**The creation of renewable energy technology in Europe - are patents per capita converging?**

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**Abstract**

This paper investigates whether a convergence or divergence of national innovation capabilities regarding renewable energy patents of the 13 EU countries occurs in the course of the time period 1990-2010. An answer to the research question permits immediate conclusions with regard to the success prospects of the EU's Renewable Energy Directive (2009/28/EC), which sets climate and energy targets for both 2020. The empirical analysis is focused on whether renewable energy patents have converged or diverged between the countries. The data is based on patents granted at the European patent office. The methodologies applied draws from the economic convergence literature. The initial results have showed signs of conditional beta and sigma divergence in renewable energy invention abilities.

**Keywords:** convergence, panel unit root test, renewable energy

**JEL Classification** O30, O40.

[*] Financial support from the Swedish Research Council Formas and The Ragnar Söderberg Research Foundation is gratefully acknowledged as are valuable comments and help from Patrik Söderholm and Carol Dahl. Any remaining errors, however, reside solely with the authors.

## 1. Introduction

In October 2014, the European Union (EU) set ambitious climate and energy targets for both 2020 and 2030 (European Commission, 2014). The EU's Renewable Energy Directive (2009/28/EC) sets a binding target of 20% final energy consumption from renewable sources by 2020. To achieve overall EU level goal, member countries have committed to reaching their own national renewables targets ranging from 10% in Malta to 49% in Sweden (European Commission, 2015a). The 2030 policy framework sets a target of at least 27% for renewable energy and energy savings by 2030. Every two years, the EU publishes a renewable energy progress report; the report indicates what results have been attained. In 2014, the projected share of renewable energy in the gross final energy consumption was 15.3%. In the EU in 2012 was 14.1%, up from 8.7% in 2005 (European Commission, 2015b). The majority of the countries are achieving the plan; however, some Member States, including France, Luxembourg, Malta, the Netherlands and the United Kingdom, and to a lesser extent Belgium and Spain need to assess whether their efforts are sufficient in meeting their renewable energy objectives (European Commission, 2015b).

Renewable energy offers a possible solution to the emission problem the 2020 and 2030 targets are created for; to reduce the renewable energy solution lets people keep their standard of living - but with a less polluting energy mix. Allot of the low hanging fruit is gone, the best locations for wind power are for example in many cases already in use and the resistance is growing the closer new plants get to people’s backyards.

The objective of this paper is to determine if a convergence or divergence pattern has emerged renewable energy patents per capita in Europe during the time period 1990-2010. The question is important to answer considering that the effect of international technology flows crucially depends on the destination country's ability to comprehend and make use of external knowledge (Mancusi, 2008). Therefore the ability to receive technological spillovers or use advancements made abroad are a function of the country's past experience in research, if there is no absorptive capacity then the spillover flow might not exist (Cohen & Levinthal, 1989).We also know that the renewable energy development record in Europe are mixed with substantial power capacity increases in some countries and far more modest developments in others (IEA, 2014b).

Considering Cohen & Levinthal (1989) and Mancusi (2008) work on technological development, it raises two possible scenarios for the movement direction of renewable energy technology in Europe. Either there will be convergence where laggard countries learn from more advanced countries. The alternative is divergence where the less technologically developed countries are not able to implement new renewable energy in an optimal phase.

The first scenario has its roots in the most basic form of economic convergence. It is assumed that developing countries will grow faster than the more developed countries in percentage term. Thus, if the process continues, the poor should eventually catch up to the rich. For our case, convergence implies countries which have a low level of patent activity at the beginning would grow at a faster rate and would eventually catch up to the technological leaders (Keefer & Knack, 1997). Speaking against the converging per capita renewable energy patent production is technological cluster theory. Cluster theory suggests that a good deal of competitive advantage lies outside companies and even outside their industries, residing instead in the locations at which their business units are based (Porter, 2000). In the technological research example this implies increasing returns to investments in areas where there already exist other research.

The paper hypothesizes that there has been a divergence in patents per capita between the EU countries during the time period 1990-2010. The development process has mainly been driven by the higher goals and the level of support some countries give to renewable energy and also because of a trend where invention and technological development are concentrating towards certain geographical areas. This hypothesis is tested by preforming several convergence tests. Firstly, conditional $\beta$-convergence, meaning convergence after differences in the steady states across countries have been controlled for, estimations on a dataset of all renewable energy patents taken in 13 Europe countries during the time period 1990-2010 are performed. Secondly, other aspects of distribution dynamics will also be investigated such as tests for sigma convergence, when the dispersion of renewable energy patents per capita across a group of economies decline over time. Thirdly, Gamma convergence, the changes in an index of rank concordance, will be presented. Finally, the density functions and contour plots will be analyzed to asses if there are convergence clubs.

The empirical part of this paper uses methodologies drawn from the economic convergence literature that have been previously applied to other fields such as environmental performance see: (Aldy, 2006; Romero-Ávila, 2008) and CO2 emissions e.g. Nguyen Van (2005), Orda´s Criado and Grether (2011) and Strazichich and List (2003). The research question is highly important to answer. The papers main contribution is that it is a novel investigation of convergence to an important field of economic growth i.e. technology, which has so far not been investigated in the form proposed. Bernard and Jones (1996, p. 1037) pointed out that technology and technological progress are featured prominently in almost every other analysis of economic growth except in the convergence literature. The importance of technological convergence comes from the fact that technology is one of the main drivers of economic development (e.g. Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Jones, 1995).

The rest of the paper is organized as follows: in section 2 previous environmental convergence research is reviewed. Section 3 briefly discusses the data and the use of patents as a proxy for innovation. Section 4 presents the empirical findings from the Neo-classical convergence models and describes their econometric modeling in detail. Section 5 presents some implications of the results. Section 6, offers conclusions and some suggestions for future research in the area of convergence for patents per capita.

