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Convergence of Inventive Capabilities within the European Union: A Parametric and Non-Parametric Analysis*

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Abstract

The development of a single economic market and rapid technological advances in the European Union (EU) have resulted in its Member States undergoing major structural changes over the past few decades. The purpose of this paper is to analyse whether or not there is convergence in the inventive capabilities across the EU. This is done by econometrically investigating, by means of parametric and non-parametric techniques, the development of patents granted per capita in 13 Member States per capita during the period 1990–2011. The findings of several β-convergence and σ-convergence tests show convergence in inventive capabilities. Moreover, a similar result is obtained when analysing the distributional dynamics of the invention capabilities. The speed of convergence is however slow. This suggests that policy efforts implemented by the EU to reduce technological gaps among its Member States have been relatively insufficient, and may imply negative long-term consequences for EU cohesion.

Keywords: convergence, patent, panel data, EU.
JEL classification: O03, O32, O33, O47.

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1. Introduction

From an economic perspective, *convergence* – from the Latin *convergere*, "to meet" or "to unite" – refers to a process where differences between entities featuring a varied initial level of development disappear over time. During the establishment and expansion of the European Union (EU), its various Member States differed from each other with respect to their economic development status. At the time, therefore, and well in line with neoclassical economic growth theory (Solow, 1956), politicians assumed that economic convergence would occur across Member States due to increased opportunities for the mobility of the factors of production.[1] Whether such economic convergence has materialised, however, is now being doubted. Economic research has shown that major technological gaps continue to exist among EU Member States, and that this gap has arguably constrained the EU's integration process (e.g., Pavitt, 1998; Lorenz and Lundvall, 2006; Dobrinsky and Havlik, 2014).

In respect of successful EU integration, convergence in national inventive capabilities is a crucial component of successful European integration. Analysing a variety of countries' long-term national inventive capabilities[2] can offer insights into economic change in general as well as into growth perspectives in particular, (Jungmittag, 2006). In addition, a converging development of national inventive capabilities can push long-run convergence of other important factors as well, such as per capita incomes and labour productivities. For example, Archibugi and Pianta (1994:19) argue that:

> "... similar economic performances might result from different combinations in the countries' production and use of technology. But the question is to what extent economic convergence can be achieved and sustained without convergence also in innovative activities. We could expect that after some point further progress in economic convergence needs to be sustained by a parallel convergence in countries' ability to carry out research and produce innovations".

Economic convergence, therefore, to some extent boils down to achieving convergence in terms of countries' inventive ability and/or their ability to appropriate knowledge developed elsewhere (e.g., Antonelli, 2008; Antonelli and Quatraro, 2010; Costantini and Crespi, 2008a, 2008b; Dosi et al., 1988; Rennings, 2000; Fagerberg et al., 2005).

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[1] The idea of EU Member States converging stretches quite far back: specific economic convergence goals were included in the Treaty on the Functioning of the European Union originally signed in Rome in 1958. Indeed, the EU is founded on three main pillars, through which different forms of convergence play an essential role.

[2] According to Stern et al. (2000), a country's *national innovation capability* can be defined as its potential to produce a stream of commercially relevant innovations.

From a theoretical point of view, the neoclassical growth model predicts that per-capita income in a country will stagnate in the absence of technological progress. Consequently, in a union of states whose members' technologies vary, convergence of per-capita incomes will only occur in the long run if there is also a converging development of national inventive capabilities. In the short run, there is room in the EU for low-skilled countries to specialise in their comparative advantages; over the longer term, however, such a strategy is risky because there are many other low-skilled countries outside the EU and remaining at a lower level of technological development within the EU will eventually mean a lower economic wealfare for the Member State concerned.

The purpose of this paper is to investigate whether or not there is convergence in the inventive capabilities of EU Member States. Besides giving indications of the direction of the EU's future economic development, the contribution of this study, is also that it applies a novel investigation of convergence of an important driver of long-run economic growth, namely technological change.

Two previous, highly relevant, papers also explore convergence in inventive capabilities in the EU, namely Archibugi and Filippetti (2011) and Jungmittag (2006). They are principally distinguishable in respect of their selection of methods and periods of study. Jungmittag (2006), for example, analyses the period 1963–1998, while Archibugi and Filippetti (2011) focus on the 2004–2008 period. Jungmittag (2006) expands this time-series approach to include panel data to some extent, while Archibugi and Filippetti (2011) use the more recent β-convergence panel test, without control variables (see further section 2.1).

Our investigation of convergence contributes to the current literature in three important ways. Firstly, our study focused on a more recent period, 1990–2011. Secondly, the econometric approach is complemented by a distributional dynamics approach, which deepens our understanding of the dynamic process of technological change. This is achieved by way of a series of parametric and non-parametric convergence models, i.e., β-, σ-, distributional and γ-convergence. Another advantage of including a distributional dynamics approach lies in its potential to see whether instead of overall convergence (to one level), there is convergence into different formations of what one could call *high-inventive* and *low-inventive groups* among countries, i.e., one group of countries that has a high inventive output and a group with low inventive output.

Thirdly, our study augments current research on technological change. Technological change is important not only because it serves as a key asset in improving competitiveness, but also because the economic development that follows is believed to facilitate cohesion in two important spheres: the social and the political (Sharp, 1998). In the EU, therefore, a major part of the budget is devoted to structural and cohesion development funds with the objective of creating economic convergence.[3] Thus, if the various innovative capacities of EU Member States do not converge overall their economies might not go in the same direction; this may jeopardise the EU's policies aimed at strengthening social and political cohesion among its members (Archibugi and Filippetti, 2011). As the EU project is being increasingly questioned, as evidenced by the United Kingdom's recent exit vote from it, citizens across the union may resist monetary transfers in the EU budget across regions and countries in the long run. Our investigation of whether or not inventive capabilities in the EU are converging will help to make policymakers aware of current trends, and offer them insight into whether further action is needed to promote convergence in inventive capabilities.

