IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2015, 5(3), 889-900.

EJ EconJournals

Influencing Factors Promoting Technological Innovation in Renewable Energy

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ABSTRACT

The issue of climate change, oil price fluctuation and the increasing environmental awareness have triggered the importance of effective energy management systems in a bid to reduce greenhouse gases. Renewable energy (RE) which is one of the effective method of effectively managing energy system has seen rapid development in recent times. Technological innovation in RE have not been generally successful due to some influencing factors in some countries. This study investigates these factors in order to identify the influencing factors promoting innovation in RE. Using patent application data for 12 Organization for Economic Co-operation and Development countries for the period of 1997-2011, we analysis the influence of government R and D, feed-in-tariff (FIT), electricity from renewables, per capita income, CO_2 emission per capita and population on patenting activity in wind and solar energy using a panel data approach. The result showed that electricity from renewables and CO_2 emission per capita significantly improves patenting activity. Per capita income showed a positive impact on patenting activity for wind energy but not solar energy. Population size was observed to reduce patent activity, while R and D expenditure and FIT did not significantly influence patent activity. We therefore recommend that investment into renewables for electricity generation should be encouraged as this will induce innovation in RE technology and reduce CO_2 emission.

Keywords: Renewable Energy Patent, Patenting Activity, CO_2 Emission, Organization for Economic Co-operation and Development Countries, Feed-in-Tariff, R and D Expenditure
JEL Classifications: O31, O34, Q4

1. INTRODUCTION

The global climate change and increased environment awareness coupled with the recent changes in oil prices has triggered the necessity of focusing on effective management of energy systems so as to reduce greenhouse gases. Three methods are available to effectively manage energy systems, and they include: Energy efficiency, energy conservation, and switching to renewable energy (henceforth, RE) source. RE technology such as solar and wind presents clean alternative to electricity production from fossil fuel. However, despite current development going on in the RE industry, only 18% of the world's electricity is generated from RE source (IEA, 2010).

The forecast of RE market penetration rates range from highly optimistic judgments to historical trend extrapolation. A cited analytical deficiency has been the linkage between research and development (henceforth, R and D) investment and future RE production costs. RE technologies are limited by their financial/production cost from penetrating the commercial market without the government and institutional support (Kobos et al., 2006). Accelerating technological innovation in RE technologies can contribute to lowering the production cost and cost of RE in the market so that they can compete on a level playing field with conventional fossil fuel source.

In order to accelerate the technological innovation in RE technologies, government support through R and D expenditure is crucial as well as other support policies and incentives such as feed-in-tariff (henceforth, FIT). Besides the role government plays in RE technological innovation, other factors exist which may increase or decrease the rate of technological innovation in RE. They include; demand factors such as electricity demand, population size, environmental factors such as CO_2 emissions, others are per capita income of the population who are the end-users or consumers.

The above mention factors affects the rate of technological innovation in RE and identifying the pattern in which they affect RE development is the aim of this study. In order to investigate these factors, we analysis their impact on RE technologies using solar and wind technologies patent application from 12 Organization for Economic Co-operation and Development (henceforth, OECD) countries. The period of observation was from 1997 to 2011. We found that among the factors under investigation, electricity generation from RE source had a strong positive effect on patenting activity of both technologies (i.e., solar and wind). We also found that the higher the patenting activity, the lower the CO_2 emission level. Per capita income had a positive significant impact on wind patent but not solar.

From a policy point of view, the overall finding that electricity generation from RE matters is welcome. Investment in RE technology will not only reduce CO_2 emission, but also create technological innovations that can further enhance the competitiveness of RE.

The reminder of the paper is organized as follows. Section 2 presents a brief literature review and formulates the hypothesis. Section 3 describes the underlying data source, methodology and result of the analysis. Section 4 provides the result interpretation, comparison with related studies and implications from the results, while Section 5 concludes the study.

2. LITERATURE REVIEW AND HYPOTHESIS FORMULATIONS

In order to identify the factors affecting the technological innovation in RE, we review relevant literatures on patenting activities in RE. The identified factors are energy demand, population, R and D expenditure, FIT, per capita income and CO_2 emission, while RE patenting activity was measured as RE patent application.

2.1. RE Patent

For the rapid deployment of RE technologies, innovation has a very important role to play. These RE technologies like any other technologies, goes through a technology life cycle. There are three steps which make up the technology life cycle and they are; from innovation, through research development and deployment (RD and D) and market development, to commercial diffusion. At each stages in the technology life cycle, different processes are attached which also include different instruments to foster the innovation process. These instruments include intellectual property right (IPR), which refers to the ownership of intellectual findings in industrial, scientific, literary and artistic fields. IPR is divided into two groups which are industrial property rights and copyright. One of the various forms of IPR is patent (IRENA, 2013).

Patent protects an invention and give the inventor a set of exclusive rights for a limited period of time in exchange for detailed public disclosure of their invention. This exclusive rights is granted by a patent office in a sovereign state or a regional patent office acting for several states (WIPO, 2008). From the initial developmental stage of RE technology to market introduction, where competitive technologies needs to be protected, patent plays a prominent role.

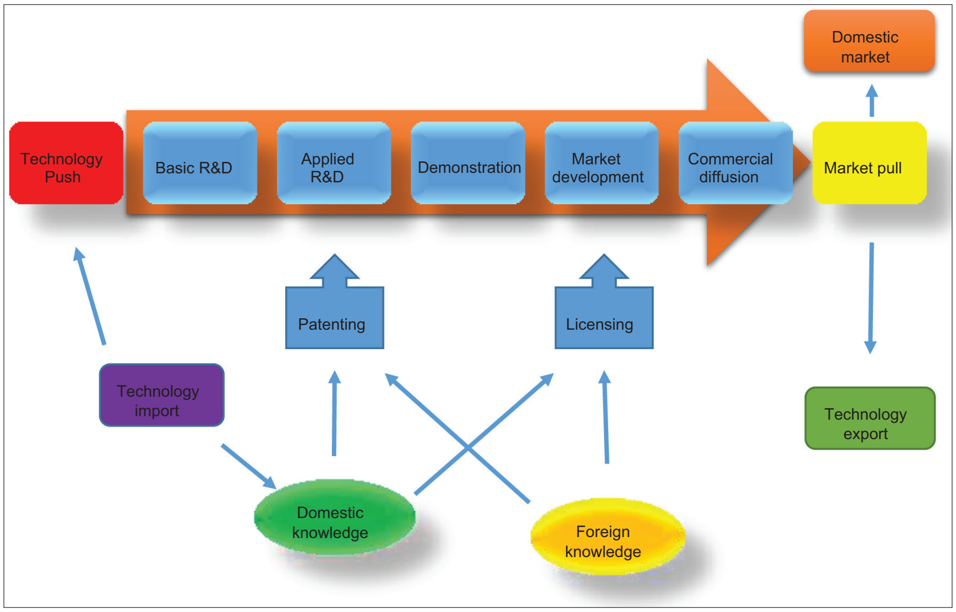
Patent (Figure 1) plays an important roles in two different stages of technology life cycle; in the R and D stage where the successful inventions are patented with patents and can be licensed out to licensees to commercialize the technology (here we can refer to the technology as RE technology). The patents are obtained from either domestic or foreign knowledge source. Technology import can also be a contributing factor to knowledge and at the same time stimulate technology push.

