly stronger for renewable energy technologies.

With the exception of R&D subsidies, the primary goal of renewable energy policy is to generate a certain volume of demand for clean energy (Popp et al. 2009). The positive demand shock is expected to stimulate innovation, particularly when the entry of new players is facilitated. Aghion et al. (2012) address the issue of complementarity between market competition and industrial policies along the lines of Schumpeterian growth models. Policies targeted at sectors with higher technological potential have a larger effect on firm innovative efforts, provided that there is a low degree of collusion in the sector. Similarly, electric utilities in a monopolistic position are likely to respond to targeted REPs with relatively low innovative efforts because profit levels for these firms are marginally affected by renewable energy innovation. Public policies will be successful when new players developing new technologies enter the market, instead of incumbents complying with regulations using existing solutions. In other words, success in public support also depends on low entry barriers to the market.

Our paper is also related to a vast empirical literature on environmental innovation that analyzes the inducement effect of policy and energy prices (Jaffe & Palmer 1997, Newell et al. 1999, Popp 2002). Although past studies have tested the effect of policy on innovation using patent data[7], only a few studies have incorporated some form of path dependency into their empirical specification. Popp (2002) investigates the effect of technology-specific knowledge stocks, energy prices and public R&D on renewable and energy-efficient USPTO patents. Aghion et al. (2011) also include technology-specific knowledge stocks to test the directed technical change hypothesis of Acemoglu et al. (2012) for the auto industry by using firm-level data. Differently from these works, we account for path dependency by including linear feedback on the dependent variable to disentangle the short- and long-run effects of our variables of interest.

Finally, our paper is complementary to Johnstone et al. (2010), who shows that targeted policies in OECD countries have had a positive and significant effect on patent applications for renewable technologies. In particular, guaranteed price schemes and investment incentives have played a major role in the early phase of the technology life cycle, whereas, for relatively more mature technologies, quantity-based instruments seem more suitable. However, their emphasis is on the heteroge-

[7]See, e.g.,Lanjouw & Mody (1996), Brunnermeier & Cohen (2003), Popp (2002, 2006*a*), Johnstone et al. (2010), Verdolini & Galeotti (2011).

neous effects of different policies, while our paper tests the policy complementarity hypothesis, including dynamic feedbacks and accounting for endogeneity in policies.

3 Empirical Protocol

3.1 Data

Our database combines several sources, gathering patent data to measure innovation using policy and regulatory variables found in various data sources. The set of explanatory variables used in this paper is almost identical to the one used by the closely related paper of Johnstone et al. (2010); we add the PMR index and build an aggregate policy index that may be instrumented.

Dependent Variable. We measure innovation by means of patent statistics. Patent counts provide readily accessible and exhaustive information on both the nature of the invention and the applicant. We use the PATSTAT database, which accounts for more than 70 million patents worldwide, covers 84 different patent offices, and spans over a long time period. PATSTAT provides codified information on the legal authorities issuing the patent document to the name of the inventor, its nationality, the priority dates and the assignee being granted ownership of the invention.

The availability of the technological content of patents by means of the so-called International Patent Classification (IPC) system is of the utmost importance for our study. The IPC allows us to distinguish an invention in renewable energy from other innovations. Following Johnstone et al. (2010) and Popp et al. (2011), we use patents registered in the sub-fields of wind, marine, solar thermal, solar photovoltaic, biofuels, hydroelectric, fuels from waste, geothermal and tidal to construct a single indicator of innovative activity in the field of renewable energy. Table 3.1 provides the definition of these subfields and displays the list of IPC classes used to identify them as belonging to the realm of renewable energy.

[Table 1 about here.]

As suggested in Griliches (1990), patent data are a good indicator of innovative activity, given their high correlation with R&D spending. However, the use of patents as a proxy for technological innovation also has important drawbacks because not all innovations are patented, the propensity to apply for a patent grant may vary a great deal across countries, differences in patent legislation can complicate cross-country comparisons, and patents may grant protection to innovations of substantially heterogeneous economic value (Pavitt 1988). In our empirical work, we rely on quality-weighted patent counts, as opposed to simple patents count, to calculate the economic value of patents.

We account for the economic value of patents using patent family size. Patent family size refers to the number of patent offices to which an application for a patent has been filed (Dernis & Khan 2004). Because of the pecuniary and time costs of filing abroad, only patent applications for the most valuable inventions are filed in other jurisdictions or countries. Filing a patent application is a signal that the inventor expects the invention to be profitable in the given country. Therefore, the patent family provides a quality threshold that eliminates low-value applications (Popp et al. 2011). Another important implication of using the patent family is that it also corrects for the so-called home-country bias. Because domestic applicants tend to file for more patents in their home country than foreign applicants, all patent statistics suffer from home bias. Patent family size is therefore an important component of our cross-country analysis. A particular patent family is the so-called Triadic Patent Family (TPF), which includes patent applications filed to the European, Japanese and US patent offices (EPO, JPO, USPTO). Often, families of invention incorporate offices that reflect either small foreign markets or countries of a lower technological intensity. Accordingly , our results are also extended to triadic patents, the use of which setting an even higher threshold on the expected patent quality[8]. For all patents, including green patents, figure 1 shows the flow of patent applications for our three innovation measures of generic patents, patent families consisting of at least 2 applications and triadic patents. Until the 1990s, both green and generic patents grow more or less at a similar pace, except for the small boom in green innovation following the oil shocks of the 1970s, when the trends began to diverge substantially, and green innovations began to increase at a much faster rate than generic ones.

[Figure 1 about here.]

Renewable Energy Policy. The main goal of this paper is to study the complementarity between targeted industrial policies and competition in energy production. The limited cross-sectional variation in environmental policies and PMR makes it difficult to identify of each interaction between a specific REP, such as tax credits, and the degree of competition. In particular, each country diversifies its energy strategy by adopting different REPs, and estimating the effect of a specific policy conditioned to the regime of competition is therefore exceedingly difficult. For these reasons, we build a renewable energy policy index combining information about several types of renewable energy policies. Stacking all variables within a single index implies a loss of information because the effect of individual policies on renewable energy is no longer able to be detected, as reported in the closely related paper of Johnstone et al. (2010). Yet an aggregate policy index allows us to address the rather unexplored issue of endogeneity in the estimation of the effect of REPs on innovation.

The REP index is based on the exploitation of a comprehensive dataset made available by the International Energy Agency (IEA 2004), which contains detailed country fact sheets and provides information on the year of adoption of selected REPs for most OECD countries (Johnstone et al. 2010), see Table 2 for a detailed description. We then build a single policy index that varies across years and countries as described below.

[8]A valid alternative to the patent family is considering only patents filed at the EPO, as in Johnstone et al. (2010) or patents filed under the PCT. Nevertheless, EPO data suffer from a strong home bias. Patent citations are also used as a proxy for patent quality, on the basis that patents citations embody prior arts that are often referred to by subsequent inventions. Although generally correct, there is a good deal of noise with patent citations, as they are also advocated for by patent offices themselves (Harhoff et al. 1999). Furthermore, PATSTAT is a work in progress, and the exhaustive retrieval of patent citations has not been completed as of today, prohibiting us from using such citations as an alternative measure of patent quality

[Table 2 about here.]

First, we create a series of dummy variables reflecting the adoption of a set of the following legal supports for renewable energy: (i) the introduction of investment incentives; (ii)economic instruments used to encourage production or discourage consumption (usually called tax measures); (iii) the adoption of incentive tariff systems, such as feed-in tariffs or bidding schemes; (iv) the establishment of voluntary programs or agreements among the actors involved in the energy sector; (v) legislation that makes it compulsory for producers to produce a share of their energy supply from renewable energy (which is not covered by a tradable certificate); (vi) the presence of tradable Renewable Energy Certificates (REC) systems; and (vii) the implementation of a publically financed R&D program. The policy index is the sum of all implemented policies expressed as dummies. Similar examples of environmental policy indices based on a synthesis of diverse policy performances can be found in Dasgupta et al. (2001) and Esty & Porter (2005). An indicator based on adoption dummies appears to reflect the overall scope of the government's support of renewable energy closely.

Our policy index screens out information held in continuous policy variables, such as public renewable R&D expenditures, feed-in tariff schemes and RECs[9]. To recover information on the intensity of public commitment to renewable energy, we consider the variables. For public R&D expenditures, we insert its per capita value in all regressions separately. For the latter two policies (feed-in tariff schemes and RECs), we analyze their individual effects in particular econometric specifications instead. However, looking at the intensity of these two policies remains somewhat misleading. On the one hand, RECs have been implemented since the early 2000s, and they have hardly been changed since then. On the other hand, the intensity of feed-in tariff schemes have been subject to downward adjustments, particularly in early adopting countries, such as Denmark and Germany.

Product Market Regulation. We characterize product market regulation (PMR) using the time-varying sector specific index developed at the OECD[10]. For each sector, the index combines information on barriers to entrepreneurship and administrative regulation (such as licenses and permits, administrative burdens, and legal barriers), state control (such as price control and ownership), and barriers to trade and foreign direct investment (such as tariffs and ownership barriers)[11].