The remainder of the paper is organised as follows: in Section 2, previous research on convergence is reviewed,– first from the standard perspective of gross domestic product (GDP) per capita, and then from the perspective of technological change and then two possible scenarios for the direction of convergence as regards patenting in the EU are presented. In Section 3, the methodological approaches are presented, with four concepts of *convergence*: β-convergence, σ-convergence, distributional convergence, and γ-convergence. Section 4 presents the data used, and discusses the use of patents as a proxy for inventions. Section 5 synthesises the empirical findings and discusses the results. Finally, Section 6 concludes the paper and highlights some key implications and a few suggestions for future research.

2. Previous Convergence Research and Two Possible Scenarios for the Convergence Direction of Patenting Activities in EU

2.1 Previous Convergence Research

[3] During the period 2000–2007, The EU implemented the Objective 1 Programme with the aim of promoting the development and structural adjustment of countries and regions which were lagging behind. Objective 1 was later replaced by the Convergence Objective, which prioritises human and physical capital, innovation, a knowledge society, the environment, and administrative efficiency (Panara and De Becker, 2010).

Convergence is a widely discussed subject in macroeconomic theory and empirical research (e.g., Barro, 1991b; Islam, 1995; Quah, 1993a), and traces its heritage to the classical Solow Growth Model (Solow, 1956). Some of the economic debate has hinged on the importance of technological change as one of the causes of growth. In the neoclassical growth model, technological change is assumed to be exogenous and technology is treated as a public good (Maurseth, 2001). Hence, long-run economic growth also essentially becomes exogenous. Theoretically then, convergence is a natural outcome of exogenous technological change migrating across countries with similar microeconomic prerequisites (e.g., Bernard and Durlauf, 1995). However, endogenous growth theorists (e.g., Barro and Sala-i-Martin, 1992; Islam, 2003; Lucas, 1988; Romer, 1986) have argued against this hypothesis. The latter theorists have attempted to incorporate some of the atypical characteristics of technology and knowledge, and where knowledge is assumed to be a non-rival and only partially excludable good (Romer, 1990). Empirical research has also addressed the EU convergence issue in terms of income, productivity and, more recently, technological capabilities.[4] Numerous papers have focused on GDP per-capita convergence, but less work has been done regarding technological progress in general and patenting granting outcomes in particular.

High invention and innovation rates – for which patents granted are used as a proxy, in this paper – have been found to lead to higher rates of economic growth (e.g., Fagerberg, 1988; Jungmittag, 2004; Jungmittag and Welfens, 2002). *Invention* can be defined as "the creation of new products and processes through the development of new knowledge or from new combinations of existing knowledge", (Grant, 2002:333). Most inventions are the result of novel applications of existing knowledge.[5] *Innovation*, which is often treated as being synonymous with *invention*, is defined by Grant (2002:334) as "[t]he initial commer-cialization of invention by producing and marketing a new good or service or by using a new method of production". However, innovations do not necessarily have to constitute new inventions per se.

As was noted above, two other papers specifically address the convergence of inventive capability among EU Member States. In his paper, Jungmittag (2006) uses data of grantedpatents to investigate the convergence of inventive capabilities. The research question

[4] The convergence approach has been applied to new aspects of economics where there has been an interest in seeing whether a specified variable such as environmental performance (e.g., Aldy, 2006; Romero-Ávila, 2008) or regional economic development (Kangasharju, 1998) showed convergence or divergence among countries.

[5] Soete (1981) distinguishes between technology output measures, such as patents granted, and input measures, such as research and development (R&D) spending. The former is often regarded as a better proxy for inventive activity than the latter, which is more, but not exclusively, oriented towards inventive activity (Fagerberg and Verspagen, 1996; Paci and Usai, 2000).

was motivated by the claim that its answer permits immediate conclusions regarding the prospects of convergence of per-capita incomes and labour productivities within the EU. The investigation looked at the EU-15 countries in the period 1963–1998 by means of unit root tests for time series and panel data. The results showed mixed evidence of granted-patent convergence, thus finding support for both β-convergence and stochastic convergence – but not for all Member States in the sample.

Archibugi and Filippetti (2011) investigate how the global financial crisis of 2008 affected convergence in research and development (R&D) investment in the EU. The motivation for their study was that growing inequalities in innovative capabilities might also lead to divergence in income and well-being. In their research, the authors used the European Inno-vation Scoreboard (EIS), a European Commission initiative, which provides a comparative analysis of the innovation performance of EU Member States. Using the β-convergence approach on data spanning the period 2004–2008, they found slow convergence in terms of the EIS indicators. The authors also looked at R&D investments at the level of the firm, and revealed that laggard countries had cut spending due to the 2008 crisis while firms in the leading countries had done so to a much lesser extent.

Other papers touch on technological convergence issues. In a regional study of some EU countries, for example, Martin et al. (2005) found that, as the distribution of patents granted and public R&D converged, income per capita converged along with it. In a study of technological convergence among the EU-15 Member States and eight that joined after them, Žižmond and Novak (2007) found significant evidence of convergence at the level of investments, i.e., gross fixed capital formation. Jungmittag (2004) looked at convergence in labour productivity between 1969 and 1998 in Europe using β- and σ-convergence panel data models. His results showed that, besides capital accumulation, transferable technical knowledge had been a driving force of growth for catching-up EU countries. Fagerberg et al. (1996) found that there was convergence in Europe in terms of income and productivity after World War II, but it slowed down and gradually ended during the 1980s. Their results were partly explained by diverging factors such as a decreased ability to diffuse new knowledge. However, Archibugi and Coco (2005) remarked that, within the EU, the level of R&D investment was so heterogeneous that a homogeneous continental innovation system would not emerge with respect to science and technological development

2.2 Two Possible Scenarios for the Direction of Convergence as Regards Patent Granting in the EU

In respect of the EU, we see two possible scenarios for the future pathway of patents granted per capita. The first scenario has its roots in the most basic form of economic convergence theory (e.g., Barro, 1991a, 1991b; Islam 1995; Quah, 1993a). According to this theory, it can be assumed that countries that are laggard in respect of technological development can grow faster (because, in percentage terms, growing from something small will show large growth rates) than their more technologically developed counterparts; in this way, laggard countries will catch up with more developed ones, at least in the long run (Keefer and Knack, 1997). The reasons for such convergence could be that, due to intensifying cross-country interactions, better opportunities present themselves to make use of knowledge spillovers from abroad. Thus, in this scenario, even though laggard countries might not produce breakthrough patents, there is room for incremental improvement.