Having patent in mind as a driver of innovation in the field of RE technologies, we review some relevant literatures which investigated the drivers of technology development (innovation) and deployment. Popp et al. (2011) investigated the effect of technological innovations (as reposed in a global technology stock) on the use of RE technologies. They used data for 26 OECD countries for the period of 1990-2004. Their knowledge stock (the dependent variable) was the patent application and the technology was studied were wind, solar photovoltaic (PV), geothermal, and biomass and waste. The independent variables included; RE capacity per capita, net renewable investment per capita, electricity capacity supplied, and some RE policies. The results showed that environmental policy played an important role in new knowledge. Individual RE policies were not significant, while country characteristics were important. Countries making greater use of nuclear power and hydropower had less investment in renewable capacity.

Bayer et al. (2013) examined the determinate of RE innovation on a global scale of which the countries used were OECD and non-OECD (China, Brazil, India and South Africa). The dependent variable used in the analysis was the count of patent filings with the patent cooperation treaty (PCT). The independent variables were oil price, installed RE capacity, democratic institutions and level of corruption. The control variables were; gross domestic product (GDP), net inflows of FDI as percent of GDP, sum of import and export, urban population, urban air pollution. Their results showed that domestic renewable electricity generation capacity and oil prices had strong positive effects on patent activity. A one standard deviation increase in renewable electricity capacity increases the predicted ratio of expected renewable patent counts by 50%, also with the oil price increase will increase the ratio of expected RE patent counts by 13%. They also found that democratic institution had a sizable effect on patent innovation, while corruption did not affect the number of patent application.

Noailly and Smeets (2015) investigated the factors affecting heterogeneous firms' decisions to patent in RE and/or fossil fuel innovation; both at the extensive margin (i.e., whether to conduct any innovation at all) and at the intensive margin (i.e., the rate of innovation conditional on a positive innovation decision). The dependent variables used were the number of granted patents,

Figure 1: The role of patent in technology life cycle



Source: IRENA, 2013 (Modified)

which in the study was termed "the change in innovation." All the model were estimated using zero-inflated Poisson model. There were two models used for the estimation of the coefficients; one was the Poisson model for the number of patents (i.e., the intensive margin of innovation), the second was estimated using the $\log_{it}$ model. Results from the study showed that fossil fuel price positively affected the level of innovation in all firms, as do past knowledge stock. RE market size only increased the level and likelihood of RE innovation of specialized firms. Fossil fuel market size increases the level of fossil fuel innovation in mixed firms but decreases their likelihood of RE innovation entry.

Kim and Kim (2015) investigated the interactions between R and D and international trade (export and import) in RE technology (solar and wind). Through empirical and simultaneous equations. The domestic knowledge stock reflected the depreciation and diffusion of past patent, while the overseas knowledge pool was modeled through summing patent applications for all the countries except country *n*, then the overseas knowledge stock was specified considering diffusion and obsolescence of stock. The export model was described as a function of the domestic knowledge stock, market-pull policies, and domestic and foreign economic size. Similarly, the import model was described as a function of domestic knowledge market potentials. The dependent variables were the export and import previously described in the last paragraph. The exogenous variables were the domestic and overseas knowledge stock.

They used public R and D, public investment, tariff incentives, renewable obligation and environmental taxes as instrument of market-pull. The control variables were population, price of coal as price of fossil fuels, amount of electricity generated, and GDP. They also used gross foreign products which was calculated by summing each country's GDP together and excluding the country *n*. They estimated the coefficient using three stage least squares techniques which was built on two stage least squares and general least squares techniques. The result showed that the interaction between R and D activity and international trade vary by RE technology. Domestic R and D of highly matured technology may be more sensitive to international market than R and D of in-matured technology.

Also, the authors found out that the more intense the domestic R and D activity, the more export and import activity is undertaken. Spillovers from the overseas knowledge stock had a positive impact on R and D activity, but this was not so with the domestic knowledge stock. The domestic stock flow act as a dominate factor to increase export flows. The accumulation of domestic knowledge played an important role in increasing imports of technology and equipment. The literature reviewed suggest the use of patent application as a measure for innovation in the RE industry. We therefore employ patent application as our dependent variable.

2.2. Energy Demand and RE Innovation

It is imperative that in the global bid to reduce carbon emissions and improve energy security, the role of RE technology is undisputed. Although RE technologies is still expensive to the final consumer, some environmental policies in some countries have been put in place to encourage its' investment, adoption and deployment[1]. These policies not only help the end-uses but also firms involved in business. However, some resources have emphasis the need for the adoption of policy regulation as a means to foster innovation in the RE industry (Gray and Shadbegian, 1998; Kerr and Newell, 2003; Snyder et al., 2003; Popp, 2010). Other researchers have

1 Some policies were developed due to the signing of the Kyoto Protocol in December 1997 by the developed countries in their bid to reduce green-house-gas emissions. An example was cited in the European Union (EU) directive of 2001 (Directive 2001/77/EC) which provides a framework for the development of renewable energy technologies in Europe. Some other support policies include production tax credits, mandatory production quotas, tradable certificate and differentiated tariff system (IEA, 2004). On the country level, six different policies can be observed and they include; tax incentives (e.g., accelerated depreciation), tradable certificates, R and D investment incentives (e.g., risk guarantee, grants, and low-interest loans), tariff incentives (e.g., FIT), and voluntary programs, obligations (e.g., guaranteed markets and production quotas).

attributed the growth of innovation activity in the RE industry to the increasing demand of energy (Popp et al., 2011; Johnstone et al., 2008; Marques et al., 2010; Marques and Fuinhas, 2011; Marques and Fuinhas, 2012; Brolund and Lundmark, 2013).