[9]Information on the former is available in the joint IEA-OECD dataset, and the main references for feed-in tariffs are two reports drawn up by the IEA (2004), Cerveny & Resch (1998) and several country-specific sources. The variable constructed by Johnstone et al. (2010) measures the stringency of REC targets, which reflects the share of electricity that must be generated by renewables or covered with an REC. Using aggregation methods that allow the exploitation of both continuous and 0-1 policy signals, such as Principal Component Analysis, do not change the presented results. For details on the possible methodologies that can be used to aggregate this heterogeneous set of policies and on the common determinants of indices derived from different aggregation methods, see Nicolli & Vona (2012).

[10]The data sources include the privatization Barometer of the Fondazione Enrico Mattei, the Integrated Data Base of the World Trade Organization and interviews with civil servants in particular areas. With regard to the building of the indicator, low-level indicators are aggregated in high level indicators, using principal components analysis. For details on the construction of the index and the weighting scheme, see Conway et al. (2005).

[11]Liberalization has generally implied the establishment of authority to regulate abuse of mar-

The sectors of interest in the field of renewable energy are electricity (ISIC 4010) and gas (ISIC 4020). The PMR index for electricity and gas essentially combines different sub-indices ranging from 0 to 6, where high values indicate a high level of regulation and therefore a low level of competition. The first is ownership that 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 that combine information on third party access to the grid (regulated (0), negotiated (3), no access (6)) and the power of minimum consumers size to freely choose their supplier (from no threshold (0) to no choice (6)). The third component is vertical integration ranging from unbundling (0) to full integration (6). In the main analysis, we used a single index, weighting the electricity and gas indices by 0.75 and 0.25, respectively. Using the simple PMR index for electricity does not alter the results.

[Figure 2 about here.]

Figure 2 displays the evolution of green family patent production, of the renewable energy policy index and of product market regulation between 1976 and 2007 for a set of large and small countries. The tendency toward convergence in the PMR index and, to a lesser extent, in REPs, contrasts with the divergent pattern observed in the flow of patent applications. This descriptive evidence suggests that the timing of policy adoption and of liberalization matters in the establishment of technological advantages, as if the time of policy adoption yields a first mover advantage. By way of example, Anglo-Saxon and Scandinavian countries that outperform most countries in terms of green innovation liberalized their electricity sector in the late 1980s and the early 1990s, significantly before the bulk of other OECD countries (Glachant & Finon 2003, IEA 2004).

Control variables. We augment the econometric specification with a series a standard control variables that may affect green innovation above and beyond the presumably lead roles of REPs and PMR (Johnstone et al. 2010). Following the literature on induced innovation (Popp 2002, Newell et al. 1999), we should expect that an increase in the price of electricity would amplify the incentives for innovation in renewable energies. We assume the price of electricity to be exogenous, considering that renewables account for only a small share of overall electricity production. We also include electricity consumption by households and industry sectors to control for the possible dimension of the potential market for renewable energies. We also included a dummy variable set to unity for years after the Kyoto Protocol in 1997 to capture changes in expectation about the context for future policy and carbon prices (Popp et al. 2011).

As additional control variables, we include the overall number of patent families generated in a particular year. This variable accounts for the overall propensity of the country to patent, ensuring that the presumably significant effect of REPs and PMR prevails even after controlling for the overall ability of the country to generate innovations. Including the total number of patents in the controls-instead

ket power, privatization and ownership fragmentation, permitting customers to freely choose their favorite supplier, and the promotion of a progressive unbundling of distribution, generation and transmission activities. In particular, transparent approval of procedures for building new plants and easing access to the electricity grid has been important in stimulating the entry of new players.

of the (log-transform of the) ratio of green over total patents as the dependent variable-generalizes the econometric strategy followed by Popp (2002) and Aghion et al. (2011) because we do not constrain the model to unit proportionality between green and generic patents. We also introduce a time trend. Our expectation is that of a negative time trend, suggesting that early innovation in a given technological domain is based on the most immediate applications. As time goes by, however, invention draws on more complex models and ideas, making future innovation more difficult to generate. Finally, we augment our model by including the lagged dependent variable, which is tantamount to controlling for past successes in innovation, therefore controlling for persistence in inventive activities (Blundell et al. 1995).

[Table 3 about here.]

[Table 4 about here.]

Tables 3 and 4 provide summary statistics by country and for the overall panel. In particular, Table 3 also shows figures for green patent intensity, confirming the leadership of the Scandinavian countries (such as Norway and Denmark) and the remarkable positions of Spain, Greece, Portugal, the Czech Republic and Poland. In turn, Germany is the only large and wealthy country with a green intensity above the mean.

3.2 Econometric Issues

Research activities are inherently uncertain, so countries do not systematically come up with promising discoveries; therefore, zero and low values represent a common outcome of the family-weighted number of patents. The consequent positive skewness suggests that conventional uses of ordinary least squares yields biased and inconsistent estimates. The discreteness of the dependent variables and the number of family-weighted patents argues for the use of count-data models that have proved more appropriate in dealing with non-negative integers. Thus, we assume that the dependent variable follows a Poisson distribution, which means that discovery is the outcome of a large number of trials with a small probability of success.

Let y_{it} be the number of family-weighted patents assigned to country i, where $i = 1, \ldots, N$, at time t, where $t = 1, \ldots, T$. As is well known, the dependent variable y has a Poisson distribution with the parameter λ_{it}. We condition parameter λ_{it} on the host of factors $\mathbf{X_{it}}$ and the associated set of parameters β that are in this case the estimated effects of the set of factors affecting innovation in renewable energy. The expected family-weighted patent count of country i is given by Equation 1, the exponential forms guaranteeing the non-negativity of the expected patent count:

$$E\left(y_{it} \mid \mathbf{X_{it}}\right) = exp\left(\mathbf{X'_{it}}\beta\right) \tag{1}$$

The major feature of the Poisson model lies in the assumption of the equality of the mean and the variance of parameters, although the empirical mean and variance reveals the presence of overdispersion. The choice of family as opposed to triadic patents to account for quality is motivated by the presence of the many zeros in the triadic patent count, rendering the overdispersion problem more severe than in the case of family patents. This choice allows us to simply use cluster-robust standard errors to account for mild cases of overdispersion, as stipulated by Cameron & Trivedi (2005).

Apart from the count- data nature of the dependent variable, the econometric specification must address three important matters in the estimation procedure. First, as in panel data settings, persistent differences across countries in renewable energy invention are likely to be present. The first option is to specify the traditional fixed effect count-data estimator developed by Hausman et al. (1984). However, this estimator is inconsistent for the parameters of interest if the regressors are not strictly exogenous, as is the case with our policy variables (see Section 5 below)[12]. An alternative is to use the (quasi-) differenced estimator as proposed by Chamberlain (1992) and Wooldridge (1997). Instead, we account for unobserved heterogeneity using Blundell et al. (2002)'s pre-sample mean (PSM) estimator. We prefer the PSM estimator to the (quasi-) differenced estimator because of the lack of consistency of the latter, particularly when series are highly persistent. Information on the dependent variable prior to the initial year of investigation (1977) captures unobserved heterogeneity. This PSM estimator is shown to be consistent when the number of pre-sample periods is large (as is the case with patent data) and to have better finite sample properties than the quasi-differenced GMM estimator (Blundell et al. 2002).

In the presence of pre-sample information, a useful alternative to mean differencing is the inclusion of the pre-sample mean value of the dependent variable as follows:

$$y_{it} = \exp(\mathbf{X_i}\beta + \gamma \ln \bar{y}_{ip}) + \varepsilon_{it} \tag{2}$$

where $\bar{y}_{ip} = (1/TP)\sum_{r=0}^{TP-1} y_{i,0-r}$ represent the pre-sample mean which grasps persistent differences across panels of the database (countries); TP is the number of pre-sample observations.

Second, we introduce dynamics by inserting a linear feedback as in Blundell et al. (2002):

$$y_{it} = \rho y_{it-1} + \exp(\mathbf{X_i}\beta + \gamma \ln \bar{y}_{ip}) + \varepsilon_{it} \tag{3}$$

The purpose of imposing a linear feedback, as opposed to an exponential feedback, is that it eliminates the possibility of an explosive series. Thus, imposing a linear feedback model is akin to imposing a lower bound to the expected patent count set to ρy_{it-1}, because $\exp(\mathbf{X_i}\beta + \gamma \ln \bar{y}_{ip})$ is always positive. Note that the inclusion of the lagged dependent variable allows us to account for lags between the set of covariates and the dependent variable without imposing a lag structure.

The last issue concerns the well-known endogeneity of policies for three reasons. The first reason is the mutual reinforcement effect initially recognized by Downing and White (1986), who posited that, if innovation in environmental technologies follows the implementation of an effective policy support, progress in the generation of renewable energy will, in turn, provide support for that policy. Second, the effect of a given policy is likely to be heterogeneous, implying that unobservable factors affect both the policy and the propensity to patents; thus, an omitted variable

[12]The results presented hereafter are robust to the use of a within estimator to account for the individual effects.

bias plagues the estimated policy-innovation relationship. Third, renewable energy policies are measured with a substantial error. For most policies, particularly the ones in place since the 1970s and 1980s, the lack of detailed information allows only for policy dummies, which at best are only rough proxies.