Technological cluster theory argues against the above scenario where per-capita production of technology converges. The latter theory predicts a scenario where knowledge production clusters around certain geographical areas,[6] in turn suggesting that a good deal of competitive advantage lies outside companies and even outside their industries (Porter, 2000). Thus, technology companies will locate to places where other innovative companies are found, and researchers will leave laggard countries to work in countries where they can be paid more for their ideas. Over time, technologically laggard countries will find themselves confined to an economic specialisation, in low-technology industries where little capital and technology is required, while the most developed countries will probably strengthen their innovation leadership (Rodriguez-Pose, 1999). For the EU, this scenario entails failing to reach convergence in invention capability across its Member States.

If the latter clustering scenario materialises, then underdeveloped countries may be stuck in a low-invention trap where no inventions are produced and there is a struggle to implement frontier technology. This is conceptually comparable to the low-level equilibrium trap of economic prosperity,[7] which is believed to exist in some poor countries (Desdoigts, 1999). One explanation as to why some countries are stuck in this low-level equilibrium trap is associated with the properties of absorptive capacity. For our purpose *absorptive capacity* concerns a country’s ability to absorb knowledge developed abroad; the effect of international technology

[6] In the technological research example, this implies increasing returns to investments in areas where other research already exists. The most commonly used example of an industry cluster is Silicon Valley, where in tech firms have established themselves even though operating costs there are significantly higher than, for example, rural Idaho.

[7] Until a certain level of per capita income is reached, all income will be spent on the necessities of life, with the consequence that adequate investments for the future, i.e., inventions, etc., are not made (Nelson, 1956).

flows crucially depends on the destination country's ability to comprehend and make use of external knowledge (Mancusi, 2008). According to Antonelli et al. (2011) and Boschma and Iammarino (2009), such a diffusion of knowledge is more likely when the competences and knowledge stocks of the inventors and adopters are closely related, i.e., when there is high technological proximity (Fischer et al. 2006).

3. Methodological Approaches

3.1 Parametric analysis 1: The Neoclassical Beta Convergence Model

Beta convergence (*β-convergence*) refers to a process where one entity, like a firm or a country, that has less of something than another grows faster in percentage terms, and catches up over time. There are two concepts of *β*-convergence: absolute and conditional *β*-convergence. *Absolute* *β*-convergence assumes that all countries will exhibit the same steady-state level of patents granted per capita. In contrast, *conditional* *β*-convergence assumes possible differences in such steady states among countries. Thus, conditional *β*-convergence can be said to be conditional on similarities in country characteristics.

This study investigats the convergence of patent applications granted per capita across inventor countries, and employs a panel data approach in doing so. The main usefulness of the panel data approach lies in its ability to allow for heterogeneity in the aggregated production function across economies.

Absolute *β*-convergence (β_a) can be examined by estimating the following reduced-form equation for pooled data (Chumacero, 2002):

$$ln\left(\frac{y_{it}}{y_{it-1}}\right) = \alpha + \beta_a ln(y_{i0}) + \varepsilon_{it} \tag{1}$$

where $ln\left(\frac{y_{it}}{y_{it-1}}\right)$ denotes the growth rate of initial logged per-capita patents granted for country *i* at time *t*, and is computed as the patents granted per capita of country *i* at time *t* divided by the sample average. Furthermore, α is the constant term and ε_i is the error term. y_{it-1} represents patents granted per capita in the previous period, *t* – 1, and is utilised as an initial invention level to endogenise varying steady states of y_{it}. If the estimated β_a is negative and statistically different from 0, then the absolute β_a-convergence hypothesis is supported.

Countries with a low initial invention level are then growing faster than those with a high level, while they are all converging to the same steady state.

The speed of convergence (λ), defined as the speed at which an EU Member State moves from its initial invention level to the balanced invention growth or a steady state, can be computed as $\beta_a = -(1 - exp^{-\lambda t})$ where τ is the length of the period (Islam, 1995). The half-life (the time needed to reach the halfway point of the steady state) can be estimated from the β-convergence equation as follows:[8]

$$1 - e^{-\lambda t} = \frac{1}{2} \rightarrow t = -\frac{ln\left(\frac{1}{2}\right)}{\lambda} = \frac{ln2}{\lambda} \qquad (2)$$

Next, we test for conditional β_c-convergence (β_c), i.e., convergence after controlling for differences in the steady states across countries. This is tested by regressing average growth rates on the initial level while controlling for other exogenous factors. Controlling for the differences in the steady states across countries is achieved by adding a set of exogenous variables to Equation (1) (e.g., Barro 1991a, 2015; Barro and Sala-i-Martin, 1992). In a panel data setting, conditional convergence is tested through a transformed Barro growth equation:

$$\Delta y_{it} = \alpha + \beta_c ln(y_{it-1}) + \beta X_{it} + \delta_i + \eta_t + \varepsilon_{it} \qquad (3)$$

where $\Delta \mathrm{y_{it}} = \ln(\mathrm{y_{it}}/\mathrm{y_{i,t-\tau}})$ is the growth rate in the number of patents granted per capita between time period $t - \tau$ and t; y_{it-1} is the lagged value of the patents per capita the previous year; δ_i addresses country-specific fixed effects; η_t represents period-specific effects; and ε_{it} is the error term. A vector X_{it} of additional explanatory variables, including: (a) a human capital variable consisting of the number of researchers per 1,000 in the country's labour force; (b) public R&D-based knowledge stock[9] to account for historical spending and proxying a country's general R&D policy engagement; (c)final government expenditure per capita; and (d) GDP per capita. The non-knowledge stock control variables are lagged by two years. For example, public R&D expenditures taking place in period t may lead to a patent application and, eventually, to a patent being granted no earlier than in period $t + x$ (x = 2) (Nicolli et al.,

[8] The delta (λ) method is utilised to compute standard errors of λ and half-life, respectively (see Greene, 1993:297).