Ever since Schmookler (1966) emphasized the role of demand factors in inducing innovation through his “demand-pull” hypothesis, innovation as a function of market pull has been widely accepted. However, a re-examination of Schmookler (1966) study was carried out by Kleinknecht and Verspagen (1990) who used the same dataset used by Schmookler (1966). Kleinknecht and Verspagen (1990) disagreed to an extent, Schmookler’s un-direction interpretation (“demand-pull”). They concluded that demand may favor innovation and innovation may create extra demand.

In Johnstone et al. (2008) study, they examined the effect of environmental policies on technological innovation of RE. In their study, electricity consumption was used as one of the explanatory variables because they believed that a growing market for electricity should increase incentives to innovate with respect to RE technologies. For this variable, they used data for household and industrial electricity consumption. Although public policies shows significant effect in their results, electricity consumption generally was insignificant. The public policies where those in-support of increased generation from RE source. They concluded that public policies and incentives that support increased generation from RE source were effective in facilitating innovation in RE technology.

Marques and Fuinhas (2011) studied the factors explaining the use of RE deployment in European countries. Energy consumption per capita was one of the independent variables used as a developmental indicator. This was the basis for the formulation of their third hypothesis (i.e., H3) which was; “the larger energy consumption per capita motivates RE deployment.” They however did not neglect fossil fuel source which may have a negative impact on RE development. This forms the forth hypothesis (H4) which was; “there is a negative relationship between the weight of the fossil sources for electricity generation and the use of renewables.”

Also, other clean-low carbon source of energy such as nuclear was considered as a demotivating factor in the development of RE. This forms the fifth hypothesis (i.e., H5); “The use of nuclear power demotivates the use of RE. Their results showed that fossil fuel and nuclear energy consumption had a positive impact in the reduction of RE deployment. However, energy consumption per capita had a significant impact on the deployment of RE.

Popp et al. (2011) assessed the impact of technological change on investment in RE capacity in 26 OECD countries from 1991 to 2004. They considered investment in wind, geothermal, solar PV, biomass and waste form of RE. Electricity supplied from nuclear power and hydropower and fossil fuel were used as a single independent variable among other variables. The results shows that countries making greater use of nuclear power and hydropower had less investment in renewable capacity.

Marques and Fuinhas (2012) re-investigated the effect of public policies on RE development through the use of empirical model on a large panel of European countries. Among the control variables, two different kinds of driver were controlled for; the first was energy consumption per capita and the second was a dummy variable (D10) which captures the contribution of RE to the total energy supply. The results showed that both variables had significant impact on the development of RE. A supporting study was carried out by Brolund and Lundmark, 2013 to investigate the effect of RE policies on innovation in bioenergy in 14 OECD countries. Among the market variables used, energy consumption had a significant positive effect on innovation in the countries analyzed.

All the literatures mentioned have expressed the importance of energy consumption (or electricity consumption, RE consumption, fossil fuel consumption, nuclear energy supply) in fostering or degrading the rate of innovation and deployment of RE technologies. We however consider this in our analysis and include electricity generation from RE. The hypothesis (henceforth, H) developed is given as follows.

H1: The higher electricity generation from renewables, the higher the patenting activity.

2.3. CO_2 Emission

CO_2 emission have been used in several literatures as a determinate factor in patenting activity. According to Dinda (2011), there is a plausible connection between emission of CO_2 or as we know as carbon dioxide emitted in country level towards the technology production. To measure the technology production, the paper used number of patents as base of measure. The dataset was time series data on for the period 1963-2008 from US patent office website. The results provide the analysis of number of patent and emission of CO_2 did have relationship. In long run, they have positive significant relationship but in short run, technology productivity can reduce the rate of CO_2 emission.

With support for the argument, Wang et al. (2012) found out that there is relationship between the emissions of CO_2 emitted in country level towards the technology patenting. In his research, the dataset used was the number of energy technology patent in China from the year 1985 to 2005. Although in the dataset, there is no division on the energy technology patents for the RE. The empirical results show that the emission of in China kept decreasing from the year of 1985 to 1997. Then it was increasing from the year 1998 towards 2001 with declining rate again after 2001.

Beside the rate of CO_2 emissions, Wang et al. (2012) also identified there was a positive significant relationship between number of technology patent and CO_2 emissions on short run. It means that in case of China that time, the number of energy technology patents did not help to reduce CO_2 emissions in short run. But for long run, there was negative significant relationship showing that for longer timeline, number of energy technology patent was actually reducing the CO_2 emissions in China. For GDP, It was found that there was negative relationship between energy technology patents and GDP.

Based on these facts, we can build hypothesis on the relationship between CO_2 emission per capita and our dependent variable, which is number of patents for RE on wind and solar technology:

H2: CO_2 emission per capita has a positive significant impact on RE patent.

2.4. R and D Expenditure

On R and D expenditure, literatures have widely acknowledge the importance of R and D expenditure on RE innovation. These expenditure may come from the government or industry concerned in the development of RE. According to Gan and Smith (2011) which attempted to identify some key factors that may have driven RE development especially in bioenergy sector. The result found that only country specific factors such as GDP and policies have significant and positive impacts. While R and D expenditures, energy prices CO_2 emission and energy policies are statistically insignificant in terms of their impact on RE supply. However, this does not necessarily mean that they are not potential drivers for RE, but rather suggests that their magnitudes have not been big enough to significantly influence energy supply based on the data used for this paper.

Albrecht et al. (2015) estimated the deployment costs for renewable generation technologies in European Union (EU) countries, they found that European governments should critically evaluate current renewables subsidy scheme and public RD and D investment to support next waves of RE technologies. Bointner (2014) provided a literature review on innovation drivers and barriers and an analysis of the knowledge induced by public R and D and patents in energy sector. The result show that appropriate public R and D funding for R and D associated with subsequent promotion of the market diffusion of a niche technology may lead to a breakthrough of the respective technology.