We will therefore estimate Model 3 using the generalized method of moments. Relying on a GMM estimator allows for use of instruments as follows:

$$\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{Z_{it}}\left(y_{it}-\rho y_{it-1}-\exp(\mathbf{X_{it}}\beta+\gamma\ln\bar{y}_{ip})\right)=0 \tag{4}$$

where we define exclusion restrictions in the case of endogeneity of the regressors as $\mathbf{Z_{it}}=\left(\mathbf{1},\widetilde{\mathbf{X}}_{\mathbf{it}},\mathbf{y_{ip}},\mathbf{P}_{\mathbf{it}-\tau},\mathbf{IV}_{\mathbf{it}-\tau}\right)$, $\widetilde{\mathbf{X}}_{\mathbf{it}}$ is the adapted set of variables, which are considered exogenous, $\mathbf{P}_{\mathbf{it}-\tau}$ are our various measures of policy indices (REP and PMR), and **IV** are instruments that serve as additional moment restrictions, which are typically out-of-sample instruments that will be discussed in later parts of the paper.

4 Baseline Results

Table 5 displays the results of regressions in which we sequentially introduce our variables of interest in the specification. In Model 1, the linear feedback and the family weighted number of patents capture a significant share of the variance of the dependent variable. The country-specific initial conditions (*Pre-Sample Mean*) and energy prices have the expected sign and are near significance. In turn, public R&D in renewable energy has no particular effect on the dependent variable. Model 2 introduces the Kyoto dummy with our Renewable Energy Policy index. Both are positive and significant, validating the idea that public authorities are essential to guide the direction of invention. Innovation in renewable energy is greater in countries in which there is substantial public support for it. Not surprisingly, estimated elasticities decrease in Model 2; the effects of the linear feedback and of the number of generic patents decline well below unity, while the time trend becomes negative[13]. These results suggest the presence of a technological frontier that becomes more difficult to move forward as the knowledge stock increases.

From the above, we can conclude that policies fostering demand for clean energy matter more than mere public R&D expenditures, which highlights the leading role of demand and learning effects, as opposed to a pure technology push (Fischer & Newell 2008). These results are consistent with those of Popp (2002), who found that public R&D expenditures have an unstable and often insignificant effect on green patents. Section 6 below addresses this issue in more detail.

[Table 5 about here.]

Model 3 shows that *PMR*, the index for product market competition, has a negative and significant effect on the generation of green patents, implying that

[13]This latter result is consistent with the idea that invention becomes harder as time goes by. For example, renewable energies are characterized by decreasing returns associated with the limited number of appropriate geographical locations (Fischer & Newell 2008).

invention in renewable energy occurs in more competitive markets[14]. Past literature has produced results that are both consistent and at odds with our findings. On the one hand, Jamasb & Pollitt (2008) (resp., Sanyal & Ghosh 2012) find that liberalization in the energy market in the UK (resp., in the US) has had a negative effect on overall energy patents. On the other hand, Blundell et al. (1995) (resp., Griffith et al. 2010) estimate a positive effect on generic innovation in the UK (resp., for a group of EU countries), particularly in sectors characterized by low initial levels of competition. These discrepancies may reveal systematic differences in the way liberalization has been implemented in these countries, or they may show the results of differences in measurements and econometric specification. Importantly, the inclusion of PMR leaves the parameter estimate of the Policy Index unaffected. This result suggests that regulations in product markets and policies in support of renewable energy are significantly distinct instruments that are available to policy makers.

Model 4 displays the key specification where we include an interaction term between PMR and the Policy Index. The negative sign and statistical significance of the interaction term is expected theoretically. These findings reveal that renewable energy policies are more effective in more competitive markets, validating the policy complementarity hypothesis. Table 3 shows that the policy mix displayed by the US seems the most appropriate, scoring highest in the REP index and achieving the lowest score in PMR, implying a policy mix of substantial support for renewable energy innovation in a broadly deregulated market. More mitigated policy mixes can be found in France and, to a lesser extent, Denmark, where substantial public support in favor of renewable energy may be made less efficient by the lack of competition in their respective energy markets. These remarks should not conceal within-country variations that would exhibit an increase in public support with an increase in competition in energy markets for both countries.

Model 5 offers an alternative way of testing our policy complementarity hypothesis that allows for nonlinearity in the interaction effect. In particular, we allow the policy index REP to interact with each tercile of the PMR index to see whether increments in policy effectiveness are best achieved with mild or full liberalization. The results show that extensive liberalization of the energy market allows for the entire benefit of REPs to be reaped. In systems with mildly deregulated energy markets, the REP index is almost significant. Conversely, REPs show no inducement effects in heavily regulated energy systems. This result has important implications for evaluating the welfare effect of REPs. In heavily regulated energy sectors, more ambitious REPs produce welfare gains only if the positive effect of installed clean energy and of the associated reduction of greenhouse gas emissions more than offset the null effect in term of innovation.

In theory, the above results may stem from the particular way of measuring the policy and the PMR indicators. With regards to the REP indicator, an element of concern is the use of dummies for all policies with the exception of public R&D per capita. Because we have reliable cross-country information on a continuous scale for feed-in tariffs and RECs, we include these policies in Model 6 and display the results in Table 6. This exercise does not affect our main results on policy complementarity and on the effect of PMR. In turn, the new policies, particularly RECs,

[14]The inclusion of PMR squared does not provide evidence in favor of a non-linear effect of PMR.

do not display statistically significant effects. This result may stem from the lack of variance in these variables. In most countries, RECs were adopted in 2000 as a national policy that complied with the Kyoto Protocol. In the same vein, the effect of feed-in tariffs is most likely weakened because they have been gradually adjusted downward in countries experiencing substantial technological improvements. Overall, policy signals appear more appropriate than policy intensities in capturing country commitments toward renewable energy over the long time span considered.

[Table 6 about here.]

The PMR index is the combination of entry barriers, vertical integration and public ownership. Understanding which of these three components has the greater effect on innovation has relevant implications for the design of energy markets. Model 7 presents a specification with the PMR split into its three components. The main observation is that the aggregate effect of PMR seems largely driven by barriers to entry and, to a lesser extent, by the percentage of public ownership in energy utilities. The lack of significant effect for vertical integration implies that easing barriers to entry is enough to stimulate clean innovations even in markets with large, vertically integrated firms. This result is also explained by the fact that local distribution networks are owned by small companies in countries such as Denmark, and municipalities have favored the transition to clean energy (Ropenus & Skytte 2005). Finally, we check the robustness of these results by adding the PMR-REP interaction in a model with PMR split into its components. This specification is presented in Model 8 and confirms the policy complementarity hypothesis. Notably, entry barriers remain the only component of the PMR index that maintains a statistically significant effect.

In Model 9 of Table 6, we jointly consider the interactions between PMR, the REP index and R&D subsidies. The estimate of the interaction term between public R &D and the PMR is of the expected sign and highly significant. In particular, public R&D positively influences green innovation when its capacity to attract private investment is magnified by the increase in market competition. Note that the inclusion of this interaction term drives the effect of the REP index to insignificance. Although significant, the interaction of deregulation with public R&D is not robust across alternative specifications. In the remainder of the paper, we therefore emphasize the complementarity between REPs and PMR rather than with public R&D in renewable energy.

5 Endogeneity

Endogeneity is a key issue in the estimation of the effects of the REP and PMR indices because both reverse causality and omitted variables can induce a bias in the estimated coefficients. Further complicating the estimation of their joint effect is a mutual reinforcement effect between them, which amplifies the sources of reverse causality, as discussed by Downing & White (1986). Historic successful innovations in clean energy reinforce the lobbying power of innovating firms toward policy makers. In turn, current policies may have a positive influence on future innovation[15].

[15]Note that the positive feedback mechanism may become negative because existing lobbies in the energy sector and large utility generators are likely to exacerbate failures in given policies and/or

In general, the recent liberalization of energy markets should have reduced the incumbents' lobbying capacity, favoring the adoption of ambitious policies and facilitating the emergence of new players in renewable energy innovation. The close interplay between competition and innovation policies points to the existence of a latent factor affecting both the liberalization process and the adoption of REPs. Moreover, because of the strong persistence of our two policy indicators, the timing of reforms is of paramount importance in establishing comparative advantages in renewable energy technologies. Accordingly, we chose an instrument that jointly influences the two policy indicators and, in particular, their time of adoption.

Our strategy is to use both within-sample and out-of-sample instruments. First, our time-series cross-country database fits perfectly with the use of lags in the policy variables. We therefore use one- and two-year lags as instruments for future levels in the REP index, in the PMR and in their interaction. Second, we included a series of out-of-sample instruments, which serve as predictors of policy implementation. In the vector of out-of-sample instruments, we include a proxy (TENSYS) accounting for the time length for which a country has had consolidated and durable democratic institutions. This information is provided by the 2010 version of the World Bank Database on Political Institutions (for details see, Beck et al. 2001). In fact, a growing literature shows that democratic countries tend to approve stricter environmental policies and to foster product market liberalizations (Congleton 1992, Murdoch & Sandler 1997, Fredriksson et al. 2005, Neumayer 2002, Pitlik 2007, Pitliks & Wirth 2003, Chang & Berdief 2011). With respect to younger democracies, our conjecture is that durable democracies ensure a longer time horizon for decision making and should be more responsive to citizens' preferences as a result of environmental activists and NGOs exerting a positive influence on environmental policies (Fredriksson et al. 2005, List & Sturm 2006).