[9] For details of the construction of the R&D-based knowledge stock, see Section 4.

2012). The speed of convergence and the half-life for the conditional β_c-convergence models were also calculated.

However, conventional panel data models may yield biased estimates due to the correlation and endogeneity issues arising from the used of the lagged dependent variable. As a remedy, Kiviet (1995) proposes the use of a least squares dummy variable (LSDV) estimator that has been corrected for bias (hence, LSDVC), which is found to be rather accurate even when sample size (N) and time (T) are small.[10] Another issue is that the use of a lagged dependent variable as a regressor with a fixed time dimension can give rise to severe bias issues, especially if T is small (Judson and Owen, 1999). However, in a two-step procedure, Kiviet (1995) tackles this problem by starting off with estimating a small bias for the LSDV estimator and then estimating proposing an LSDVC version of the previous estimator. Thus, the LSDVC approach is used in the conditional β_c-convergence regression to cater for bias.[11]

3.2 Parametric Analysis 2: The Sigma Convergence Model

Over time, it has been noted that the concept of β-convergence is a necessary but not a sufficient condition for cross-country convergence.[12] For this reason, the notion of *sigma (σ) convergence,* i.e., where σ represents the coefficient of variation, has been put forth as a complementing measure of convergence (Quah, 1993b; Sala-i-Martin, 1996; Young et al., 2008). Friedman (1992) and Quah (1993b) also suggest that σ-convergence is important because it addresses the issue of whether or not a distribution is becoming more balanced.

While β-convergence focuses on discovering a catching-up process among dissimilar countries in terms of patents granted per capita, σ-convergence refers to a reduction of their dispersion in those terms. In our case, σ-convergence would imply that the dispersion of patents granted per capita is decreasing over time, something that would probably mean that countries are moving towards a common granted-patents per-capita level. In this context then, the advantage of additionally investigating the σ-measure is twofold. Firstly, it produces an unbiased measure of β-convergence: by observing a process over time (as we can do when the sample dispersion is plotted graphically for each year), one can see if there have been any periods with significant

[10] In this paper, $N = 13$ and $T = 21$. For more details, see Section 4.

[11] We used the Standard BB (Blundell and Bond, 1998) estimator with no intercept, as implemented by Stata routine xtlsdvc. In addition, 100 and 200 bootstrap iterations were tested for robustness.

[12] For an early presentation of this idea, see Barro and Sala-i-Martin (1992:227–228).

breaks in the development. Secondly, it allows for the identification of visible peaks in the distribution.

We estimate the annual standard deviation of the natural logarithm of patent applications granted per capita. If the dispersion declines over time, then patents granted per capita are converging in a σ-sense (Barro and Sala-i-Martin, 1992). The σ is given by:[13]

$$\sigma_t = \sqrt{\left(\frac{1}{N-1}\right)\sum_{i=1}^{N}\left(\ln y_{it} - \overline{\ln y_t}\right)^2} \tag{4}$$

where $\ln y_{it}$ represents the patents granted per capita for country i at time t, and $\overline{\ln y_t}$ is the mean value of the number of patents granted per capita at time t. If σ_t follows a downward trend towards 0, or if $\sigma_{t+T} < \sigma_t$, then σ-convergence of patents granted per capita is supported (e.g., Ezcurra, 2007; Liddle, 2009, 2010). It should be noted, however, that σ-convergence may fail to capture polarisation phenomena (i.e., if there are two groups forming where one is developing fast and the other is falling behind) in case of tendencies toward multimodality. Hence, further distributional investigation is motivated (Ordás Criado and Grether, 2011).

3.3 Non-parametric Analysis 1: The Distributional Convergence Model

While the σ-convergence approach described previously (e.g., Barro and Sala-i-Martin, 1992) reveals whether the variance in patents granted per capita has decreased or increased, aspects of the distribution remain unknown. It has been argued that the dynamics for the full distribution of the studied variable need to be taken into account, and not only the conditional mean (β-convergence) or the variance (σ-convergence) (Quah, 1993a, 1993b, 1996a, 1996b, 1997). In line with Quah (1997), therefore, we also employ the distributional convergence approach to analyse the various countries' intra-distribution mobility. This allows us to determine the degree of convergence. *Intra-distributional mobility* refers to moving within the cross-sectional distribution of the variable studied (Jaunky, 2010).

Using the methodology proposed by Quah (1993a, 1997) offers some benefits: unlike the σ-plot, employment of the Distributional Convergence Model can reveal distributional dynamics such as twin peaks, stratification and polarisation. The *twin peaks* phenomenon refers to a distribution moving towards a binominal state, where inventive countries cluster together, and

[13] For small samples such as the present one, the denominator is replaced with (n-1) instead of n.

non-inventive countries cluster together. The formation of two or more peaks indicates stratification of the distribution. Polarisation is two peaks concentrated at both ends of the distribution. The occurrence of convergence involves a progressive budge towards a single-peak distribution in which the probability mass will be concentrated around a certain value, i.e., the countries in the sample move towards the same value. In contrast, within the concept of the convergence club, a twin-peak or multiple-peak distribution is tantamount to divergence. The probability mass is spread out over a range of the distribution, or moves to more than one centre (Jaunky, 2013).