From the above mentioned literatures, we formulate our hypothesis for FDI which is given as follows;

H3: Government R and D investment improves patenting activity in the RE sector.

2.5. FIT

Government support policies for RE development such as FIT were also considered as a determining factor for innovation in RE. From the literature, Johnstone et al. (2010) found that public policy plays a significant role in determining patent applications. Different types of policy instruments are effective for different RE sources. Broad-based policies, such as tradable energy certificates, are more likely to induce innovation on technologies that are close to competitive with fossil fuels. More targeted subsidies, such as FIT, are needed to induce innovation on more costly energy technologies, such as solar power.

Brolund and Lundmark (2013) investigated the various RE policies used in 14 OECD countries have affected innovation in the RE (bioenergy) field. Innovation have been estimated using patent counts for the period 1978-2009 and the policies examined are FIT, quota obligations and different types of investment support schemes. The result from the study found that FIT have affected innovation positively. Another finding is that electricity prices seem to be an important determinant of innovation and that the accumulated stock of knowledge in the bioenergy sector also has a positive impact on bioenergy innovation.

The effect of environmental policies on innovation under different levels of competition was investigated by Nesta et al. (2014). Their result showed that public policies were more successful when new players developing radical technologies enter the market. Public interventions such as investment incentives and tax credits can help alleviate financial constraint and make entry more profitable. FIT will help reduce the uncertainty associated with the future option of selling RE once the upfront costs have been paid and at the end will induced innovation.

From the literature, we derive our hypothesis which is given as follows;

H4: FIT incentives positively influences the rapid innovation in RE technologies.

2.6. Population and Per Capita Income

The population of a country and the per capita income may be termed as a market demand which can have an impact of RE patenting activity. If the size of the country's population is high, so does the energy demand which may force the deployment of RE technologies. Also the purchasing power of the end-user which is the per capita income can also determine the rate of innovation in RE (if the end-user earns more money, they will have more tendency to purchase RE technology which will increase the demand and so more reason to invest in R and D by the manufacturers). According to Yueh (2009) who studied the determinants of patenting activities in China, the log of per capita was one of the independent variable used in the study. The result showed that per capita GDP is significantly positive. The result is consistent with higher income incentivizing technological improvement to produce more sophisticated output to suit the more developed market.

Kim and Kim (2015) studied role of policy in innovation and international trade of renewable technology. In this study, population was used as one of control variable to determine interrelation between domestic R and D and internal trade. Accordingly the analysis result shows that population has more negative significance while using wind power technology. We however take both population and per capita income as independent variables which may have impact on the development of RE technologies, hence the hypothesis is given as follows;

H5: The size of a country's population have the tendency to influence the innovation level of RE technology.

H6: The per capita income of a country plays a vital role in inducing and improving RE patenting activity.

3. DATA AND METHODOLOGY

3.1. Data

3.1.1. Patent application

Data used for this analysis are from 12 OECD countries in total included in the sample (Austria, Canada, Denmark, France, Germany, Italy, Japan, Republic of Korea, Netherland, Norway, Spain and United Kingdom) constituting a panel data set for time period 1997-2011. In our analysis, patents as an output measure were generated from OECD patent database which classified as patent application deposited at European Patent Office (EPO). We count the total number of patent applications for two RE technology, solar and wind power technology, which we considered as the most develop RE technology recently. Figures 2 and 3 shows wind and solar technology patent from 1997 to 2011 in our selected countries.

3.1.2. Independent variables

For our independent variables we include several data regarding RE R and D expenditure, electricity generation, population, GDP per capita and CO_2 emission. We also use FIT as dummy variables to our estimation. RE R and D expenditure are measured as annual R and D expenditure (in million US$ 2013 price) in solar and wind technology. The annual total sum of solar and wind R and D expenditure in 12 countries included in this study has risen from US$ 459 million to US$ 2.323 million for the period 1995-2011 (in 2013 US$ million).

Figure 2: Wind technology patent application

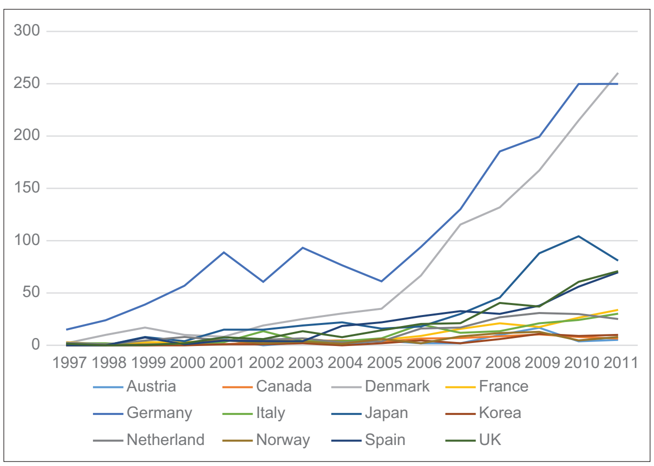
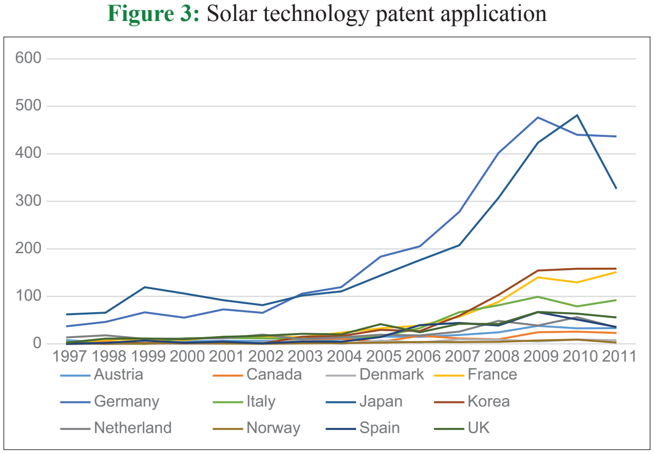


Figure 3: Solar technology patent application



In our estimation we considered two years lag time before expenditures is considered could be presented as innovation (Söderholm and Klaassen, 2007). Electricity generation measures the electricity generation that comes from RE in the countries in gigawatthours value. Electricity generation represent the market demand for RE technology innovation which we considered have correlation with patent.