To capture complementary aspects that may affect agents' expectations about political decisions, we use two additional variables provided by the World Bank that measure the length of time the government has been in office (YRSOFF), and the time the government will remain in office before the next election (YRCURNT). In democracies, the duration of the chief executive may advocate a government that is successful in meeting citizens' interests or may be an index of political strength and perpetuation of existing elites, e.g., Chang & Berdief (2011), Levy-Yeyati et al. (2010), Grossman & Noh (1990). For the energy sector in OECD countries, where there is a certain degree of policy homogeneity, a long-term democracy, along with the presence of a more stable governments, may influence the speed of both liberalization and environmental policy adoption. Lastly, the robustness of our choice of instruments is tested by using a different set of out-of-sample instruments: per capita income and a proxy for a 'pre-sample' share of energy from distributed generation. The use of the first variable is motivated by the robust evidence that ambitious environmental policies tend to be adopted in more developed countries (Dasgupta et al. 2001, Esty & Porter 2005, Nicolli & Vona 2012). The second instrument is a proxy for initial know-how in decentralized energy production[16]. Appendix A displays the

green innovation output by postulating a reduction in the support for renewable energy (Jacobsson & Johnson 2000, Nilsson et al. 2004, Lauber & Mez 2004, Nicolli & Vona 2012).

[16]In the late 1980s, energy generation was essentially centralized when liberalization started. However, Nordic and central European countries were previously committed to dispersed ownership

results of the regression between the policy variables and the set of instruments.

Table 7 shows estimates of the pre-sample mean estimator with endogenous regressors using alternative vectors of instruments. First, all sets of exclusion restrictions pass the Hansen test on exogeneity of the instruments, particularly for the set of political instruments (Models 12 and 13). Second, as in Popp (2002), the effect of R&D per capita is greatly underestimated without properly accounting for endogeneity. Depending on the specification, the effect of public R&D per capita is inflated by a factor of 2. In turn, the effects of all remaining variables are of similar size of those obtained in the model with exogenous (or pre-determined) regressors.

[Table 7 about here.]

Regarding the main variables of interest, both the effects of PMR and of the REP index maintain the identical sign, but their effects decrease. The decrease in the estimated coefficient is particularly impressive for PMR, making it insignificant in most specifications. In turn, the magnitude of the estimation bias for the REP index is negligible across specifications, ranging from 6% to 15% of the original effect. The synergetic effect is amplified by 20 to 37%. A final point must be stressed in the comparison with the case of exogenous regressors. Accounting for endogeneity leads to a slight but relevant change in the interpretation of the results. While in Models 4 and 5, REPs seem effective only in liberalized markets, liberalization of the energy market here appears to have a positive effect on clean innovation, particularly when combined with ambitious policies.

6 Quality of Inventions

The use of patent families, as opposed to patent counts, aims to address the quality of invention when simply calculating numbers of patents. The intuition is that an economically valuable invention should benefit from intellectual property rights across several legal authorities, whereas a local, small-scale invention should focus on the local market only. However, the use of patent families does not control for the quality of patent offices. Imagine an invention being granted by, for example, 10 legal authorities, none of which cover a large market. How would that compare with an invention being granted in the three largest markets worldwide, which are the US, the European and the Japanese markets? Therefore, an even more stringent proxy for high-quality inventions may be obtained by filtering families of inventions with the quality of the patent offices, keeping only the ones associated with the three abovementioned markets.

In this section, we use triadic patents, that is, all patents jointly registered at the Japanese, US and European patent offices, as the best approximation for top quality innovations. The only drawback associated with using triadic patents is time-truncation, because the European Patent Offices was first established in 1978. We overcome this problem by using the pre-sample mean information with patent families[17]. It is worth noting again that we do not use triadic as our favorite

structures with a significant share of energy produced in local heating systems or as a by-product of farm and industry activities (Glachant & Finon (2003)).

[17]Between 1978 and 1985, both triadic patents and patent families are highly correlated, with a Pearson correlation coefficient reaching .97.

measure of innovation because green triadic patents contain many more zeros than green families. The problem with zero-inflated count variables is that the issue of overdispersion may not be successfully resolved using cluster-robust standard errors, as we do with the pre-sample mean GMM estimator (Cameron & Trivedi 2005)[18]. Finally, in addition to triadic patents, we also use simple patent count in renewable energy as our dependent variable to compare results with respect to low-quality innovations.

Using Model (4) as our baseline specification, Table 8 shows the results for green patent counts (Columns 14 and 15) and for the number of triadic patents (Columns 16 and 17). Columns 14 and 16 show the PSM estimator with exogenous regressors, whereas Columns 15 and 17 show the PSM estimator when the policy variables are considered endogenous. Our comments focus on Columns 15 and 17.

[Table 8 about here.]

First and foremost, the complementarity hypothesis seems to hold for high-quality patents. To produce frontier innovations in the realm of renewable energy, countries with substantial public support will perform better if their energy market has liberalized. Although the PMR has the correct sign, its individual effect is non-significant, suggesting that it is the commitment of public authorities into supporting green innovation-not market deregulation-which is a first order condition to yield high-quality innovation. Deregulation thus remains a second order condition that renders REPs more effective in frontier research. The sequence of reforms in successful countries follows this priority order. Denmark and Germany, for instance, adopted ambitious policies first and then fully liberalized the energy market.

A similar pattern holds for public R&D in renewable energy, which becomes statistically significant for triadic counts; a 1% increase in R&D intensity yields a .24% increase in high-quality inventions. Therefore, public policies and particularly public R&D seem to be important for top quality inventions, reconciling our results with the ones of Norberg-Bohm (2000), Jamasb & Pollitt (2008) and Popp (2006*b*), all of which show that public research has a significant effect on fundamental innovations. In essence, public support is crucial to inventive activities that are located near or at the technology frontier.

The pattern for green patent counts, irrespective of patent quality, is remarkably different (Model 15). We observe no significant relationship of patent counts to either public R&D or the REP index. Instead, product market regulation displays larger effects for low-quality generic patents. This result may stem from the strategic behavior of existing companies because knowledge appropriation by incumbents may deter innovation by potential rivals, thereby deterring entry. In the same vein, the Kyoto Protocol has had a remarkably positive effect on low-quality green innovations. Its lack of significance with high-quality inventions may reveal the presence of a resource mis-allocation problem, implying that the Kyoto Protocol had no particular effect on the technology frontier, although it provided incentive for countries to strengthen their property rights in the knowledge space.

[18] However, the results are robust to the use of a negative binomial model.

7 Quantifying the Effect of Policies

The difficulty for policy makers is to grasp whether a given policy instrument will eventually deliver a significant improvement in the desired output. Statistical significance in the policy-innovation relationship may conceal insufficient economic returns, and low levels of critical probability values may not equate with substantial economic effects.

This section examines the actual magnitude of the effect of policy variables on inventive activities in renewable energy. To do so, we rely on the specifications that properly account for the endogeneity of policy variables for all three types of output: patent family (Model 12), number of patents (Model 15) and number of triadic patents (Model 17). We compute the short-run marginal effects of policy j as the discrete change in the expected output, holding all variables at their mean with the exception of the policy of interest ($\mathbf{\bar{X}_{-j}}$). For the policy of interest j, we use variations of x_j from the 1^{st} quartile ($x_{j,q1}$) to the 3^{rd} quartile ($x_{j,q3}$). More precisely, the short-run marginal effect is computed as follows:

$$\frac{\Delta E(y_{it} \mid \mathbf{X_{it}})}{x_{j,q3} - x_{j,q1}} = exp(\mathbf{\bar{X}_{-j}}\hat{\beta} + x_{j,q3}\hat{\beta}) - exp(\mathbf{\bar{X}_{-j}}\hat{\beta} + x_{j,q1}\hat{\beta}). \tag{5}$$

Specification 3 also allows the computation of the long-run marginal effects. Arguably, policy makers establish a given policy mix to reach a desired level of green innovation y^*_{it} that represents the long-term objective of stakeholders. In any given period, the observed level of innovation may only partially adjust to the desired level so that $y_{it} - y_{it-1} = \phi(y^*_{it} - y_{it-1})$, where $0 < \phi < 1$. This partial adjustment allows us to recover the long-run multiplier for each of the short-run policy effects. Setting $\phi = 1 - \rho$, the long-run multiplier LRM is simply the sum of an infinite series, such that $LRM = \frac{1}{1-\rho}$. The long-run effect then reads:

$$\frac{\Delta E(y_{it} \mid \mathbf{X_{it}})}{x_{j,q3} - x_{j,q1}} \times \frac{1}{1-\rho} \tag{6}$$

Table 9 shows for each policy variable the short-term variations in the expected number of patents in absolute terms (1^{st} row) and relative to the median (3^{rd} row)[19]. Our discussion focuses primarily on the marginal effects derived from significant parameter estimates.

[Table 9 about here.]

In the case of patent families, the expected increase is mostly accounted for by the Policy Index and the interaction term with PMR. Holding all variables at the mean, an increase from the first to the third quartile of the REP Index yields an increase in patent families by one unit (1.236), representing almost a 3% increase with respect to the mean. A similar policy change in more deregulated markets would (holding PMR at its first quartile) make this policy change twice as effective; an increase from the first to the third quartile of the Policy Index would then yield an increase in patent families by 2.6, representing more than 6% of patent family production.

[19]For triadic patents, we choose to express this relative to the mean, the median of triadic patents being 1.