We apply the methodology proposed by Quah (1993a, b, 1997) for estimating kernel density functions for the relative patents granted per capita, denoted as Ry_{it}.[14] The sum of relative patents granted per capita are calculated as the log of one country's i.e., of a cross-section of countries at time $t + \tau$ and with $\tau > 0$) patents granted per capita relative to the yearly sample average $\overline{y_t}$:

$$\boldsymbol{Ry_{it} = ln\left(\frac{y_{it}}{\overline{y_t}}\right)} \tag{5}$$

which gives the kernel function:

$$\boldsymbol{f(Ry_0) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{Ry_i - Ry_0}{h}\right)} \tag{6}$$

where $K(.)$ is a bivariate kernel function and is assumed to follow the Epanechnikov kernel function; and $K(q) = \left(\frac{2}{\pi}\right)(1 - q'q)I(q'q \leq 1)$, where $I(.)$ is the indicator function, h is the bandwidth. Equation (6) describes the transition over a period – in our case, the beginning and the end of the sample years – from a given country's granted-patent level in period t. Equation (6) explains how the cross-sectional distribution of the patents granted per capita at time t evolves into the next period, e.g. t+1. A large sample size is arguably preferred for a reliable estimation of multivariate kernel densities; hence, the extent to which we can draw conclusions from the distribution plot is somewhat restricted by the small sample size (e.g., Ahamada and Flachaire, 2010). Nonetheless, for our purposes, the main usefulness of the distribution plot is to determine whether or not the distribution is twin-peaked.

[14] In Equation (1), we have ln $(\frac{y_{it}}{y_{it-1}})$, which is somewhat different from Equation (5) and, hence, an R is added.

Even though the distributional dynamics approach offers information about the distribution of patents granted per capita, it does not give us sufficient information about (a) substantial intra-distributional dynamics, i.e., if countries' growth paths are crossing each other; or (b) if inventive and non-inventive countries maintain their respective statuses.

3.4 Non-parametric Analysis 2: The Gamma-convergence Model

Boyle and McCarthy (1997) argue that the kernel approach has its own weaknesses, including the fact that there is a lack in generality for the σ-convergence when testing for β-convergence. They therefore suggest a supplement by way of an index of rank concordance. The index of rank concordance is referred to as gamma (γ) *convergence*, and it measures the intra-distributional mobility over time, i.e., entities' relative positions. The motivation in this study for calculating γ-convergence as well is that, even if the dispersion of patents granted per capita declines over time, it is possible that such dispersion for individual countries with the highest and lowest intensities does not decline (Liddle, 2009).

To measure the inter-temporal distribution of the sample countries' granted-patent output, the change of ordinal ranking is examined. This is done to improve our understanding of changes in the complete distributions over time. This, in turn, can shed additional light on the intra-distributional dynamics not captured by a single parameter that characterises the variance of the cross-section (σ-convergence). A single country's patents granted per capita are expressed as the ratio of its patents granted per capita to the EU average for that year, i.e., the relative patents granted per capita. Normalising a country's patents granted per capita against the EU average allows us to discern country-specific movements from overall EU growth or trends in patents granted. A binary version of the Kendall's index of rank concordance is computed to reveal the γ-convergence development over time. We employ the following equation as suggested by Boyle and McCarthy (1997):

$$\boldsymbol{\gamma_{it}} = \frac{\boldsymbol{Variance(AR(y)_{it}+AR(y)_{i0})}}{\boldsymbol{Variance(2AR(y)_{i0})}} \tag{7}$$

Where $AR(y)_{it}$ is the actual rank of country i's patent granted per capita output in year t; and $AR(y)_{ot}$ is the actual rank of country i's patent granted per capita in the initial year (i.e., $t = 0$). A change in a countries relative position (ranking) will lead a $\gamma_{it} < 1$ after summing all countries $\sum_{n=1}^{N} \gamma_{it}$ we get a value for how much the countries changed position relatively to each other. In addition, γ captures the evolution of the ordinal ranking over a time interval and assumes a value between 0 and 1. The closer this value is to 0, the greater the extent of the mobility within the distribution.

In our empirical context, a significant movement among the sample countries between two years only is not expected. Our data are aggregates of the countries' entire granted-patent output. Hence, a major breakthrough in one technology field does not affect the rankings as overwhelmingly as it might if a separate and narrower technological field were at stake. Over time, however, the rankings can change considerably; but for a single year, that is not expected. This less dramatic result is because a country with a granted-patent output that is growing faster than the rest would probably not advance in terms of that many ranks in a single year.

4. Data Sources and Definitions

The data set consists of a balanced panel including 13 of the EU-15 Member States during the period 1990–2011. [15] The selection of the period and countries is based on several considerations that took into account the global technological milieu, the EU's expansion, and the historical development of the dependent variable, namely the change in granted patents by inventor country per capita.

The early 1990s saw the dawn of the information technology age and the reunification of Germany, both of which had a fundamental impact on the EU. Austria, Finland and Sweden, who had not been part of the initial 12 Member States, joined the EU in 1995. These three countries are included in the sample because they were members of the EU for most of the period studied.[16] The sample total of 13 countries excludes Greece and Luxembourg owing to insufficient quality data being available on them.

4.1 The Dependent Variable

The dependent variable ($\Delta y_{it} = \ln(y_{it}/y_{i,t-\tau})$) is the growth rate in granted patents (claimed priorities date) by inventor country per capita.[17] The dependent variable is based on data from

[15] The 13 included countries are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Portugal, Spain, Sweden, The Netherlands and the United Kingdom. Greece and Luxemburg were omitted because of data availability issues; this is in line with several other papers that have also had problems obtaining quality data for these two countries (e.g., Hussler, 2004).

[16] Several more countries joined in 2004 and thereafter The motivation for not including the post-2004 Member States is because they have (pree-2004) been exposed less to the convergence efforts before they entered the Union, and the Eastern European countries did not become a member of the EPO until 2002.

[17] For more descriptive statistics on the dependent variable, see Appendices B1 and B2.

the European Patent Office (EPO) as obtained from the Organisation for Economic Co-operation and Development (OECD) statistical database. The advantage of using EPO-granted patents as a data source is that they are in a standardised format, i.e., all patents are applied for and accepted under the same rules (Rübbelke and Weiss, 2011).[18] The *priority date* refers to the date when the patent was filed. Only patents filed under the Patent Cooperation Treaty were included in order to approximate innovations in line with OECD (2009). Figure 1 shows that patents granted per million inhabitants in the EU in 1990 were far lower than in 2011.