## 2. Literature review

The convergence literature has its origins from the classical Solow model (Solow, 1956). Neoclassical growth models have shown that a country's per capita growth rate often is negatively correlated to the starting level of income per person (Barro, 1991). In the neo-classic model, decreasing returns to capital are assumed; the consequence is that poorer countries are predicted to experience higher growth rates than richer countries. Capital will flow to countries were the return to investment is larger, usually where wages are low, if the institutions are favorable (Maurseth, 2001). The theory is plausible but the evidence is mixed; Baumol (1986) found evidence of this pattern in a dataset of OECD countries while DeLong (1988) failed to find evidence supporting the theory. Recent endogenous growth theorists (Romer, 1986; Lucas, 1988; Barro and Sala-i-Martin, 1992; and Islam, 2003; among others) have strongly spoke against this argument by pointing at several failures of per capita income to equalize across poor and rich countries.

Jungmittag (2004) showed that if technologies vary across countries, convergence of per capita incomes and labor productivities will only occur if there is a converging development of national innovation capabilities. If this is not the case, countries will only converge to their own steady states and therefore stay on different economic development levels. Furthermore, Jungmittag (2006) shows, by means of unit root tests for time series and panel data approach, mixed evidence of patent convergence during the time period 1963-1998, concluding that evidence of an absolute convergence of innovation capabilities is an exception among European countries.

Several papers have emphasized the decisive role technology plays for long run economic convergence. Fagerberg et al. (1996) found that there had been a convergence of income and productivity level in Europe during the post war period, but that the convergence process slowed down and gradually came to an end during the 1980s. In a study of technological convergence between the fifteen first EU members and the eight that joined after them. Žižmond and Novak, (2007) found significant technological convergence when looking at the level of investments (i.e. gross fixed capital formation). Mulas-Granados and Sanz (2005) found, in a regional study over some European countries, that as the distribution of patents and public R&D converged, income per capita converged too. Maurseth (2001) found that convergence re-emerged at the end of the 1980s and in the 1990s. It was explained by combined result of poor regions catching up with richer ones again, peripheral regions grew faster than central ones, innovation and of technology spillovers.

There are arguments against a convergence process. Speaking against the scenario of a converging per capita production of technology, like the thoughts of GDP convergence, is technological cluster theory. Technological clustering implies that knowledge production is clustered to certain geographical areas. Clusters suggest that a good deal of competitive advantage lies outside companies and even outside their industries, residing instead in the locations at which their business operations are based (Porter, 2000). In the example of technological research, clustering theory implies increasing returns to investments in areas where other research already exists. Companies will locate to places where other innovative companies are and researchers will leave laggard countries to work in countries where there are larger returns on ideas. The most commonly used example of a cluster in an industry is the Silicon Valley, where high-tech firms establish themselves even though the costs are significantly higher there than in for example rural Idaho.

The convergence approach has previously been taken to environmental applications For instance, Strazicich and List (2003), Nguyen-Van (2005) and Brock and Taylor (2010) and Ordás et al. (2011) who studied the convergence of $CO_2$ emissions in the world. An important finding of the environmental literature is that an inverted-U relationship exists (frequently termed the environmental Kuznets curve, or EKC) between country wealth and environmental degradation

(Grossman and Krueger 1995). The basic notion is that emissions increase with income in lower income countries to a certain point and decrease with income in higher income countries. From the economic convergence literature, it is theoretically established that all countries will have the same income level following the economic convergence hypothesis. Therefore, if the EKC and economic convergence hypotheses are valid, environmental convergence is expected (Strazicich and List 2003).

A number of country specific general macroeconomic conditions are expected to affect the rate and direction of innovation with respect to renewable energy, including (size and openness of an economy, international trade and cross country labor market mobility). Further, general propensity to patent determined by the strength of intellectual property rights regimes, scientific and research capacity also play a part for the groundwork. However, while such factors affect patents in total they do not specifically affect those associated with emission-control technologies (Hascic et al. 2009).

Johnstone et al. (2010, 2012) have empirically investigated different aspects of policies that drive innovations in renewable energy finding that the innovation rate can be affected by policy instruments. Popp (2002) uses U.S. patent data from 1970 to 1994 finding that both energy prices and the quality of existing knowledge have strongly significant positive effects on innovation. Another way is to look at to what extent environmental policies drive the creation of patents (Nicolli, et al. 2012; Trajtenberg, 1990). Johnstone et al. (2010) focus on a renewable energy case, studying the effect of environmental policies on technological innovation by using patent data from 25 countries over the time period of 1978 to 2003. Johnstone et al. (2010) showed that both general innovative capacity and environmental policy stringency have a positive effect on environment- related innovation creation.

## 3. Data Sources and Methods

### 3.1 Data Sources and Definitions

Firstly, conditional beta-convergence assumes possible differences among countries. What will be tested is whether the renewable energy patents per capita among 13 EU countries countries are converging or not. Convergence is thus conditional on similarities in country characteristics. Conditional β- convergence can be examined by adding a set of exogenous variables to the regression equation in equation (1), where differences in the steady states across countries are controlled for (Barro and Sala-i-Martin, 1992). Secondly, sigma convergence is considered. It consists of a dispersion measure widely used in the economic growth literature. The inter-temporal change (i.e., data normalized to the initial year) in the CV (the standard deviation divided by the average) of the cross-country renewable energy patent per capita intensity distribution. If this measure is falling over-time, that result is interpreted as evidence of convergence. Thirdly, the last convergence measure (gamma), the intra-distribution mobility was investigated. Intra-distribution mobility shows whether the countries patent intensity remains the same over the years in relation to each other. Further, in line with Liddle (2010), to determine whether the shape of the distribution of renewable energy patents has changed and converged over time, the kernel of the density estimates of the distribution is created.

The data set is a balanced panel of 13 of the 15 first EU member states in a time span between 1990 and 2010. Greece and Luxemburg have been omitted because of data issues. Renewable energy patents per capita are used as a measure of inventive capacity in a country. The national renewable energy patent statistics were extracted from *OECD´s statistical database*. The data contains the number of patents in the categories; Wind energy, Solar thermal energy, Solar thermal-PV hybrids, Geothermal energy, Marine energy, Hydro energy - tidal, stream or dam less, Hydro energy – conventional. The count is based on the number of approved patents by inventor´s orgin at the European Patent Office (EPO).