Note that the effectiveness of renewable energy policies vanishes for green patent production irrespective of quality. By contrast, the effectiveness of such policy changes becomes remarkably high for triadic patents; in deregulated markets, an increase by two quartiles of the policy index yields 1.5 more triadic patents, which is nearly 20% of the mean of triadic patents. Therefore, such policies matter for research located near or at the frontier but not for innovation in general.

Market deregulation also has a sizeable effect on invention: a two-quartile increase in PMR, holding the REP index at the mean, yields an increase by 15% in patent counts and by 12.5% in patent family counts. The effect on frontier innovation-triadic patent counts-is somewhat less significant but still of substantial magnitude. This result suggests that the effect of PMR on quality innovation has a larger variance, with a high significance for most countries and little or no significance for others. Although of a second order, market liberalization as a policy tool cannot be ruled out as a means to achieve quality innovation.

The last row of Table 9 also displays the marginal effects of a policy change combining increased policy support with more deregulated markets. The combination of both policies is impressively large, amounting to 15% of the median of patent family counts and 25% of the mean of triadic patents. Success in green innovation is fostered by policy changes which combine increased public support and market liberalization. The example of country leaders in renewable technologies such as Denmark, Germany and the US suggests that the adoption of ambitious policies should precede market liberalization, creating a critical mass of innovative firms, particularly in the sub-sector of specialized suppliers of electrical equipment[20].

Table 9 also reveals the positive association of public R&D in renewable energy and quality research. This policy instrument becomes gradually more effective with our control for patent quality. Being null for patent counts, public R&D investments become significant for triadic patents, with a marginal effect reaching 7.5%. Ultimately, ground-breaking innovation requires public research funds. Without substantial scientific stimulus, policy makers should not hope to reach the technological frontier, at least not in the realm of renewable energy. For generic green patents, neither R&D nor the Policy Index displays any sizeable effect, either alone or in interaction with PMR. The singular, marginal effect of PMR is large, reaching 15% of the median of patent counts. This effect remains of the identical magnitude irrespective of the level of the REP Index. The effect of the Kyoto dummy is also substantial, implying a 10.5 percentage increase in patent counts. Despite being highly statistically significant, the increase in patents because of a standardized two-quartile increase in energy prices remains of a smaller magnitude.

Why would policy makers bother about stimulating green patent generation, regardless of quality? Our answer is based on the distance-to-frontier analogy. Countries willing to reach the frontier should not aim at top innovation all at once. Building the critical mass of competencies is of importance at the outset, which is accomplished by inflating generic patent production. In this regard, it is important to note that the value of the linear feedback for patent counts exceeds .8, imply-

[20]The important role of small suppliers is documented for wind and solar energy by Jacobsson & Bergek (2004). In particular, the expansion of wind energy was implemented by German suppliers of machinery and electrical equipment, particularly through the entry of 14 new firms. The identical dynamics of entry of local wind turbines firms has been observed in Netherlands and Germany.

ing a high level of persistence in patent generation. Such persistence also renders the long-run multiplier remarkably high, inflating all marginal effects by a factor of 5. However, once competencies gradually accumulate, policy makers seeking to encourage innovation at the technological frontier should adapt their policy mix accordingly. Note however that past successes in quality patents do not guarantee production in the future. The decrease in persistence ($\rho = .536$) entails a corresponding decrease in the long-run multiplier, inflating short-term marginal effects only by a factor of 2. Therefore, as countries draw near the technological frontier, the effectiveness of policies will gradually decrease, consistently with the rising costs of path-breaking invention.

8 Conclusions

Innovation in renewable energy is now widely regarded as the key to sustaining and improving the quality of life for current and future generations. In addition to standard differences in overall technological levels and life standards, targeted national-level policies alone appear important but not sufficient to explain cross-country differences in innovation. Our empirical analysis shows that the extent to which these policies are effective largely depends on complementary regulatory features. In particular, the combination of public policies and market deregulation is the most effective method of inducing innovation in renewable energy, particularly near the technological frontier. This finding corroborates the complementarity hypothesis that public support to innovation is more effective in competitive markets.

Our results are in line with previous studies showing that the effect of public policies increases with the quality of inventions. This effect is particularly evident for public R&D that proves to be a key ingredient for quality innovation. Although our results are inconclusive in shedding light on the demand-pull versus supply-push debate, they do suggest that both scientific input and demand factors are crucial for frontier innovation.

Our results partially contrast with previous country-level studies pointing to a negative effect of energy market deregulation on innovation. In fact, we show that the effect of deregulation is mainly driven by the barriers to entry component of the PMR index and is larger on lower quality patents. In addition, the effect of PMR seems substantially overestimated without properly accounting for endogeneity. Our conclusion is that part of the effect of deregulation should be to encourage strategic decision making by large incumbents because incumbents tend to accumulate industrial property rights to deter potential entrants.

Our research agenda addresses three important issues. First, this research has identified the effect of liberalization and policy on innovation as a whole. However, this effect is driven by heterogeneous firm responses, and a better understanding of the response function would allow us to unravel the channels by which policy changes translate into overall country performance. Second, our dynamic specification can be enriched to test the directed technical change hypothesis put forward by Acemoglu et al. (2012). In particular, we could empirically test whether the effect of energy market deregulation and public policy adoption will be able to revert previous patterns of green versus conventional patent production. Third, the EU integration of energy markets may have had unintended consequences on green innovation insofar as integration may select out small players, reinforcing the power of incumbents. EU incumbents are more likely to lobby for policies that are less conductive to innovation, i.e., RECs rather than feed-in tariffs (Jacobsson et al. 2009). These concerns could be rigorously tested using firm-level data for EU countries within the appropriate time frame.

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Appendix A. On the Quality of Instruments

Table I reports the results of the first-stage estimates using alternative vectors of instruments.

Table I: Common determinants of REP Index and PMR

	Renewable Energy Policy Index			
Time dem.	0.040***	0.038***		
	[0.003]	[0.003]		
Years gov. off.		-0.046***		
		[0.015]		
Years gov. left		-0.019		
		[0.048]		
GDP pc			0.000***	0.000***
			[0.000]	[0.000]
DG bef. lib.				0.242***
				[0.074]
Constant	0.812***	1.124***	-0.437***	-0.573***
	[0.122]	[0.176]	[0.143]	[0.148]
Obs.	864	846	850	850
R square	0.23	0.22	0.37	0.38
	Product Market Regulation Index			
Time dem.	-0.026***	-0.025***		
	[0.002]	[0.002]		
Years gov. office		0.013		
		[0.011]		
Years gov. left		0.044		
		[0.035]		
GDP pc			-0.000***	-0.000***
			[0.000]	[0.000]
DG bef. lib.				-0.155***
				[0.058]
Constant	5.405***	5.225***	6.105***	6.193***
	[0.090]	[0.130]	[0.110]	[0.115]
Obs.	864	846	850	850
R square	0.18	0.17	0.27	0.28

Pooled OLS Regressions. (***), (**) and (*) denote statistical significance at 99%, 95% and 90% respectively. Estimation time span: 1976-2007.
DG bef. lib.: share of distributed generation before liberalization starts
Time dem.: length of democracy
Years gov. off.: years in office of the government.
Years gov. left: years remaining in the government.

The results corroborate our expectations showing that the consolidation of democracy, i.e., variable *timedem.*, is an excellent predictor of both policy variables, explaining 23% and 18% of the variance of the REP and PMR indexes, respectively.

Income per capita and the DG share are good explanatory variables for both PMR and REP index. Therefore, although less convincingly exogenous than the duration of the political system, they represent appropriate alternative instruments to test the robustness of our main results. Lastly, contrary to our expectations, the time the government has been in office and the time that it will remain in office have both the identical negative effect on environmental policies and the identical positive effect on PMR.

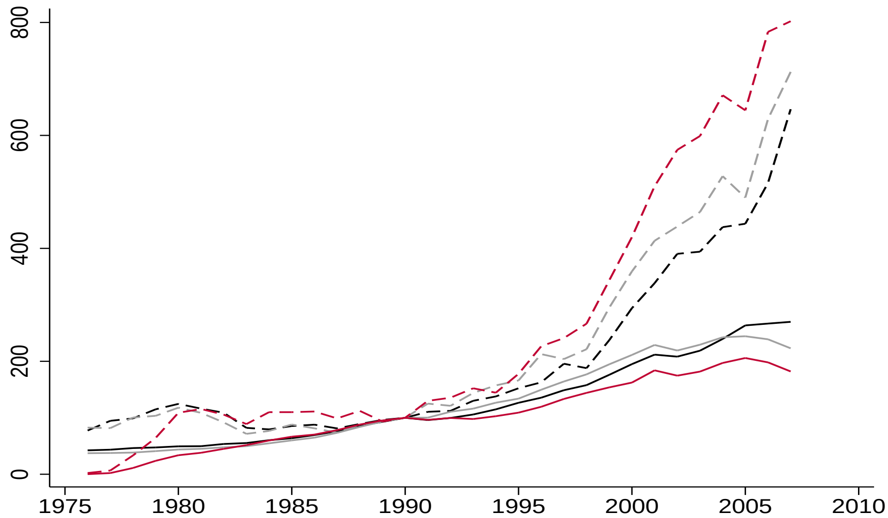

Figure 1: Evolution of Patent Generation Between 1976 and 2007 (1990 = 100, patent count in black, patent family in grey, triadic patent family in red. Dashed lines denote green patents.)