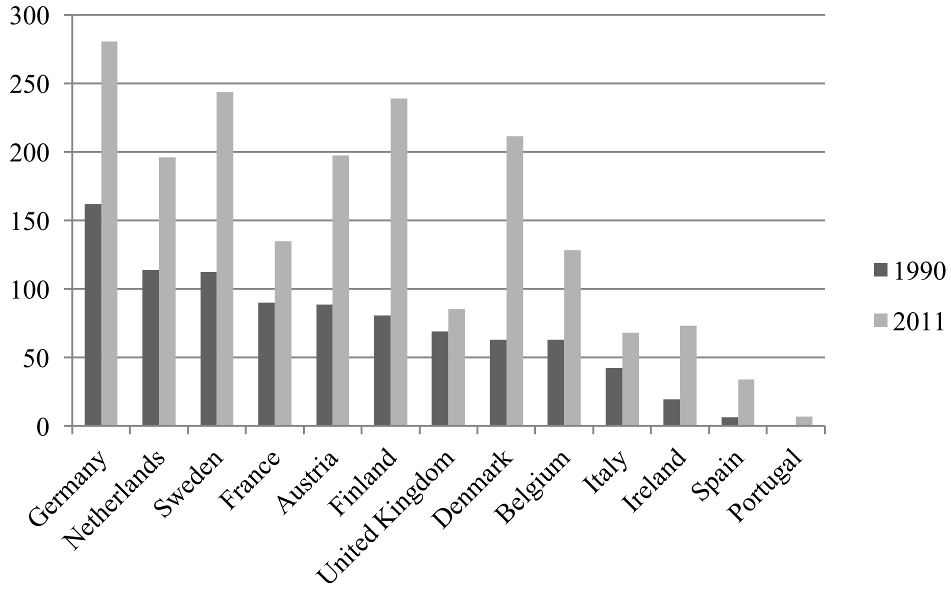

Figure 1: Granted patents (claimed priorities date) per million inhabitants in 13 EU Member States by inventor country, 1990 and 2011.Source: EPO

The geographic location of the inventor rather than the formal patent applicant is considered for the data analysis, since the latter can be a company registered in a country other than that in which the knowledge was initially produced (e.g., Fischer et al., 2006).[19]

Using patents granted to represent technological output has a solid foundation in much of the previous empirical work in this regard (e.g., Griliches 1987; Hall and Ziedonis 2001; Johnstone et al., 2010; Popp, 2002).[20] Being awarded a patent is by no means easy; fundamentally, the

[18] There is a significant difference in the level of patent applications submitted to the EPO by the various Member States; see Appendices B1 and B2.

[19] When a patent is awarded to multiple inventors from different countries, the count has been divided equally among those countries.

[20] In these studies and others, the number of patents granted was used as a variable to measure a country's inventive and innovative output. For example, Popp (2002) and Johnstone et al. (2010) used the variable to empirically

inventor must disclose to the public something that is a "novel", "useful" and "non-obvious" invention. If the invention does not meet these criteria, then a patent cannot be awarded (Griliches, 1987; Hall and Ziedonis, 2001).

Nonetheless, the methodology of using patents granted as a variable when doing research on inventive outputs has been criticised from an econometric and conceptual perspective. The main arguments are that not all new inventions are patented, and patents may differ greatly in their economic significance (Adams, 2005; Cohen et al., 2000; Pakes, 1985; Pakes and Griliches, 1980; Schankerman and Pakes, 1987; Trajtenberg, 2001). [21] Despite these and other shortcomings, however, using patents granted as a proxy for inventions is valuable since, as Griliches (1998:336) states, "nothing else comes close in quantity of available data, accessibility and the potential industrial organizational and technological details".

4.2 The Independent Variables

In the β-convergence Model, several control variables were used. These variables included (a) the number of research personnel per 1,000 employees; (b) the knowledge stock of public R&D expenditure in the country concerned in million US Dollars; (c) final government consumption expenditures per capita; and (d) GDP per capita.

Summary statistics for both the dependent and all independent variables are presented in Table 1. In the econometric model, the control variables were run in natural logarithmic form and are lagged by two years; in the descriptive statistics, they are presented in their non-logarithmic form to convey more information about the state of the technological development.[22]

Table 1: Definitions of variables and descriptive statistics

Variable	Definition	Mean	S.D.	Minimum	Maximum
Dependent variable: The growth rate in patents per capita ($\ln(y_{it}/y_{i,t-\tau})$).	Growth rate in granted patents per capita in country i at time t	0.02	0.16	-0.65	0.58

investigate different aspects of policies that drive innovation. For instance in Popp's (2002) study, US granted-patent data from 1970 to 1994 were used to estimate the effect of energy prices on innovations that improved energy efficiency.

[21] A large portion of patents are without economic value when granted, or become worthless within a short period (Pakes, 1985; Schankerman and Pakes, 1987). The top 10% of patents granted capture between 48% and 93% of total monetary returns (Scherer and Harhoff, 2000).

[22] For example, R&D and the number of researchers can, in many cases, be suspected to be related; if there is a strong correlation between them, biased results will be generated. When we checked these variables, no such high correlation rates were found (see the correlation matrix, Appendix C (Table C1).

The β_c-convergence parameter (y_{it-1})	The one period lag of the granted patents per capita for country *i* at time *t*–1	118,75	83,2	0,52.30	310,3
Research personnel	Number of researchers per 1,000 employees in the labour force in the country	10.73	4.02	2.43	22
Stock of public R&D in the country	Accumulated public spending on R&D from 1990, adjusted for depreciation, time lags and expenditure in all sectors in million USD, see Equation (8) for details (in 2005 prices, adjusted for PPP*)	2,984	2,285	52	10,596
Final government consumption expenditure per capita	Final government consumption expenditure per capita in USD (in 2005 prices, adjusted for PPP)	17,139	28,445	2,120	100,293
GDP per capita	Gross domestic product per capita, based on PPP (per capita in USD (in 2005 prices, adjusted for PPP)	5,281	1,446	2,120	9,004

* PPP = purchasing power parity

In the panel data setting β_c-convergence parameter (y_{it-1}) is the one period lag granted patents per capita in country *i* at time *t*, allowing us to see whether or not there is convergence in the data (e.g., Barro, 2015; Wang et al., 2014).