3.1.3. Data source

The data for population, GDP per capita, electricity generation from RE source were sourced from the World Bank database (World Bank, 2015). CO_2 emission, R and D expenditure and patent application were sourced from OECD statistical database (OECD, iLibrary). FIT history for the countries were obtained from The institute for building efficiency[2]. Population was measured as thousand person and GDP per capita valued as current US$ per capita in sample countries. CO_2 emission was the environmental factor since our countries in the sample are OECD countries which has to limit their emission. So, RE use for electricity generation could be tools to reduce their emission target. Under a FIT, eligible renewable electricity generators are paid a cost-based price for the renewable electricity they supply to the grid. This enables diverse technologies (wind, solar, etc.) to be developed and provides investors a reasonable return. In our estimation we considered that each country implemented FIT in different year. Table 1 shows descriptive variables of all data that used in our estimation.

3.2. Methodology

3.2.1. Model

In order to investigate the factors that influenced patent application in RE sector based on our independent variables, we set following model equation is specified:

$$PATENTS_{i,t} = \beta_0 + \beta_1\, R\&D_{i,t-2} + \beta_2\, EG_{i,t} + \beta_3\, GDP_{i,t} + \beta_4\, Pop_{i,t} + \beta_5\, CO_{2i,t} + + \beta_6\, FIT_{i,t} + \varepsilon_{i,t}$$

Where i = 1, 12 indexes the cross-sectional unit (country) and t = 1997, 1998, 2011 indexes time. As our explanation before, our dependent variables is patent application is measured by the number of patent applications in each of the technological areas of RE (wind and solar). The independent variables include specific R and D expenditures (R and $D_{i,t-2}$), electricity generation from RE ($EG_{i,t}$), GDP per capita ($GDP_{i,t}$), Population ($Pop_{i,t}$), CO_2 emission (CO_2), $FIT_{i,t}$. All the residual variation is captured by the error term ($\varepsilon_{i,t}$).

3.2.2. Estimation

For our estimation, we use panel data estimation in order to measure patent as our output value from our independent variables across countries and time. In statistics and econometrics, the term panel data refers to multi-dimensional data frequently involving measurements over time. According to Green (2003) panel data contain observations of multiple phenomena obtained over multiple time periods for the same firms or individuals. Panel data allows you to control for variables you cannot observe or measure like cultural factors or difference in business practices

2 www.institutebe.com/energy-policy/feed-in-tariffs-history.aspx.

Table 1: Descriptive statistics of variables

Variable	Shortened variable names[3]	Observation	Mean	SD	Min	Max
Year		158	2004.696	4.098639	1997	2011
Country		158	6.544304	3.428236	1	12
Electricity generation from RE (log of GWh)	log_EG	158	3.863359	0.5634604	2.029384	5.024674
Population (log in thousand unit)	log_pop	158	4.503474	0.4491679	3.649521	5.107403
Carbon dioxide emission (ton per capita)	CO2	158	9.378556	2.611983	5.198147	17.5
FIT (dummy)	FIT_dum	158	0.6708861	0.4713855	0	1
Number of wind tech patent application based on EPO (dependent variable)	Wind_patent	158	28.48985	49.17345	0.25	260.45
Number of solar tech patent application based on EPO (dependent variable)	Solar_patent	158	58.58483	96.36567	0.4	481.1536
GDP per capita (log of $US)	log_GDP	158	4.531644	0.1661061	4.051382	4.996035
RE R and D expenditure (solar and wind) (log of million US$)	log_RD	158	1.615929	0.4953626	0	2.506949

SD: Standard deviation, GWh: Gigawatthours, FIT: Feed-in-tariff, EPO: European Patent Office, GDP: Gross domestic product, RE: Renewable energy

across companies; or variables that change over time. With panel data you can include variables at different levels of analysis suitable for multilevel or hierarchical modeling. A general panel data regression model is written as $y_{it} = \alpha + \beta' X_{it} + U_{it}$ Different assumptions can be made on the precise structure of this general model. Two important models are the fixed effects model and the random effects model. The fixed effects model is denoted as,

$$y_{it} = \alpha + \beta' X_{it} + U_{it}$$

$$u_{it} = \mu_i + v_{it}$$

μ_i are individual-specific, time-invariant effects (for example in a panel of countries this could include geography, climate etc.) and because we assume they are fixed over time, this is called the fixed-effects model. The random effects model assumes in addition that,

$$\mu_i \sim i.i.d. N(0, \sigma^2_{¼})$$

And,

$$v_{it} \sim i.i.d. N(0, \sigma^2_v)$$

That is, the two error components are independent from each other.

In the end we will test those two model with Hausman test and decide which model is better which will be used as our final estimation. All data and estimation results are available upon request from the author, while the estimation was carried out using STATA 12 software. As the Table 1 shows the descriptive summary of the variables that we used on the regression, which the result will be presented later on this section. Before the regression is done, we have to check the correlation on the independent variables to know which variables that have high correlation between each other. If the one of the variables has high correlation with some other variables, then those variables should not be regressed together in order to avoid the multicollinearity. The result on the correlation test of the variables that will be used on the regression shown in Table 2.

3 Shortened variable names are used to simplify the use of long variable names on the regression and other statistical result on this section onwards.

Table 2: Correlation test result

log_EG	log_pop	CO_2	FIT_dum	log_GDP	log_RD
log_EG	1				
log_pop	0.5017	1			
CO_2	−0.0339	−0.0873	1		
FIT_dum	0.0406	−0.2303	−0.1706	1	
log_GDP	0.2042	−0.4379	0.0229	0.1804	1
log_RD	0.6641	0.4044	0.0451	0.0874	0.2368

FIT: Feed-in-tariff, GDP: Gross domestic product

The result on the correlation test shows that the variables do not correlate with high correlation coefficient. This will imply on the regression that all the variables can be used with all the combinations possible in order to get the best estimation for the dependent variables with avoidance of multicollinearity.