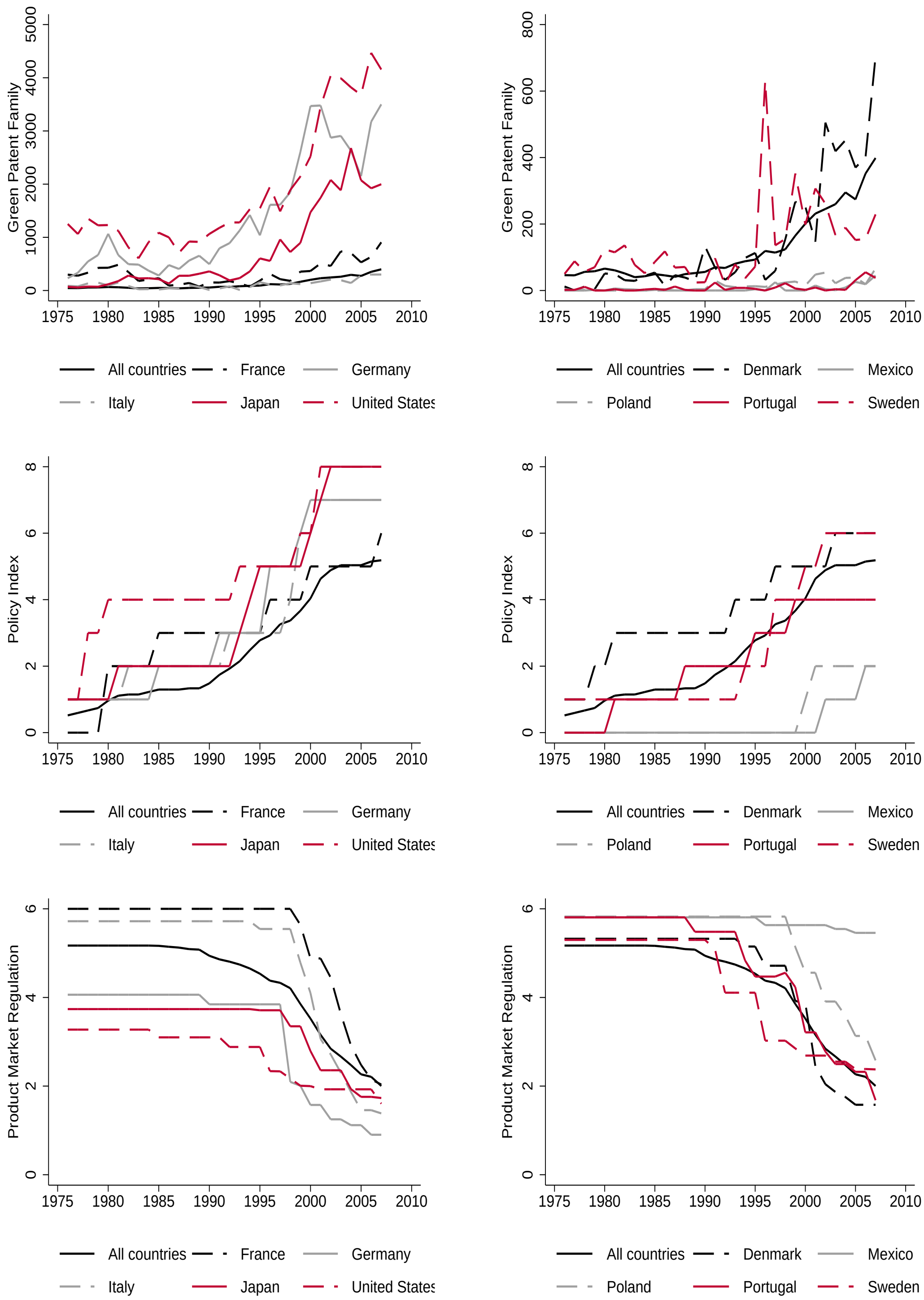

Figure 2: Evolution of Green Family Patent Production, of the Renewable Energy Policy Index and of Product Market Regulation between 1976 and 2007 in Large Countries (left panel) and Small Countries (right panel)

Table 1: Description of technologies in Renewable Energy Sources (RES) and their corresponding International Patent Classes (IPC)

RES	Description	IPC Classes
Biomass	Bioenergy generally refers to energy produced from biomass, that is, organic matter, including dedicated energy crops and trees, agricultural food and feed crops, agricultural crop wastes and residues, wood wastes and residues, aquatic plants, animal wastes, municipal wastes, and other waste materials.	F02B43/08; C10L5/44; B01J41/16; C10L5/42; C10L5/43;C10L1/14
Geo-Thermal	Thermal energy derived from magma heat and stored in soil, underground water, or surface water can be used for heating or cooling buildings by means of a ground coupled heat pump system. Such systems operate with a heat exchange embedded in a borehole to supply the energy for the evaporation and condensation of a refrigerant. Geothermal liquid can also be used to drive turbines to generate electricity.	F24J3/02; F24J3/06; F03G4/06; F24J3/01; F24J3/04; F03G4/03; F03G4/02; F24J3/08; F24J3/07; F03G4/01; F03G4/04; F24J3/03; H02N10/00; F24J3/05; F03G4/00; F03G4/05; F24J3/00
Hydro	The energy from incoming and outgoing tides can be harnessed to generate electricity-using turbines, for instance. Electricity can be generated through the conversion of the potential energy of water contained in a reservoir using a turbine and a generator.	F03B17/06; F03B13/08; F02C6/14; F03D9/00; E02B3/02; F01D1/00; F03D9/02; B62D5/06; F03B13/10; F03B13/00; F03B3/00; F03B3/04; E02B3/00; H02K7/18; B62D5/093
Ocean	Energy from waves, excluding tidal.	F03B13/15; F03G7/04; F03B13/22; F03B13/12; F03B13/21; F03B13/20; F03B13/18; F03B13/13; F03G7/05; F03B13/16; F03B7/00; F03B13/24; F03B13/17; F03B13/19; F03B13/23; F03B13/14

Continued on next page

RES	Description	IPC Classes
Solar	Heat captured from the sun may be used for residential heating, industrial processes or thermal power generation. Technologies involved in solar thermal energy production include solar heat collection, heat storage, systems control, and system design technologies. Specially adapted semiconductor devices are used to convert solar radiation into electrical current. Related technologies include solar cell design, storage batteries, and power conversion technologies.	F24J2/49; F24J2/15; F24J2/26; H01L31/042; F03G6/04; F24J2/00; F24J2/13; F24J2/02; F24J2/03; F24J2/05; F24J2/17; F24J2/23; F24J2/38; F24J2/09; F24J2/10; F24J2/37; F24J2/51; F24J2/33; F24J2/50; F24J2/16; F24J2/11; F24J2/14; F24J2/21; F24J2/20; F24J2/06; F24J2/22; F24J2/28; F24J2/08; F03G6/08; F24J2/30; F24J2/18; F24J2/25; F03G6/06; F03G6/02; F24J2/39; F03G6/00; F25B27/00; F24J2/40; F24J2/24; F03G6/03; F03G6/05; E04D13/18; F24J2/43; F24J2/41; F24J2/04; F24J2/27; F03G6/07; F24J2/31; F24J2/53; F24J2/45; F24J2/54; F03G6/01; F24J2/34; H02N6/00; F26B3/28; F24J2/12; F24J2/19; F24J2/07; B60L8/00; F24J2/42; F24J2/36; F24J2/48; F24J2/46; F24J2/52; F24J2/35; F24J2/47; F24J2/32; F24J2/44; F24J2/29; F24J2/01
Waste	Household and other waste can be processed into fuels (liquid or solid) or burned directly to produce heat that can then be used for power generation (mass burn). Refuse derived fuel (RDF) is a solid fuel product. It has high energy content and can be used as fuel for power generation or for boilers and is obtained by shredding or treating municipal waste in an autoclave, removing non-combustible elements, drying the product, and finally shaping it. It has high energy content and can be used as fuel for power generation or for boilers.	F02G5/04; F02G5/02; F23G7/10; F02G5/03; F23G5/46; C10L5/48; C10L5/47; F25B27/02; F02G5/00; C10L5/46; F02G5/01; C10J3/86; F12K25/14; H01M8/06
Wind	Wind currents can be used to generate electricity by using wing-shaped rotors to convert kinetic energy from the wind into mechanical energy and a generator to convert the resulting mechanical energy into electricity.	F03D11/00; F03D7/05; F03D5/02; F03D11/04; F03D5/00; B63H13/00; F03D5/03; F03D3/06; B60L8/00; F03D3/04; F03D7/00; F03D3/03; F03D7/01; F03D1/02; F03D5/06; F03D5/05; F03D7/02; F03D1/00; F03D5/04; F03D9/02; F03D1/05; F03D5/01; F03D1/01; F03D3/01; F03D11/02; F03D7/04; F03D3/00; F03D11/03; F03D7/03; F03D1/04; F03D1/06; F03D3/05; F03D9/01; F03D1/03; F03D11/01; F03D9/00; F03D7/06; F03D3/02

Table 2: Description of Renewable Energy Policies.