The independent variables were mostly gathered from OECD's R&D statistics database, as will be detailed below. According to economic theory, the invention capabilities of a country are considered to depend fundamentally on three factors: (a) its common invention infrastructure, such as R&D employees or R&D expenditure, as well as its stock of previous innovations (e.g., Grossman and Helpman, 1991; Romer, 1990); (b) its technological and economic specialisation; and (c) the quality of the linkages between its common invention infrastructure and the industries that engage in inventive efforts (Jungmittag, 2006).

Through R&D investments in human capital, individuals acquire knowledge and skills that can be transferred to certain goods and services of commercial value (Romer, 1990). Therefore, the variable *Research personnel* is included in the model to capture the human capital input in the knowledge production function. This input is approximated using data on the number of researchers per 1,000 employees in the respective countries in the sample. These data were derived from the Main Science Technology Indicators database published by the OECD.

Different types of R&D inputs is commonly used as a variable for analysing a country's inventive capacity (e.g., Dechezleprêtre et al., 2013; Furman et al., 2002).The knowledge stock in a country is expected to be a major determinant of innovation, hence the variable *Stock of public R&D in the country* is constructed (Klaassen et al., 2005; Krammer, 2009; Söderholm and Klaassen, 2007). We constructed the knowledge stock for our study by using the perpetual inventory method, which is commonly employed for such constructions (Coe and Helpman, 1995; Ek and Söderholm, 2010). Specifically, the *Stock of public R&D in the country* is constructed according to the following equation, namely –

$$K_{it} = (1 - \delta)K_{i(t-1)} + R\&D_{i(t-x)} \tag{8}$$

where, K_{it} is the knowledge stock in country i during period t. The knowledge stock is determined by public R&D spending in the same period, $R\&D_t$; and x is the number of years (lag) it takes before the new spending adds to the knowledge stock. In this case, the time lag is assumed to be two years (Klaassen et al., 2005). Moreover, $K_{i(t-1)}$ is the knowledge stock inherited from the previous period, taking into account a depreciation rate δ $(0 \leq \delta \leq 1)$ (Hall and Scobie, 2006). The depreciation rate is set to 10%, but other levels were also tested (see Appendix A). We need to allow for the possibility that there was some public expenditure before the period specified for our study; hence, the knowledge stock was not 0 in 1990, our first sample year. Thus, the initial public R&D stock (K_o)is calculated as:

$$K_0 = \frac{R\&D_0}{g + \delta} \tag{9}$$

where, $R\&D_0$ is the public R&D expenditure dedicated to renewable energy in the first year for which public R&D data were available (1974); and g is the average geometric growth rate for R&D spending by country over the first ten years (e.g., Hall and Scobie, 2006; Madsen and Farhadi, 2016). δ is the depreciation rate.

The explanatory variable *Final government consumption expenditure per capita* takes its cue from other convergence research that has employed it as such (Carmela et al., 2005). For instance, Barro (1991a) found that the ratio of real government consumption expenditure to real GDP had a negative correlation with overall growth and investment. Arguably, government consumption should have no direct effect on private productivity, although it would lead indirectly to lower private savings and growth through the distorting effects of taxation (Barro, 1991b). The data for this variable were retrieved from the OECD's Economic Outlook – Annual Projections.

Finally, *GDP per capita* was also included as an explanatory variable. The data for this variable were retrieved from the International Monetary Fund's World Economic Outlook Database.

5. Results

5.1 The β-convergence Model

As a first step, *absolute β-convergence* was tested. Table 2 presents the empirical results from the specification in Equation 1, and here the β_a coefficient was found to be negative and statistically significant at conventional levels. The results also reveal that countries with low levels of invention intensity tended to evolve faster than those with high levels. This implies that the sample countries were in the process of converging towards a common steady-state level of invention.

To determine the statistical significance of λ and half-life, respectively, standard errors were computed via the delta method. In these calculations, λ was found to be statistically significant. The λ and half-life range were equal to 0.04, meaning that it would take 4% per year and 25 years, respectively, to reach the sample mean. Absolute β-convergence in terms of inventive capabilities across the EU seems to be a slow process, therefore.

Table 2: Absolute β-Convergence Model

Coefficients	Estimates
β_a *Patents per capita*$_{it}$	-0.027
	(0.005)***
α	-0.0006
	(0.006)
R^2	0.081
Number of Observations	260
Number of Countries	13
λ	0.027
	(0.005)***
Half-Life	25.67
	(5.216)***
Speed of convergence	0.04

Note: The standard errors are in parentheses.
***, ** and * denote statistical significant at the1%, 5% and 10% levels respectively

Secondly, our analysis of conditional β-convergence, in which we control for the various countries' structural characteristics, reveals statistically significant β-convergence. Table 3 shows that the estimated convergence coefficient β_c is negative and statistically significantly different from zero (0), thus indicating convergence rather than divergence.

Table 3: Conditional β-Convergence Model

Coefficients	Estimates
β_c Convergence parameter	-0.363*** (0.063)
β_1 Research personnel	-0.203** (0.05)
β_2 Stock of public R&D in the country	0.07* (0.09)
β_3 Government final consumption expenditure per capita	0.104 (0.14)
β_4 GDP per capita	-0.235 (0.235)
Country dummies	Yes
Year dummies	Yes
Number of observations	260
Number of countries	13
Number of Years	21
λ	0.197 (0.047)***
Half-Life	1.53 (0.852)***
Speed of convergence	0.47

Note: The standard errors are in parentheses.
***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Since $0<\beta_c<1$, conditional β-convergence of invention is confirmed. The λ – the speed at which a country's granted patents per capita approaches its own steady-state level – is 0.47 years, while the half-life, i.e., the time needed to reach the halfway point in respect of the country's final steady state, is equal to 1.53 years.

The need to control for steady-state determinants is necessary in international analysis using data from many heterogeneous countries. The EU countries are converging rapidly to their individual steady state levels. For additional robustness, different depreciation rates on the knowledge stock (5 and 15 %) were tested and the results for the convergence variable remained robust and the results are presented in Appendix A, (Table A1). Furthermore, some additional specifications were tested with fewer control variables and the results remained robust. The Research personnel variable was statistically significant and negative. The negative relationship between changes in renewable energy patents per capita was unexpected.