Patents, the dependent variable of interest in this paper, have in several econometric analyses been used as indicators to approximate the impact of technological change and innovations (e.g. Fagerberg (1988), Budd and Hobbis (1989a,b), Jungmittag et al. (1999), Jungmittag and Welfens (2002) and Jungmittag (2004)).

*Figure. 1.* displays graphical patterns of total renewable energy patents by country for the sample[1]. During the last ten years there has been a fast growth in wind and solar energy while the other source seems to be gaining some momentum just in the last decade.

[1] The selection is based on the OECD´s classification where all categories of renewable energy are included.

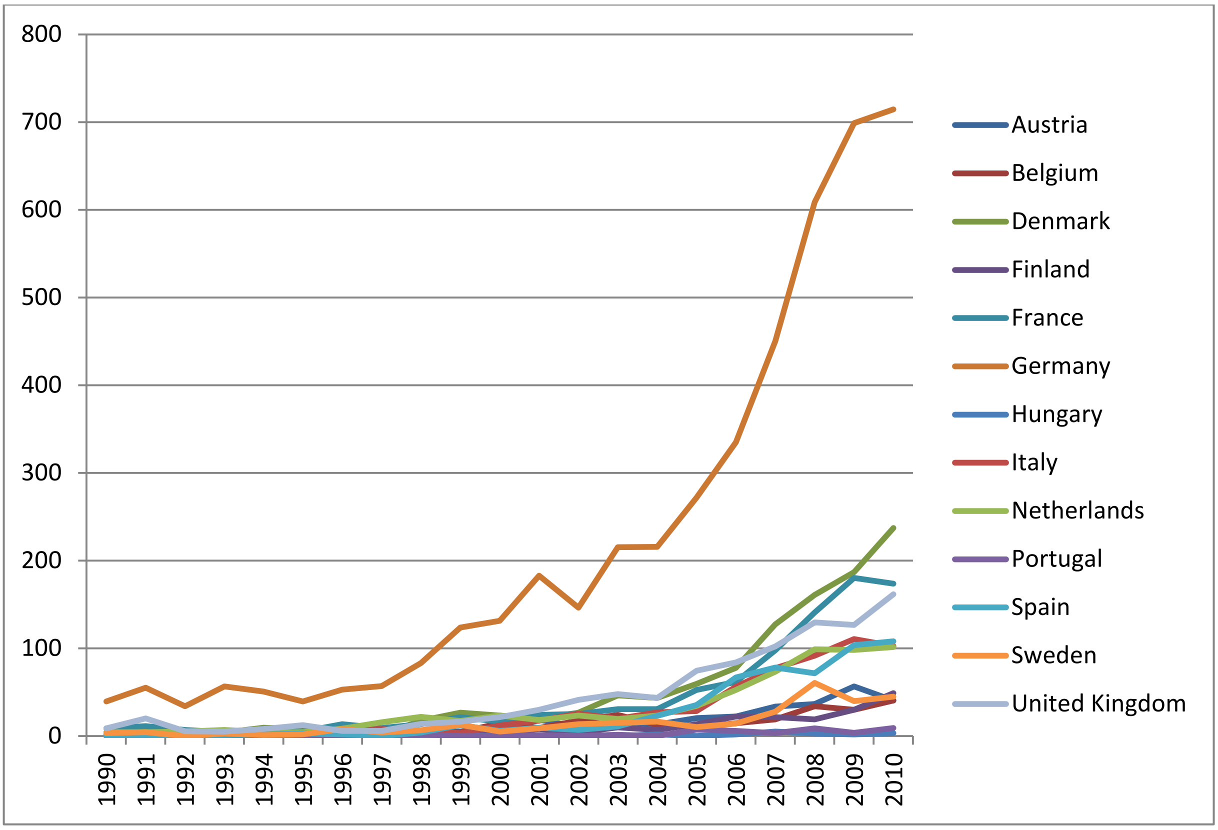


**Figure 1 Total number of renewable patents, by country. Source OECD (2014)**

Aside from environmental policy that affects investment decisions, there are, of course, other determinants of patenting activity for environmental energy production technologies. Based upon Johnstone et. al.´s (2012) review of the literature, four variables are used, which are believed to be particularly important for knowledge production: R&D expenditures, openness to trade, the strength of intellectual property rights (IPR) regimes, and aggregate GDP.

Control variables were used when running the beta-convergence model and the variables were mostly gathered from the OECD's Research and Development Statistics database. With regard to economic theory, the innovation capability of a country is considered to depend fundamentally on three factors: it's common innovation infrastructure, its technological and economic specialization and the quality of the linkages between its common infrastructure and industries (Romer, 1990; Grossman and Helpman, 1991).

The existing knowledge stock in a country has in many papers been found to be a major determinant of innovation (Klaassen, Miketa, Larsen, & Sundqvist, 2005; Krammer, 2009; Söderholm & Klaassen, 2007). R&D spending is commonly considered and used as a variable when determining countries innovative capacity (Furman, Porter, & Stern, 2002). On the GDP side and to some extent the technology side of convergence research different representations of government expenditures have been used as explanatory variable (Barro, 1991a, Carmela, Granados, & Ismael, 2005). Internet penetration is indispensable infrastructure for the diffusion of knowledge. In the scientific community this is evident when assessing internationally co-authored papers from 1986 to 2001, the percentage of internationally co-authored papers has doubled in the majority of countries (Archibugi & Coco, 2005). The access to information should therefore determine a countries ability to catch up and, hence, it is controlled for. The data is presented in the table 2. The variables were in the econometric models run in natural logarithm form.