After testing the correlation on the variables, ordinary least squares (OLS) regression was done to get the best estimation. After numbers of simple OLS regressions, final estimation for both the dependent variables of number of wind tech patent application based on EPO and number of solar tech patent application based on EPO based on the OLS regression method. The final OLS results for both dependent variables can be shown in Table 3.

The OLS regression provides result on the significant variables that affecting both the dependent variables. For the wind technology, the GDP is significantly affecting number of patent applied. The GDP gives positive significant coefficient towards the dependent variable. For the case of solar technology, the number of patent also significantly positive related with GDP from the countries that included on the regression. Both dependent variables of number of solar and wind RE technology applied also have positive significant correlation with the R and D expenditures by the government on the RE specified for the solar and wind RE technology. The difference between both the dependent variable is the last significant variables for both the dependent variables. Number of patent on the wind technology is negative significantly affected by the carbon dioxide emission in the countries. With the number of patent on the solar technology, it has positive significant relationship with the population in the countries included in the regression.

3.2.3. Panel data regression on number of patents for wind RE technology

The result of OLS regression will not be the final estimation that this paper will use. The data set will also be regressed on the panel data estimation with both fixed and random effect regression. Considering the dataset are divided on countries and years, panel data regression will help to identifying the effect towards the dependent variables considering certain timeline. After the panel data regression on both the fixed and random effect, we will test them with Breusch–Pagan Lagrange multiplier (LM) and Hausman test. The Breusch–Pagan LM will be tested to decide which estimation is better between the final OLS regression and the random effect regression. Then Hausman test will decide whether the fixed effect regression is better than the random effect regression for our dataset. For the first panel data regression for wind RE technology, fixed effect regression was done. The result can be shown in Table 4.

Based on the result above, the number of patent for wind technology has significantly positive coefficient towards the electricity generation from RE, also with GDP per capita population. On the other hand, population and carbon dioxide emissions in the dataset countries give negative significant effect on the number of patent for wind renewable technology. For R and D and FIT policy seem do not produce significant effect to the dependent variable. *F*-test result also resulting lower than 0.05, which means that all the coefficients are different than zero. For the same dependent variable, the result on the random effect panel data regression can be shown in Table 5.

The result on Table 5 shows that there are different variables that have significant effect towards the number of patent on the wind RE technology. If the fixed effect identified that the electricity generation from RE and GDP per capita population have positive significant relationship with wind technology amount of patent, then for random effect, it identifies only electricity generation from RE gives positive significant effect. As for carbon dioxide emissions and the FIT policy produce negative significant effect towards the number of patents for the wind technology. Population, GDP, and R and D do not provide significant effect to the dependent variable. The value of Chi-square also below than 0.05 showing that the model is suitable.

After doing both panel data regression on fixed and random effect, we can do the LM test to see whether the random effect regression result is better than the OLS regression that previously had been done. The result on the test can be seen on Table 6.

The Breusch–Pagan LM test gave the result on the value of test result is lower than 0.05, we can reject the null hypothesis which is variances across entities is zero. So in result, we can say that random effect regression gives better result than the OLS regression. Also we have to compare which one between the random effect and fixed effect panel data regression gives better result. To decide this, the Hausman test can be used. Table 7 will give the result on Hausman test on both the regression on panel data. Based on the result, we can derive that fixed effect regression is better than random effect regression since the value from the test shows lower than 0.05.

Table 3: OLS regression results for both dependent variables

Variables	Number of wind tech patent application			Number of solar tech patent application		
	Coefficient	SE	*t*	Coefficient	SE	*t*
log_GDP	67.348**	21.851	3.08	166.624***	46.368	3.59
log_RD	32.638***	7.332	4.45	49.028*	15.283	3.21
CO_2	−2.542*	1.351	−1.88			
log_pop				107.26***	18.215	5.89
_cons	−305.602**	97.576	−3.13	−1258.77***	254.265	−4.95

P<0.05, ***P*<0.01, ****P*<0.001, OLS: Ordinary least squares, SE: Standard error, GDP: Gross domestic product

Table 4: Result on fixed effect panel data regression on number of patent for wind technology

Wind_patent	Coefficient	SE	*t*
log_EG	60.0***	14.850	4.04
log_pop	−1631.042***	353.799	−4.61
CO_2	−23.673***	3.658	−6.47
FIT_dum	−10.934	8.717	−1.25
log_GDP	135.967**	41.7	3.26
log_RD	−1.856	7.072	−0.26
_cons	6758.107***	1503.115	4.5
		F (6,140)	22.29
		P>*F*	0

P<0.05, ***P*<0.01, ****P*<0.001. SE: Standard error, GDP: Gross domestic product

Table 5: Result on random effect panel data regression on number of patent for wind technology

Wind_patent	Coefficient	SE	*t*
log_EG	56.106***	14.086	3.98
log_pop	−35.066	26.682	−1.31
CO_2	−11.434***	2.868	−3.99
FIT_dum	−15.539*	8.917	−1.74
log_GDP	36.605	34.419	1.06
log_RD	−3.134	7.601	−0.41
_cons	−72.148	198.268	−0.36
n		Wald χ^2 (6)	86.42
		$P>\chi^2$	0

P<0.05, ***P*<0.01, ****P*<0.001. SE: Standard error, GDP: Gross domestic product

Table 6: Breusch pagan LM test result for wind technology

Breusch and Pagan LM test for random effects	
Chi-bar2 (01)	141.27
P>Chi-bar2	0

Table 7: Hausman test result on wind RE technology

Hausman test	
H_0: Difference in coefficients not systematic	
χ^2 (6)	30.32
$P>\chi^2$	0.000

3.2.4. Panel data regression on number of patents for solar RE technology

For the second part, number of patents on solar RE technology will be the dependent variable. With the same steps of regression as the wind technology, the regression will begin on the fixed effect regression. Table 8 shows the result on the fixed effect regression on the solar technology.

Table 8 provides the result on the fixed effect regression for the solar technology. As the coefficients show, electricity generation from RE has positive significant effect into the number of patents applied on the solar RE technology. But for population and the carbon dioxide emissions in those countries inside the dataset, they create negative significant result towards the number of patents applied on the solar RE technology. FIT policy, GDP, and R and D didn't leave significant results. The *F*-test also rejects the null hypothesis, so that all the coefficients are different than zero, which makes this regression is suitable. Next result on Table 9 is the random effect regression result on the number of patents on solar RE technology.