Instrument	Brief explanation	Variable Construction	Source
Investment incentives	Capital Grants and all other measures aimed at reducing the capital cost of adopting renewables. They may also take the form of third party financial arrangements, in which governments assume part of the risk or provide a low interest rate on loans. They are generally provided by state budgets.	Dummy Variable	International Energy Agency (IEA)
Tax Measure	Economic instruments used either to encourage production or discourage consumption. They may have the form of investment tax credit or property tax exemptions to reduce tax payments for project owner. Excises are not directly accounted here unless they were explicitly created to promote renewables (for example, excise tax exemptions).	Dummy Variable	IEA
Incentive tariff	Through guaranteed price schemes, the energy authority obliges energy distributors to feed into the production of renewable energy at fixed prices varying according to their sources. This system is considered one the main factors in the development of renewable technologies,in particular, because it reduces uncertainty, offering investors long-term security (Reiche & Bechberger 2004). Some countries (such as the UK and Ireland) have developed so-called ”bidding system” schemes in which the most cost effective offer is selected to receive a subsidy. This last specific case is also accounted for in the dummy, because of its similarity to the feed-in systems.	Dummy Variable	IEA
Feed-in Tariff	The most well-known form of incentive tariff, i.e., guaranteed pricing that may vary by technology and level of price guaranteed	USD, 2006 prices and PPP	IEA, Cerveny and Resch (1998), country specific sources
Voluntary program	These programs generally operate through agreements between the government, energy utilities and energy suppliers, whereby the utilities agrees to buy energy generated from renewable sources. One of the first voluntary programs was in Denmark in 1984, when utilities agreed to buy 100 MW of wind power.	Dummy Variable	IEA
Obligations	Obligations and targets generally take the form of quota systems that place an obligation on producers to provide a share of their energy supply from renewable energy. These quotas are not necessarily covered by a tradable certificate.	Dummy Variable	IEA
Tradable Certificate	Renewable Energy Certificates (RECs) consist of tradable financial assets, issued by the regulating authority, who certifies the production of renewable energy, and can be traded among the actors involved. Along with the creation of a certificate scheme, a separate market is usually established in which producers can trade certificates. The price of the certificate is determined through trading between the retailers.	Share of electricity that must be generated by renewables or covered with a REC.	Data made available by Nick Johnstone, OECD Environment Directorate plus country specific sources
Public Research and Development	Publically financed R&D program disaggregated by types of renewable energy	Public sector per capita expenditures on energy R&D (USD, 2006 prices and PPP).	IEA
EU directive 2001 − 77 − *EC*	Established the first shared framework for the promotion of electricity from renewable sources at the European level.	Dummy Variable	European Commission

Table 3: Country Characteristics in Green Patenting and Policy Indices

Country	PF	GPF	TRY	GTRY	GFINT	GTINT	REP	PMR	DG
All countries	19,083	224.2	1,499	7.942	11.75	5.300	2.483	4.332	0.556
Australia	4,429	85.63	308.8	3.438	19.33	11.13	2.313	3.395	0.000
Austria	5,996	89.97	358.1	1.781	15.00	4.974	2.969	4.418	1.000
Belgium	5,583	35.78	468.6	1.188	6.409	2.534	3.000	3.792	0.000
Canada	10,464	151.3	623.9	4.594	14.46	7.363	2.594	3.540	0.000
Czech Republic	694.5	26.97	23.34	0.125	38.83	5.355	1.375	5.035	1.500
Denmark	4,136	146.2	220.9	2.688	35.34	12.17	3.719	4.404	2.000
Finland	5,939	58.31	276.8	1.594	9.819	5.759	3.063	3.973	0.000
France	35,043	325.3	2,360	9.875	9.282	4.184	3.125	5.346	0.000
Germany	87,129	1402	5,313	35.19	16.10	6.623	3.531	3.170	2.000
Greece	251.1	7.813	24.22	0.125	31.11	5.161	1.406	5.428	0.000
Hungary	1,158	16.91	45.03	0.188	14.60	4.164	1.094	4.820	0.000
Ireland	1,281	16.75	97.22	0.625	13.07	6.429	2.406	5.309	0.000
Italy	14,119	114.2	674.8	2.969	8.085	4.400	3.406	4.812	0.000
Japan	84,244	735.7	9,655	53	8.733	5.489	3.813	3.309	0.500
Luxembourg	798.7	10.53	62.34	0.375	13.19	6.015	1.875	4.878	0.000
Mexico	364.3	5.438	23.06	0.094	14.93	4.065	0.250	5.720	0.000
Netherlands	15,108	142.4	1,659	5.594	9.424	3.372	3.031	4.615	2.000
New Zealand	666.0	8.938	44.53	0.281	13.42	6.316	1.625	3.842	1.000
Norway	2,230	65.19	97.16	1.594	29.24	16.40	2.281	3.592	0.000
Poland	475.8	14.69	22.53	0.031	30.87	1.387	0.469	5.265	1.000
Portugal	214.6	8.375	17.16	0.125	39.02	7.286	2.156	4.702	1.000
Spain	3,533	102.9	164.1	1.656	29.12	10.10	2.563	3.404	1.000
Sweden	14,015	137.4	810.3	3.438	9.802	4.242	2.563	4.164	2.000
Switzerland	17,195	137.9	1,402	5.219	8.018	3.721	3.094	4.964	0.000
Turkey	244.0	3.250	19.69	0.031	13.32	1.587	1.844	5.315	0.000
United Kingdom	27,577	338.2	2,109	12.91	12.26	6.120	2.531	3.032	0.000
United States	172,358	1,865	13,582	65.72	10.82	4.839	4.938	2.710	0.000

Considered time span: 1976-2007; PF: Family weighted overall number of patents ; GPF: Family weighted overall number of green patents; TRY: Triadic filtered overall number of patents; GTRY: Triadic filtered overall number of green patents; GFINT: Green Intensity (PF/GPF, per thousand); GTINT: Green Intensity using triadic (GTRY/TRY, per thousand); REP: Renewable Energy Policy Index; PMR: Product Market Regulation aggregate index; DG: Distributed Generation before Liberalization (0=none, 1=average, 2=high). Source: Our elaboration on information in Glachant & Finon (2003), IEA (2004) and country reports of the International Energy Agency.

Table 4: Descriptive Statistics.

Variable	Mean	Median	St. dev.	Min.	Max.
Green Patents (Family weighted)	224.2	42	557.9	0	4,468
Green Patents (Triadic weighted)	7.942	1	23.24	0	193
Number of Patents (Family weighted)	19,083	3,338	44,480	3	336,096
Number of Patents (Family weighted, log)	8.009	8.113	2.182	1.386	12.730
Pre-Sample Mean (Green Patents)	10.350	1.133	23.660	0.000	114.300
Electricity Consumption (log)	11.030	10.990	1.332	7.920	14.660
Energy Price Index (log)	0.105	0.102	0.044	0.015	0.234
Public R&D in renewable Energy (log)	0.615	0.567	0.538	0.000	2.442
Kyoto (dummy)	0.344	0.000	0.475	0.000	1.000
REP index	2.483	2.000	2.062	0.000	8.000
Product Market Regulation	4.332	4.720	1.472	0.254	6.000

N = 843. Time span: 1976-2007.

Table 5: Sequential Pre-Sample Mean Poisson Model with Linear Feedback. GMM Estimator with Exogenous Regressors. Dependent Variable: Family Weighted Number of Green Patents.

	Model 1	Model 2	Model 3	Model 4	Model 5
Linear ρ	0.827***	0.783***	0.740***	0.675***	0.730***
	[0.037]	[0.058]	[0.068]	[0.075]	[0.071]
Families (log)	0.810***	0.762***	0.793***	0.792***	0.803***
	[0.146]	[0.152]	[0.121]	[0.113]	[0.119]
Time trend	0.023***	-0.011**	-0.029***	-0.027***	-0.027***
	[0.006]	[0.005]	[0.002]	[0.002]	[0.005]
Pre-Sample Mean	0.003	0.003	0.004*	0.004**	0.004**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Electricity Consumption (log)	0.011	0.003	-0.117	-0.102	-0.147
	[0.156]	[0.151]	[0.114]	[0.107]	[0.122]
Energy Price Index (log)	3.74	4.152*	2.849	2.701	3.082
	[2.336]	[2.422]	[1.934]	[1.781]	[1.898]
Public R&D in Renew. (log)	0.058	0.029	-0.001	0.054	-0.038
	[0.174]	[0.161]	[0.129]	[0.113]	[0.147]
Kyoto		0.272*	0.13	0.153	0.153
		[0.146]	[0.154]	[0.150]	[0.149]
REP Index		0.090***	0.090***	0.143***	-0.05
		[0.029]	[0.035]	[0.040]	[0.082]
Aggregate PMR			-0.234***	-0.135**	-0.164**
			[0.048]	[0.064]	[0.064]
REP Index × PMR				-0.024*	
				[0.012]	
REP Index × medium PMR					0.078
					[0.058]
REP Index × low PMR					0.148**
					[0.073]
Constant	-50.638***	18.354*	55.024***	51.004***	51.639***
	[11.756]	[11.152]	[3.897]	[3.393]	[10.547]
Observations	843	843	843	843	843
Moments	8	10	11	12	13
REP Index × low PMR					0.102***
REP Index × medium PMR					0.029
REP Index × high PMR					-0.049

Pre-Sample Mean information computed for the first 15 years available. Estimation time span: 1976-2007. Standard errors are cluster-robust by countries. Statistical significance at 99%, 95% and 90% is denoted by (***), (**) and (*), respectively.

Table 6: Specific Policies. PSM Poisson Model with Linear Feedback. GMM Estimator with Exogenous Regressors. Dep. Var.: Family Weighted Number of Green Patents.