TABLE 1

VARIABLES AND DEFINITIONS

| Full Variable name | Definition | Source |
|---|---|---|
| Dependent variable: Renewable energy patents per capita | Patents per capita in country i at time t; from all sources patents are divided by million persons in the population. Granted patents by the EPO. | OECD, science and technology indicators. |
| Stock of renewable energy patents taken in the country | Cumulative patents from 1990. Data for an explanation of the construction of the stock. | OECD, science and technology indicators. |
| Aggregate R&D expenditures | R&D expenditures in all sectors in millions of PPP-adjusted 2005 $ | OECD, science and technology indicators. |
| Government final consumption expenditure | Government final consumption expenditure, volume per capita | Economic Outlook - OECD Annual Projections (GDP, unemployment) |
| Oil price in a country | Real petroleum prices are computed by dividing the nominal price in a given month by the ratio of the consumer Price Index (CPI) in that month to the CPI in some "base" period. No national taxes considered. | International Energy Agency data. |
| Imports of energy | Energy imports, net (% of energy use), are estimated as energy use less production, both measured in oil equivalents. | World Development Indicators. World bank. |

**Table I** presents the definitions for the data used for the conditional convergence model.

The paper considers four measures of renewable energy patent convergence. The first measure, called beta-convergence, is applied to determine whether a catch up process takes place between the countries. That is, do countries that had a low patent intensity in the beginning of the time period catch up to those who had a high patent intensity?

β-convergence is said to occur when the renewable energy patent per capita production of a laggard country, with lower initials levels of patents per capita, grows faster than strong invention countries and there is a catching-up effect with the more inventive countries. There are two concepts of $\beta$-convergence; absolute and conditional β-convergence. The $\beta$-convergence is absolute, in the case of this paper, if countries with a low level of patent production and those with a high level have similar determinants of steady state or the long run level of produced patents.[2] A panel approach is

[2] The terminology that is somewhat paraphrased here was first introduced in Sala-i-Martin (1990).

applied; its main usefulness lies in its ability to allow for differences in the aggregate production function across economies. The approach leads to results that would be significantly different from those obtained from single cross-country regressions (Islam, 1995).

We start the conditional beta-convergence test by considering a transformed Barro growth equation in equation (1). The null hypothesis tested is $H_0: \gamma = 0$ and β<0 for all *i*; and the alternative for conditional convergence $H_1: \gamma \neq 0$ and β<0 for all *i*. In a panel data setting, the concept of conditional convergence is tested through

$$\ln(y_{it} / y_{i,t-\tau}) = \alpha' + \beta' \ln(y_{i,t-\tau}) + X_{i,t-\tau} + \delta_i + \eta_t + \varepsilon_{it} \tag{1}$$

where $\ln(y_{it} / y_{i,t-\tau})$ is the growth rate in per capita R&D expenses between $t-\tau$ and *t*, *δ* addresses country-specific effects, and *η* represents period-specific effects. $\varepsilon$ , is the error term A vector( $X_{i,t-\tau}$ ) of additional explanatory variables including R&D spending, human capital, a knowledge stock and internet access is added to equation. The above specification enables testing of the hypothesis that per capita patent growth rates tend to slow down in the long-run as they approach their own long-run growth path. A few noteworthy aspects of equation (4) deserve a brief mention. First, the empirical estimates of (1) is quite straightforward, an estimate of β< 0 implies convergence, while failure to reject the null of β = 0 cannot reject divergence (Strazicich and List, 2003). Conditional *β*-convergence occurs if 0 < $\beta_c$ < 1. Similarly we can also calculate the speed of convergence and the half-life for the conditional *β*-convergence models. As in Islam (1995), the formula is now $\beta_c = \exp^{-\lambda\tau}$ . λ measures the speed at which the level of invention of an EU country approaches its own steady state level.

Starting with the same two measures of sigma-convergence as Ezcurra (2007) and Liddle (2010), first, the inter-temporal (i.e., the data is normalized to the initial year) change is tracked. In order to further investigate, the findings the standard deviation of the logarithms (SDlog) and the coefficient of variation (CV), the standard deviation divided by the average of the distribution were calculated. If this measure is falling over time the result is perceived as a convergence pattern.

$$\sigma = \left( \frac{var\ (GEPPC_{ti}) / mean(GEPPC_{ti})}{var\ (GEPPC_{t0}) / mean(GEPPC_{t0})} \right) \tag{2}$$

After the sigma test, for the last convergence measure (gamma), the intra-distribution mobility was investigated. The intra-distribution mobility shows whether the country with the highest and lowest patent intensity remains the same. An index was constructed ranging from zero to unity. The denominator of the index is the maximum sum of ranks. The closer the index value is to zero the greater the extent of mobility within the distribution. The index, as constructed by Boyle and McCarthy (1999), called gamma-convergence is calculated as:

$$\gamma = \frac{Variance(AR(I)_{it} + AR(I)_{i0})}{Variance(2AR(I)_{i0})} \tag{3}$$

Where $AR(I)_{it}$ is the actual rank of country *i´*s patent intensity in year *t*; and $+AR(I)_{i0}$is the actual rank of country *i´*s patent intensity in the initial year 0.

Further, in line with Liddle (2010), to determine whether the shape of the distribution has changed and converged over time the kernel of the density estimates of the distribution is created. The density of environmental technology patents per capita in the time periods 1990-1995 and 2005-2010 is given by the kernel method. The density of *x* at point $x_0$ is given by

$$f(x_0) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x_o - x_i}{h}\right), \tag{4}$$

Where *n* is the number of observations, K(.) is a univariate kernel function, and *h* is the bandwidth, also called smoothing parameter. The Epanechnikov kernel is used. The Epanechnikov kernel is optimal in a mean square error sense, though the loss of efficiency is small for the other kernels specifications also. The bandwidth, a smoothing parameter, is used and the bandwidth chosen is a common one in the convergence literature, the data-based bandwidth estimation from Silverman (1985).

### 3.3 Econometric Issues

While there have been several convergence studies on data in the realm of GDP, the methods have not extended very far into the environmental or technological development literature. There are a number of drawbacks with the approach which is formally known as Galton's fallacy, regressions turning towards the mean, dating back to 1886.