Random effect regression gives unique result on the significant variable. The only significant variable is the electricity generation from RE, which affect positively. The other variables don't provide significant effect towards the number of patents for wind RE technology.

The same systematic with the solar technology, both Breusch–Pagan LM test and Hausman test also have to be done. As explained before, LM test gives decision on which one is better between random effect regression and the OLS regression. As for the Hausman test gives the better regression among fixed and random effect regressions. Table 10 provides the result on Breusch–Pagan LM test.

Table 10 results prove that the random effect regression is better than the OLS regression result. This can be seen on the value of test, which is lower than 0.05. We derive that variances across entities is not zero.

Table 11 presents the results on Hausman test for the solar technology. The results manage to show that fixed effect regression is better than random effect regression. This is proven by seeing the value of the test is lower than 0.05. We can reject the null hypothesis and prove that fixed effect regression gives better results.

To be simplify the regressions that have been made and considering all the test results including the Breusch–Pagan LM test and Hausman test, we can derive that the best regressions for both the technology are the fixed effect ones. Table 12 provides simplified information with the re-statement on the variables that are significant and insignificant variables for better view on the perspectives from both technologies.

Table 8: Result on fixed effect panel data regression on number of patent for solar technology

Solar_patent	Coefficient	SE	*t*
log_EG	219.479***	26.957	8.14
log_pop	−3789.612***	642.228	−5.9
CO_2	−25.733***	6.641	−3.87
FIT_dum	−8.353	15.824	−0.53
log_GDP	81.533	75.697	1.08
log_RD	3.222	12.838	0.25
_cons	16149.34***	2728.51	5.92
		F (6,140)	28.46
		$P>F$	0

$P<0.05$, **$P<0.01$, ***$P<0.001$, SE: Standard error, GDP: Gross domestic product

Table 9: Result on random effect panel data regression on number of patent for solar technology

Solar_patent	Coefficient	SE	*t*
log_EG	125.974***	25.07	5.02
log_pop	6.744	40.409	0.17
CO_2	−7.462	4.732	−1.58
FIT_dum	−23.597	16.876	−1.4
log_GDP	2.123	62.985	0.03
log_RD	6.566	14.912	0.44
_cons	−390.424	345.947	−1.13
		Wald χ^2 (6)	84.3
		$P>\chi^2$	0

$P<0.05$, **$P<0.01$, ***$P<0.001$, SE: Standard error, GDP: Gross domestic product

Table 10: Breusch Pagan LM test result for solar technology

Breusch and Pagan LM test for random effects	
Chi-bar2 (01)	82.02
P>Chi-bar2	0

LM: *Lagrange multiplier*

Table 11: Hausman test result on solar RE technology

Hausman test	
H_o: difference in coefficients not systematic	
χ^2 (6)	105.31
$P>\chi2$	0.000

4. IMPLICATIONS AND COMPARISON

4.1. Implication

Based on our estimation to test the factor influencing in RE patent activity in 12 OECD countries, our result show that in both wind and solar patent application activity only electricity generation give positive statistically significant while population and CO_2 emission gave a negatively significant effect. In addition to that the only different is in wind technology, GDP also give positive significant effect.

For electricity generated from RE source, the result is in-line with the future energy innovation. The more a country invest in electricity from RE source, the more patenting activity because the manufacturers will be encouraged to develop the technology to be more efficient and cost effective. As RE electricity generation will continually increase across OECD countries, the capacity to innovate will also increase on the long run. However, the increasing oil prices may force the OECD countries to innovate more in RE technologies.

The decrease in CO_2 emission will increase the number of patent applications. This invariably means the more patenting activity the OECD countries engage in, the less CO_2 emission. In a bid to reduce the rising CO_2 emission level which according to the IEA (2010) report, should be reduced by 50% in 2050, OECD countries have been making drastic effort to reduce CO_2 emission by 4% per year. These effort includes investment into RE innovation which is believed will reduce CO_2 emission. This implies that patenting activities in OECD countries in RE technologies have reduced

Table 12: Comparison on both RE technology with fixed effect regression

Variables	Wind technology			Solar technology		
	Coefficient	SE	*t*	Coefficient	SE	*t*
log_EG	60.0***	14.850	4.04	219.479***	26.957	8.14
log_pop	−1631.042***	353.799	−4.61	−3789.612***	642.228	−5.9
CO_2	−23.673***	3.658	−6.47	−25.733***	6.641	−3.87
FIT_dum	−10.934	8.717	−1.25	−8.353	15.824	−0.53
log_GDP	135.967**	41.7	3.26	81.533	75.697	1.08
log_RD	−1.856	7.072	−0.26	3.222	12.838	0.25
_cons	6758.107***	1503.115	4.5	16149.34***	2728.51	5.92

SE: Standard error, GDP: Gross domestic product, ***P<0.001

CO_2 emission. So OECD countries bid to reduce CO_2 emission has increased RE innovation. From the above, our hypothesis one and two (i.e. H1 and H2) were strongly supported for both technologies.

For RE R and D expenditure which was statistically not significant in our estimation, implies that the country need to change their focus to stimulate market implementation approach for developing RE (solar and wind) patenting activity (IEA, 2004; Roos et al., 1999). FIT had no significant impact on the patent activities which implies that government approach in guaranteeing a set price for RE, do not induced additional innovation for more cost-competitive technologies such as wind power. This result was supported by Johnstone et al. (2010) who explained that this is due to installation cost of some renewables which are usually capital intensive and sometime require some sort of "technology forcing" by the government. Government support to RE innovation through R and D expenditure and incentives such as FIT may not directly increase patenting activity but may indirectly support innovation in RE. The above results did not support our third and fourth hypothesis (i.e. H3 and H4).

The negative significant level observed for the population variable implies that an increase in population reduces the level of patent activities. This implies that countries with higher population tend to patent less than countries with lower population. This result is a bit controversial because the higher the population, the more energy demand which may indirectly stimulate innovation from the RE manufacturers. However, it may also have a negative impact if the country refuse to engage in patenting activity, rather they choose to meet the electricity demands and CO_2 emission reduction. Our result is consistent with Kim and Kim (2015) study where population was used as a control variable but showed a negative significant level. This invalidates our fifth hypothesis (i.e.. H5).