	Model 6	Model 7	Model 8	Model 9
Linear ρ	0.668***	0.708***	0.637***	0.698***
	[0.078]	[0.059]	[0.057]	[0.063]
Families (log)	0.792***	0.772***	0.778***	0.828***
	[0.105]	[0.110]	[0.103]	[0.120]
Time trend	-0.027***	-0.034***	-0.031***	-0.026**
	[0.002]	[0.001]	[0.001]	[0.012]
Kyoto	0.146	0.074	0.106	0.132
	[0.146]	[0.192]	[0.175]	[0.168]
Public R&D in Renew. (log)	0.056	0.051	0.093	0.526*
	[0.103]	[0.113]	[0.107]	[0.310]
REP Index	0.149***	0.069*	0.130***	0.105*
	[0.044]	[0.040]	[0.039]	[0.060]
Aggregate PMR	-0.122*			-0.095*
	[0.067]			[0.054]
REP Index × PMR	-0.025*		-0.025**	-0.014
	[0.013]		[0.010]	[0.014]
REC new	0.001			
	[0.028]			
Average Feedin	1.817			
	[1.804]			
PMR: barriers to entry		-0.166***	-0.110**	
		[0.062]	[0.047]	
PMR: public ownership		-0.065*	-0.031	
		[0.038]	[0.043]	
PMR: vertical integration		0.01	0.018	
		[0.047]	[0.040]	
R&D in Renew. × PMR				-0.142**
				[0.072]
Constant	51.224***	65.622***	59.134***	49.618**
	[4.290]	[2.232]	[2.651]	[23.732]
Observations	843	843	843	843
Hansen J	0	0	0	0

Estimation time span: 1976-2007. Independent variables *15y Pre-Sample Mean*, *Electricity Consumption (log)*, and *Energy Price Index (log)* are not reported for convenience only, although they are always included. Standard errors are cluster-robust by countries. Statistical significance at 99%, 95% and 90% is denoted by (***), (**) and (*), respectively.

Table 7: Pre-Sample Mean Poisson Model with Linear Feedback. GMM Estimator with Endogenous Regressors. Dependent Variable: Family Weighted Number of Green Patents.

	Model 10	Model 11	Model 12	Model 13
Linear ρ	0.668***	0.731***	0.706***	0.648***
	[0.091]	[0.089]	[0.084]	[0.079]
Families (log)	0.745***	0.842***	0.879***	0.764***
	[0.102]	[0.115]	[0.121]	[0.103]
Time trend	-0.016	-0.012	-0.018	-0.017*
	[0.013]	[0.016]	[0.015]	[0.009]
Pre-Sample Mean	0.003**	0.004***	0.004***	0.003*
	[0.002]	[0.002]	[0.001]	[0.002]
Electricity Consumption (log)	-0.019	-0.155	-0.209*	-0.037
	[0.110]	[0.122]	[0.124]	[0.110]
Energy Price Index (log)	2.252	2.289	1.778	1.777
	[1.590]	[1.999]	[2.052]	[1.915]
Public R&D in Renew. (log)	0.121	0.187	0.138	0.078
	[0.145]	[0.134]	[0.134]	[0.071]
Kyoto	0.169	0.102	0.115	0.177*
	[0.134]	[0.130]	[0.120]	[0.106]
REP Index	0.121**	0.121**	0.134***	0.130***
	[0.052]	[0.054]	[0.047]	[0.038]
Aggregate PMR	-0.129	-0.095	-0.114	-0.116**
	[0.086]	[0.076]	[0.077]	[0.058]
REP Index × PMR	-0.021	-0.033**	-0.029*	-0.023*
	[0.017]	[0.016]	[0.015]	[0.013]
Constant	29.919	22.13	34.798	32.073*
	[26.987]	[31.962]	[29.538]	[19.383]
Observations	819	811	819	814
Moments	15	17	17	18
Hansen's J	4.461	8.324	8.598	5.082
Hansen d.f.	3	5	5	6
Hansen critical probability	0.216	0.139	0.126	0.533

Pre-Sample Mean information computed for the first 15 years available. Estimation time span: 1976-2007. Standard errors are cluster-robust by countries. Statistical significance at 99%, 95% and 90% is denoted by (***), (**) and (*), respectively.
List of endogenous regressors: R&D in renewable energy; Policy Index; Aggregate PMR; Policy Index × PMR.
List of instruments: Model 10: R&D in renewable energy lagged one year, Policy Index, Aggregate PMR, Policy Index × PMR lagged one and two years; 2. Model 11: instruments from Model 10 augmented with DG before liberalization and with GDP per capita; Model 12: instruments from Model 10 augmented with DG before liberalization and democracy longevity (Tensys); Model 13: instruments from Model 10 augmented with democratic longevity (TENSYS), the number of years in office (YRSOFF) of the government and remaining to the government (YRCURNT).

Table 8: Robustness Checks Using Number of Green patents (Models 14 and 15) and Triadic Filtered Number of Green Patents (Models 16 and 17) as Alternative Measures of Innovation. PSM estimators with exogenous (Models 14 and 16) and endogenous regressors (Models 15 and 17).

	Model 14	Model 15	Model 16	Model 17
Linear ρ	0.793***	0.807***	0.480***	0.536***
	[0.059]	[0.045]	[0.151]	[0.096]
Number of patents (log)	0.798***	0.781***	*0.773****	*0.768****
Number of triadic patents (log)	[0.122]	[0.071]	[*0.057*]	[*0.059*]
Time trend	-0.048***	-0.044***	-0.025**	-0.024*
	[0.003]	[0.012]	[0.012]	[0.014]
Pre-Sample Mean	0.009**	0.010**	-0.003***	-0.004***
	[0.004]	[0.004]	[0.001]	[0.001]
Electricity Consumption (log)	-0.128	-0.122	0.112	0.152***
	[0.112]	[0.091]	[0.070]	[0.055]
Energy Price Index	3.877**	3.505**	-0.897	-1.314
	[1.789]	[1.749]	[1.448]	[1.348]
Public R&D in Renew. (log)	0.086	-0.055	0.177**	0.240**
	[0.117]	[0.162]	[0.082]	[0.108]
Kyoto	0.492***	0.577***	0.255*	0.124
	[0.136]	[0.126]	[0.148]	[0.170]
REP Index	0.085**	-0.016	0.232***	0.233***
	[0.038]	[0.047]	[0.052]	[0.042]
Aggregate PMR	-0.174**	-0.337***	-0.076	-0.103
	[0.079]	[0.091]	[0.047]	[0.069]
REP Index × PMR	-0.021	0.006	-0.027**	-0.023**
	[0.017]	[0.024]	[0.014]	[0.011]
Constant	91.550***	85.433***	43.595*	41.924
	[5.049]	[23.629]	[23.607]	[27.858]
Observations	843	819	843	814
Moments	12	17	12	18
Hansen's J	0	5.431	0	6.894
Hansen d.f.	0	5	0	6
Hansen prob.	.	0.366	.	0.331

Standard errors are cluster-robust by countries. Statistical significance at 99%, 95% and 90% is denoted by (***), (**) and (*), respectively. Models 15 and 17. List of endogenous regressors: R&D in renewable energy, Policy Index; Aggregate PMR; Policy Index × PMR. List of instruments: (Model 15) R&D in renewable energy lagged one year, Policy Index, Aggregate PMR, Policy Index × PMR lagged one and two years; (Model 17) Model 15 augmented with tensys (length of democracy), yrsoffc (years in office of the government) and yrcurnt (years remaining to the government).

Table 9: Marginal Effects of Policies on Various Forms of Innovation in Environmental Energy

Variable	Patent Family Model (13)	Patent Number Model (15)	Triadic Patents Model (17)
Unconditional median and *mean*	42	25	*7.942*
Long Run Multiplier	3.4	5.2	2.2
Energy Price	*1.577*	0.910	*-0.256*
	3.76	3.64	*-3.23*
Public R&D in Renew. (log)	*0.900*	*-0.030*	0.595
	2.14	*-0.12*	7.50
Kyoto	*2.510*	2.629	*0.381*
	5.98	10.51	*4.79*
PMR varies, REP Index at the mean	5.233	3.757	*1.065*
	12.46	15.00	*13.41*
PMR varies, REP Index at the 25^{th} per.	3.524	3.828	*0.559*
	8.39	15.31	*7.04*
PMR varies, REP Index at the 75^{th} per.	6.107	3.723	*1.384*
	14.54	14.89	*17.43*
REP Index varies, PMR at the mean	1.236	*0.063*	1.070
	2.94	*0.25*	13.47
REP Index varies, PMR at the 25^{th} per.	2.631	*-0.012*	1.501
	6.26	*-0.05*	18.90
REP Index varies, PMR at the 75^{th} per.	0.047	*0.094*	0.677
	0.11	*0.37*	8.52
REP Index × PMR (Both vary)	6.154	*3.816*	2.061
	14.65	*15.27*	25.95

Italics denote marginal effects derived from non-significant parameters at the 10% level.
Each cell displays the variations in the expected number of patents and the change in the expected number of patents relative to the median or *mean* for triadic patents.
All marginal effects have been computed as discrete changes in the expected number of patents. The expected number of patents has been computed using the *mean* values of all explanatory variables, while fixing the variable of interest x_j at the 1^{st} and 3^{rd} quartiles.