The main usefulness of using a panel data setting is its ability to allow for differences in the aggregate production function across economies. Following the panel model will lead to significantly different results compared to cross sectional regressions (Islam, 1995). When it comes to the conditional convergence model conventional panel data models may yield biased estimates due to the correlation and endogeneity issues arising from the lagged dependent variable. Kiviet (1995) proposes the use of the least squares with dummy variables bias-corrected (LSDVC) version which is found to be quite accurate even when N and T are small, this method is applied.

As noted by Boyle and McCarthy (1999) - both Sala-i-Martin (1995) and Quah (1993) point out in their papers that σ-convergence is sufficient but not necessary for β-convergence. The implication of this result is that the absence of σ-convergence cannot be taken as implying the absence of β-convergence.

## 4. Empirical Results

First *conditional convergence* is tested. Countries with a low level of invention are expected to be developing faster than those with a high invention level and are all converging to a common level of invention.

TABLE 4 CONDITIONAL *Β*-CONVERGENCE MODEL

| Coefficient | Ln Renewable energy patents$_{it}$ |
|---|---|
| $\beta_c$ Lagged dependent variable | 0.392 |
| | (0.000)*** |
| $\alpha_{1-}$ Researchers per capita | -0.001*** |
| | (0.018) |
| $\alpha_{2-}$ Oil price | 0.317*** |
| | (0.002) |
| $\alpha_{3-}$ Energy imports | -0.006 |
| | (0.432) |
| $\alpha_{4-}$ - Knowledge stock | -0.04 |
| | (0.754) |
| Year Dummies | (See appendix) |
| Number of Observations | 247 |
| $\lambda$ | 0.503 |
| | (0.102)*** |
| Half-Life | 1.377 |

| | |
|---|---|
| | (0.280)*** |

Note: The standard errors are in parenthesis. ***, ** and * denote 1%, 5% and 10% levels respectively.

Intuitively we can understand convergence as a catching-up process, where the distance between two (or more) entities, like countries, diminishes in the course of time and finally becomes a constant. The β coefficient has a positive (0.392) and statistically significant sign, indicating that we cannot say that the renewable energy patents capacity are converging. A positive sign indicates that the countries are growing apart over time.

β-convergence is a necessary condition for σ-convergence, however not a sufficient one. Quah (1993) suggests a methodological approach that allows the complex dynamics of evolving cross-country distributions to be discovered in their entirety. The simple measure of σ-convergence is but a subset of his approach, however a good starting point. The advantage of using the σ measure is twofold. First, it is an unbiased measure of β-convergence. Secondly, it allows one to track the evolution of the convergence process over time. Following the sigma convergence over the years enable us to see if there are any visible peaks in the distribution, a sign that something might have affected the samples development process around that time period. Below the paper explore whether or not σ-convergence is occurring in the selected European Union countries. The inter-temporal change (i.e., data normalized to the initial year) in the CV (the standard deviation divided by the average) of the cross-country renewable energy patent per capita intensity distribution. If this measure is falling over-time, that result is interpreted as evidence of convergence.

As can be observed in Fig. 5, *sigma convergence* results are displayed (normalized to the initial year). The values of CV increased, between 1990 and 2010, thus indicating an increase in the cross-sectional spread of renewable energy patents over time. Thus, for many individual countries, as well as for the full sample of European Union states that are investigated in this paper, σ-divergence occurred from 1990 to 2010. The spread also seemed to be increasing with time after year 2000, up until then there had been sigma convergence that was rather erratic but to some extent stable while there seems to be a break after year 2000. This can possible be explained by the fact that there were a sharp increase in patent activity after that year and that this activity might not have been evenly spread between the countries. The results that were calculated with equation (2)[3] for each year are presented in figure (5) below.

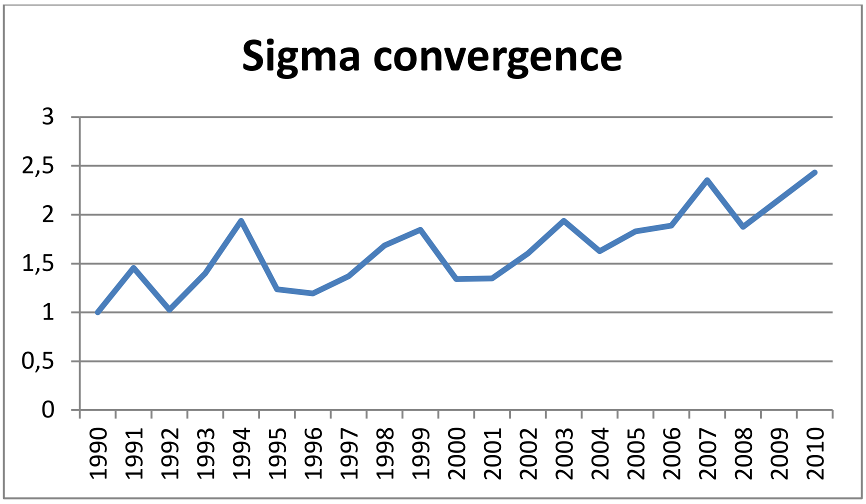


**Figure 5:** Sigma - (CV) divergence in patent intensity for the time period 1990-2010.

The main advantages of the sigma measure are twofold. First, it is an unbiased measure of beta-convergence and second it allows one to track the evolution of the convergence process over time offering the possibility to see if there were time periods where convergence was more prevalent. By looking at the process over time, one can see if there were any significant time periods where some sort of break in the development occurred. Some researchers (e.g., Quah 1997,

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[3]
$$\sigma = \left(\frac{var\ (GEPPC_{ti})/mean(GEPPC_{ti})}{var\ (GEPPC_{t0})/mean(GEPPC_{t0})}\right)$$

Desdoigts 1999) have suggested that interpreting measures of dispersion may not be straight-forward if the distributions are not unimodal[4]. However, as Figure 7, in the gamma case demonstrates, for the EU country-level data the distribution of patents per capita is unimodal for both the period 2005-2010 (with an outlier) and the period 1990-1995.