The per capita income showed a positive impact on patent activity for wind but not for solar energy. This may be true due to the following reasons; (1) wind energy technologies have changed in recent times with the constant patent filings for wind energy, and they include patent rotor form, regulation and pitch adjustment (Dubarić et al., 2010), (2) the wind technology has been evolving from its early discovery to data with manufacturers making several improvement in the blade, rotor, size, megawatt capacity, etc., (3) wind power technology is the fastest growing RE technology in the EU which make up a large number of the OECD (9 EU countries were included in our OECD selected countries). The EU have also made a binding target to increase renewable generation to 20% by 2020 of which wind energy potential is high (Dubarić et al., 2010). Solar energy on the other had have not been the most preferred choice for EU countries as compared to wind power. According to Liu et al. (2011), solar PV technologies still have not been going strong and suggested government support to induce innovation in solar energy technology. Our sixth hypothesis (i.e. H6) is supported here for wind energy but not solar energy.

4.2. Comparison with Other Works

The regression results that had been done gave the results that the fixed effect panel data regression gives the best estimation for the dataset. The identified factors from our regression can be compared with another work to provide more robust identification on factors determining the development of the RE by measuring the patent propensity on this case, solar and wind technology. Some papers actually offer different factors than the results from our regression. Table 13 provides more insight in different factors from the other works also.

As the Table 13 shows our result on the significant variables based on the result on fixed effect panel regression. The significant variables are electricity generation from the RE, population, carbon dioxide emission, and the GDP per capita for the wind technology. Population and carbon dioxide gives negative implication, the other significant variables create positive significant implications. Another paper with similar topic by Johnstone et al. (2010) stated different implications with different significant variables for the same technology. As for wind, among the variables, Johnstone et al. (2010) provided significant positive result on the number of patent on the wind RE by R and D expenditures but negative significant implication by the FIT policy.

Other significant variables that are identified in our results were not identified as significant on the Johnstone et al.'s paper. This also applies to the solar technology results. According to our results, electricity generation from the RE makes positive significant implication and population with carbon dioxide emission give negative significant implications. Johnstone et al. (2010) came up with R and D expenditures and FIT policy as significant variables. As the R and D gives positive effect, FIT gives negative effect towards the number of patent on the RE technology respectively. Different dataset for different countries and timeline can be the reason why there are differences on the results of the factors. As the timeline, our paper has shorter timeline but more updated. As the countries, we had 12 countries and some of them differ between paper and our dataset.

Table 13: Comparison with other studies

Variables	Our Results		Johnstone et al. (2010)		Brolund and Lundmark, (2013)
	Wind Technology	Solar Technology	Wind Technology	Solar Technology	Bioenergy
Electricity Generation from Renewable Energy	✓	✓		✓	
Population	✓ (−)	✓ (−)			
Carbon Dioxide Emission	✓ (−)	✓ (−)			
GDP	✓				
R&D Expenditures			✓	✓	✓
Feed in Tariff			✓ (−)	✓	✓

✓ denotes significant level, (+) positive, (−) negative

Another work was from Brolund and Lundmark (2013) also differs with our work. Based on our research objectives, we are trying to identify in the wind and solar technology for the development of RE. On Brolund and Lundmark (2013), they main technology was bioenergy. As both the technology from our results and Brolund and Lundmark (2013) are still qualified in RE, we can compare them together. Again we can identify different significant factors on those RE technologies. As we mentioned that for wind technology, electricity generation from the RE and GDP per capita for the wind technology have significant positive effect, population and carbon dioxide emission, gives negative implication but significant.

Solar energy which is the electricity generated from the RE source, build positive significant effect and population with carbon dioxide emission, which give negative significant implications. For Bioenergy technology, it seems that among all factors that we use, the factors that affecting the technology are R and D expenditures and FIT policy for both give significant positive effect. Although the differences can be explained, as the technologies are different, the dataset of the patent filling also differs. We used the EPO patent application, but on the Brolund and Lundmark (2013) used PCT application. This explains the alteration between results.

5. CONCLUSION

Addressing the issue of climate change through the development of RE can be achieved in several ways and one of them is through the rapid technological innovation in RE technology. However, some factors influence the growth in innovation of RE and this study identifies these factors. The study used patent application data for 12 OECD countries to identify the influencing factors such as government R and D, FIT, electricity from RE, per capita income, CO_2 emission per capita and population. The technology focused in this study was wind and solar energy for the period of 1997-2011. We carried out our empirical analysis using a panel data approach.

The result from the analysis showed that electricity from renewables and CO_2 emission per capita significantly improves patenting activity. As electricity generation capacity from renewables increases, patenting activity also increases. Also the more patenting activity, the less CO_2 emission. This implies that a country's effort in increasing electricity generation from RE will boost innovation in RE technology while reducing CO_2 emissions. Per capita income showed a positive impact on patenting activity for wind energy but not solar energy. This may vary from country to country because wind energy is most preferred by EU a country which forms a large sum of the OECD countries analyzed in our study. Also, wind potential is very high in EU countries as compared to solar energy.

Population size was observed to reduce patent activity, while R and D expenditure and FIT did not significantly influence patent activity. This implies that country with lower population engage in patenting activities more than countries with larger population. While this may not be the case in every situation, most countries with larger population intend to focus more on improving electricity supply from RE to its large populace while considering reducing CO_2 emission. For R and D expenditure and FIT, these policies may indirectly encourage innovation through the supply chain but not directly and so we may not be able to catch the direct significant impact on patenting activity. Our recommendation is for the increase investment in renewables for electricity generation which will induce innovation in RE technology and reduce CO_2 emission.

Limitations exist in our study as we did not separately classify patents based on foreign and domestic source so as to examine the impact of the factors based on foreign and domestic knowledge (although Kim and Kim, 2015 used this as knowledge stock in their study). We also did not consider several other influencing factors used by other researchers and we needed to expand our work to other source of RE technologies so as to capture the influencing factors as a whole. Another limitations is on the OECD countries, we only used 12 countries which may not explain to a wider range how this factors influences other OECD countries and non-OECD countries like China, Brazil, India and South Africa. We therefore point this as a future research direction for researchers.

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