Fig. 6 shows the *gamma-convergence* or intra-distribution mobility for the samples (normalized to the initial year). First some comments about what we can expect to see. The gamma approach has been tested on the ranking of teams in high sports divisions. There it is expected to see a rather large movement among the teams between the years. If a quarterback gets injured or a lot of important players quit a good team can struggle to make the playoffs. In the case of countries research output there should be slightly less movement since the research output can be expected to be a function of knowledge accumulation as well as spending. The spending can also be expected to be somewhat correlated with external shocks that might strike all the countries, like an economic recession. If the sample is small two things are likely to happen.

If the countries are on a similar path then it is likely that they change ranking more often. If they, however, are significantly on different level compared to each other, then there is less room for changes in the ranking even if there is a lot of change in the countries capacity. In the case of patents, a rather large amount of ranking change could be expected. First of all a patent is a binary event; either you get it or not, and there can be several rejections. On the other hand if a patent is awarded that might be a break true that leads to several new patents following the event. The GDP can be expected to be roughly the same as last year plus some growth rate, unless something unexpected occur.

A value of 1 indicates that there was no change in the intra-distributional ranking. This did not occur a single year. However, most of the years the value was above 0.8 indicating that less than 20 percent of the sample changed place relative to each other, with reservation for that a large change could play a large role. The sample, begining in 1990 display a small amount of change in rank concordance: the declining y-axis value from 1 down to around 0.84 indicate a small change from the 1990 ranking of renewable energy patent intensity. The year 1995 seems to be the where most countries changed rank in per capita production of patents.  Even though it can be noted that there was a period between 1999 and 2005 where there was more movement in the distribution.

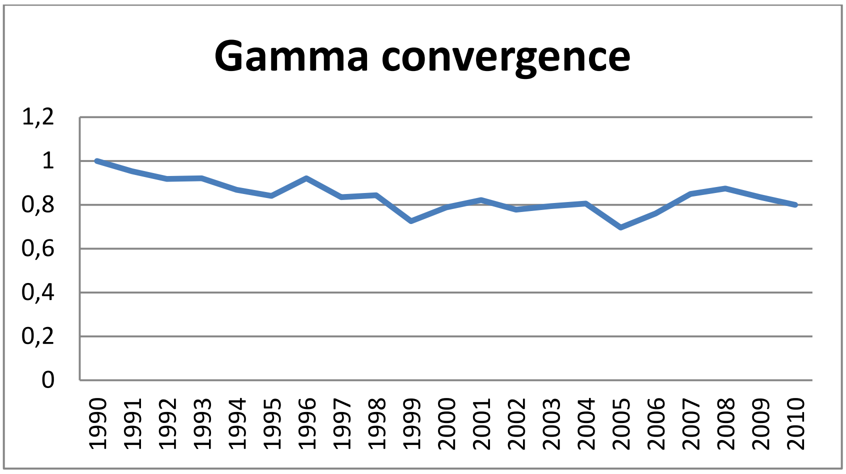


**Figure 6:** Gamma for the time period 1990-2010.

While gamma-convergence clearly does not capture all the potentially wide-ranging features of changing renewable energy patent distribution it nonetheless provides an important additional summary indicator to sigma-convergence regarding the nature of the evolving distribution. It also seems interesting that while no significant change in ranking of renewable energy patents per capita occurs around this time as showed by the small change in gamma distribution, in the subsequent period the process of σ-divergence gathers increased momentum. In other words, we get 'leap frogging' in terms of renewable energy patents per capita leading to a subsequent widening of inter- country gap. The gamma-convergence index main advantage is that it considers a single number traced over time in two dimensions, analogous to the CV sigma-convergence measure.

[4] In mathematics, unimodality means possessing a unique mode. More generally, unimodality means there is only a single highest value, for example the bell shaped normal distribution

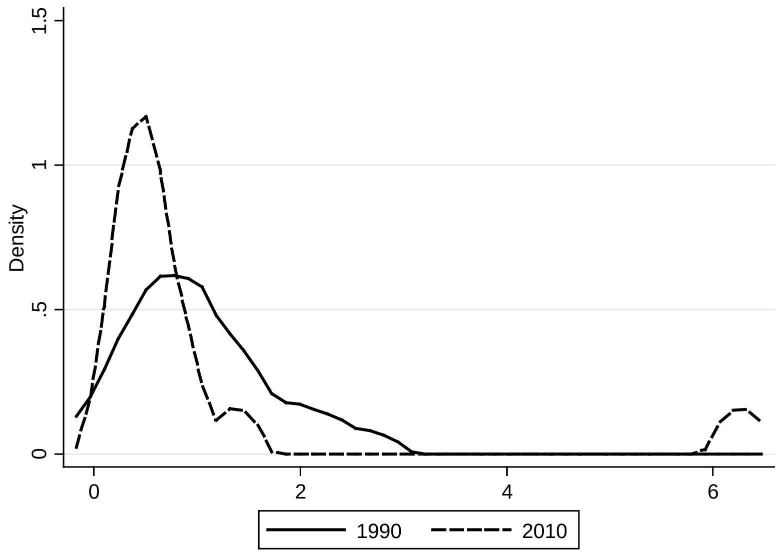


**Figure 2** Density functions of energy patent intensity distribution for the time periods 1990 and 2010.

To complement the findings of the sigma-test and to further assess determine if the shape of the distribution has changed over-time, I look at kernel density estimates of the distribution—a smoothed version of a histogram. Fig. 7 compares the *density functions* of the first and last year of the dataset (13 countries, during the time periods 1990 and 2010). Each country's patent intensity level was normalized to the sample average of that year. The density figures do indicate a narrowing of the distribution. The distribution of renewable technology patents per capita displays a fairly different pattern over the period of study. In addition, countries with relative patents per capita lower than 1 take the highest proportion in the sample.

**5. Implications**

Based on the results, it is evident that in order to develop a proper invention strategy, EU must recognize that its structure is more con-federate than federal where a number of states which retain substantial autonomy. What the Union gains in variety and diversity compared to other large economic block, it loses through a lack of cohesion and central policy decision-making. Europe is a collection of different innovation systems. Some regions of the European Union seem to be strongly integrated in knowledge transmission, while others continue to be peripheral. The enlargement from EU-15 to EU-25 has increased the variety of innovation systems even further, but also the range of countries' technological expertise and stages of development. Even more than before, EU policy needs to take explicitly into account the existing variability in technological competence, innovation performance and industrial structure. The EU 25 is far more different from each other than the 13 countries in this study.

Since Cohen and Levinthal (1989) and Mancusi (2008) found that a low level of own research hampers the possibility to take in technological spillovers from abroad, one core issues for the European Union must therefore be both national and European policy level to promote renewable energy. Johnstone et al. (2010, 2012) showed that there are positive roles of environmental policy stringency but also general innovative capacity. A further next step is to look at which countries are lagging behind and look at what policies can be done to make countries converge in renewable energy output.

**6. Concluding Remarks**

This paper combined both cross-sectional and time series tests for convergence using data on renewable energy patents from 13 industrial countries over the period 1990–2010. In both the conditional beta convergence test and sigma convergence test, the null hypothesis that inventive capabilities have diverged is supported. Overall, these empirical findings provide evidence that per capita patents have spatially diverged. The initial results have showed signs of conditional beta and sigma divergence in renewable energy invention abilities. For the gamma convergence, the movement in the ranking is not especially large over the years but with some exceptions.

Clearly, the result does not support the hypothesis of existence of β-convergence and sigma convergence. Therefore, we cannot reject the occurrence of a divergence pattern. Of particular interest in this paper was the question whether there is a convergence or divergence of national renewable energy innovation capabilities, i.e. whether the different rates are persistent or if they diminish. If there is a converging development of national innovation capabilities, this might also push adoption of the use of renewable energy per capita and hence achieving the 2020 and 2030 goals. Jungmittag (2004) showed that if technologies vary across countries, convergence of per capita incomes and labor productivities will only occur if there is a converging development of national innovation capabilities. If this is not the case, countries will only converge to their own steady states and therefore stay on different economic development levels.

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**Appendix 1**

**Energy generation from renewable and non-fossil sources**

- Renewable energy generation
    - Wind energy
    - Solar thermal energy
    - Solar photovoltaic (PV) energy
    - Solar thermal-PV hybrids
    - Geothermal energy
    - Marine energy (excluding tidal)
    - Hydro energy - tidal, stream or damless
    - Hydro energy - conventional
- Energy generation from fuels of non-fossil origin
    - Biofuels
    - Fuel from waste (e.g. methane)

Table 7 presents descriptive statistics for the data used for the conditional convergence model.

| **Variables** | **Definition** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| Patent counts | The patent counts with respect to wind power technologies. | 3 | 6 | 0 | 31 |
| Research personnel | Number of researchers per 1000 employees in the country. | 5 | 2 | 3 | 12 |
| R&D | Domestic public R&D expenditures to wind power in US$ Million, 2012 prices | 10 | 10 | 0 | 49 |
| Patent-based national stock of knowledge | Stock of granted patents in wind technology, domestic inventors. | 12 | 23 | 0 | 112 |
| Patent-based international (global) stock of knowledge | Stock of granted patents in wind technology. | 97 | 66 | 24 | 211 |
| Natural gas price | Natural gas price, US$ /mmbtu, 2012 prices | 5 | 3 | 3 | 14 |

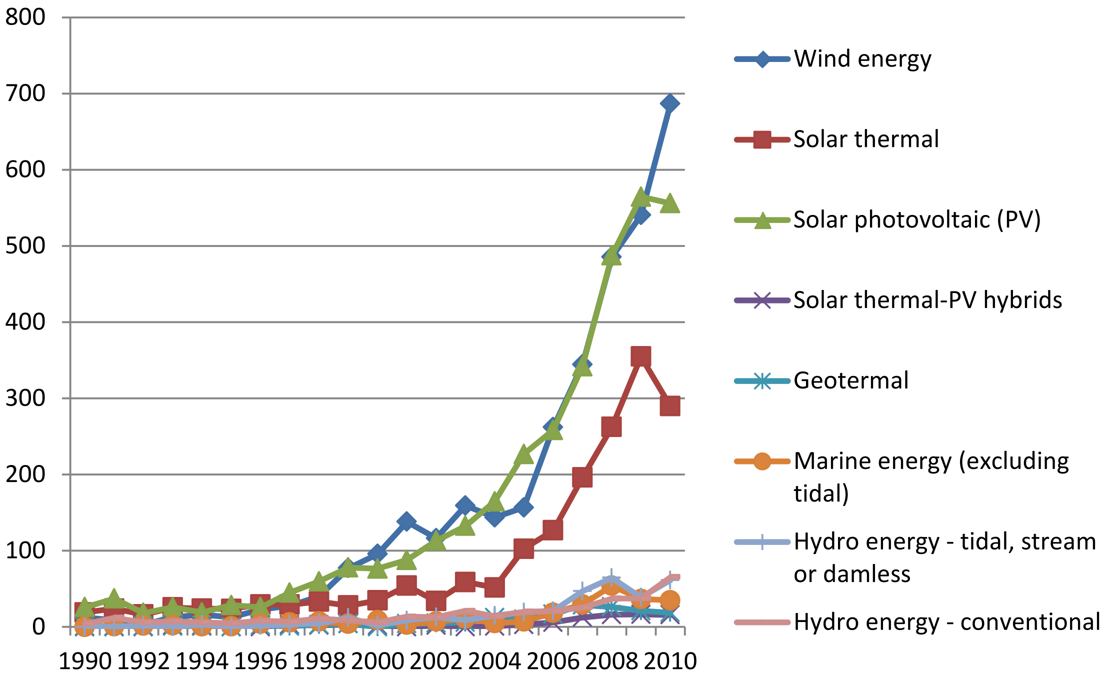



**Figure 6:** Granted renewable energy patents, OECD (2014).

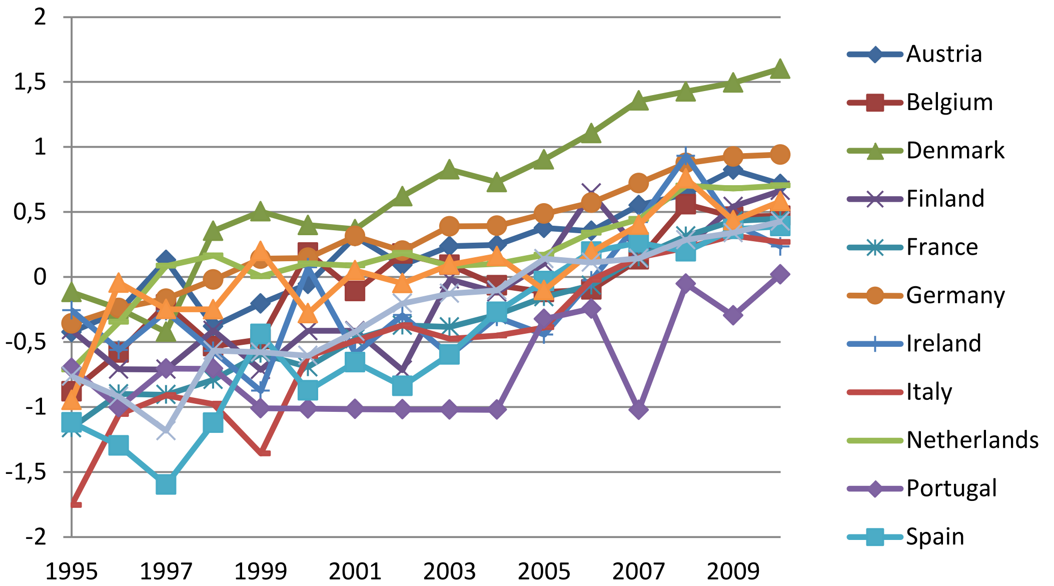
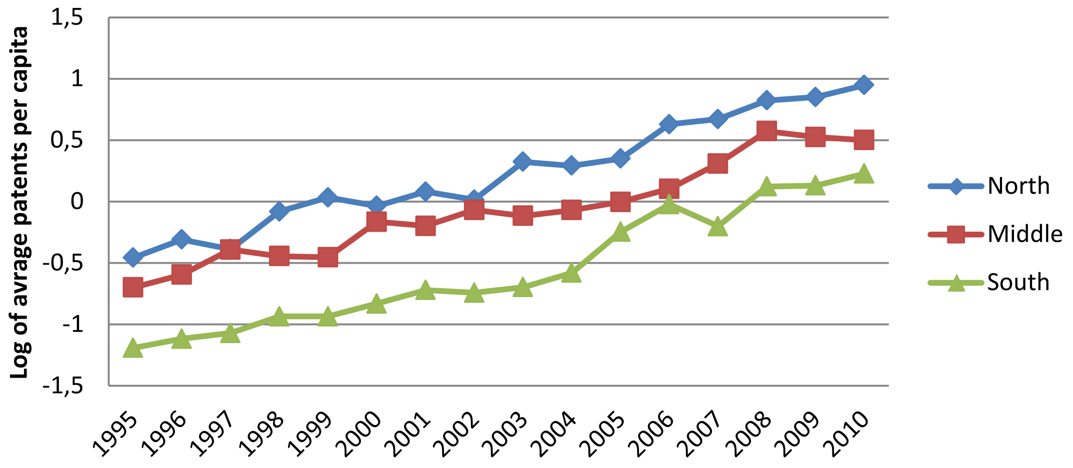



**Figure 7**: The logarithmic patent levels of the whole data set[5] and its development from the 1995 to 2010, OECD (2014).

[5] Finland, Sweden, Germany and Denmark, Austria, Belgium, France, Netherlands, Ireland and United Kingdom, Italy, Portugal and Spain.




**Figur 8:** Logaritmic scale of renewable energy patents per capita. Grouped after region, OECD (2014).

*Figure 3*. plots the logarithmic patent levels of the northern (Finland, Sweden, Germany and Denmark), middle (Austria, Belgium, France, Netherlands, Ireland and United Kingdom) and the southern (Italy, Portugal and Spain) sub region during the period from 1995 to 2010. The figure illustrates how the average patent per capita has developed during the period.

**Results for beta convergence**

| VARIABLES | (1)<br>RnD capita + lnElectricityregulation +real intrestrate All |
|---|---|
| lndpercapitaGreen = L, | 0.392*** |
| | (0.0733) |
| Country RnD per capita | -0.00185** |
| | (0.000780) |
| OilPrices | 0.0116*** |
| | (0.00365) |
| energyimports | -0.00619 |
| | (0.00787) |
| lnknowledgestock | 0.0464 |
| | (0.148) |
| year== 1992 | -0.999*** |
| | (0.362) |
| year== 1993 | -0.589 |
| | (0.502) |
| year== 1994 | -0.664** |
| | (0.326) |
| year== 1995 | -0.440 |
| | (0.390) |
| year== 1996 | -0.188 |
| | (0.399) |
| year== 1997 | -0.240 |
| | (0.378) |
| year== 1999 | -0.179 |
| | (0.385) |

| | |
|---|---|
| year== 2000 | -0.0832 |
| | (0.318) |
| year== 2001 | -0.0281 |
| | (0.388) |
| year== 2002 | -0.115 |
| | (0.328) |
| year== 2003 | -0.0335 |
| | (0.520) |
| year== 2004 | -0.170 |
| | (0.571) |
| year== 2005 | -0.127 |
| | (0.445) |
| year== 2006 | 0.0945 |
| | (0.386) |
| year== 2007 | -0.131 |
| | (0.193) |
| year== 2009 | 0.0434 |
| | (0.487) |
| year== 2010 | -1.295*** |
| | (0.401) |
| Observations | 241 |
| Number of Country | 13 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1