5.2 The σ-convergence Model

We track the inter-temporal change, i.e., data normalised to the initial year, in the coefficient of variation (the standard deviation divided by the average) of the cross-country granted-patent distribution. If this measure, termed *σ-convergence* in the economic growth literature, falls over time, it can be interpreted as evidencing convergence (Liddle, 2009). As noted above, σ-convergence is a stricter type of convergence than β-convergence. Figure 2 shows that the coefficient of variation of patents granted per capita tends to exhibit an erratic convergence movement over most of the years of the period studied.

From 1997, the measure was greater than 0.95, indicating a slow σ-convergence phase. During some of the years before 2008, the distribution showed divergence. After 2008, the distribution started to converge again. Over longer periods, dispersions increased, especially from 1994 until 2007. However, from 2008 onwards, granted-patent dispersion per country decreased. Figure 2 indicates that granted-patent dispersion in the EU was at a reduced level for most of the 21 years analysed here.

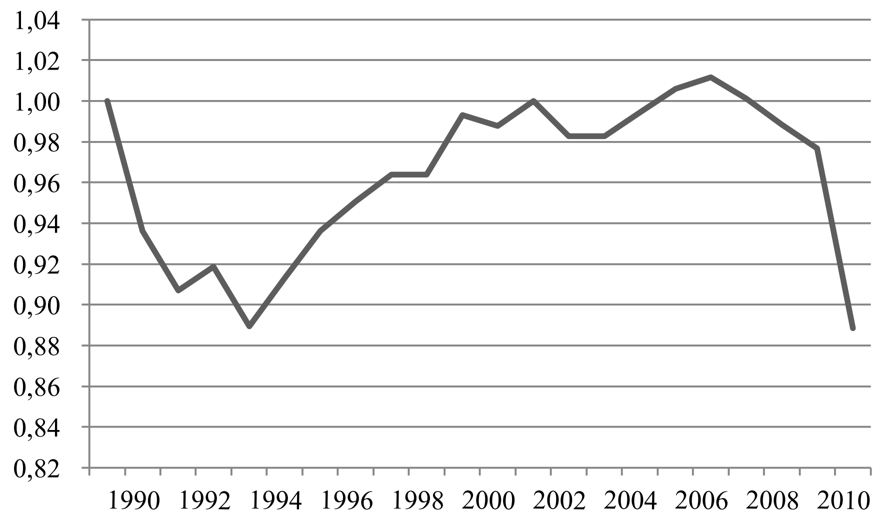

Figure 2: Coefficient of variation of granted patents per capita in EU countries, 1990-2011

A possible explanation for this pattern is that shocks might temporarily have increased the dispersion of patents granted per capita, even in the presence of β-convergence, or that countries might be approaching their steady-state shares (conditional convergence), with higher dispersion towards the end in comparison with the beginning of the period studied. This would be in line with Archibugi and Filippetti's (2011) finding, namely that the economic crisis in 2008 had a negative impact on innovative investment in almost all EU countries, but that the catch-up countries were the most affected, thus leading to increasing divergence during the period 2004–2008.

5.3 The Distributional Convergence Model

As shown in Figure 3, the surface plot of patents granted per capita shows characteristics of nascent multi-peakness and a tendency of club formations among the sampled EU countries. Over the 21 year horizon, a large portion of the probability mass remains clustered around the main diagonal. However, along that principal ridge, a dip in the middle portion is apparent. The implication of such clustering is a tendency for the countries to remain in their initial positions regarding patent-granting intensity. In many other cases, the existence of these multiple-peak distributions could imply the occurrence of divergence among countries. However, it could also be a sign of a distribution that has not changed much over time.

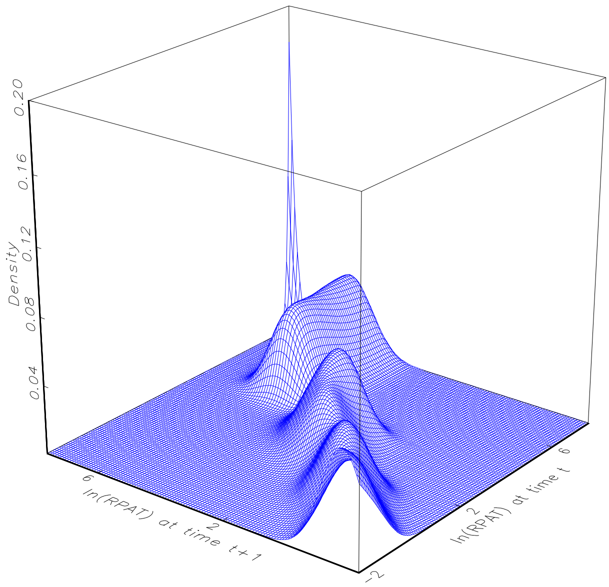

Figure 3: Surface plot of relative[23] granted patents per capita in EU countries, 1990 to 2011.

A final – and perhaps the most likely – interpretation is that the technologically developed countries in our sample tended to have more stable growth rates in their patents granted per capita than those of the less-developed counties. This interpretation is based on studies by Archibugi and Filippetti (2011), who found that economic shock affected less-developed countries' R&D spending. However, there is no compelling reason to think that the very long-run growth rates of technological capabilities vary across EU Member States. Instead, it is

[23] Patents granted per capita relative to the yearly sample average (see Section 3.3).

possible that we are leaving a situation where we have an underlying 'majority club' among EU Member States, and that we are now seeing a 'minority club' evolving into the majority part of the distribution.

In Figure 4, the contour plot represents a bird's-eye view of the surface plot and indicates various levels of iso-probability, i.e., the probability of a country *i* moving its relative position compared to the rest of the sample between period *t* and *t*+1, where the first period is 1990 and the second is 2011. A peak along the 45° line suggests that that point acts as a basin of attraction. A peak along the 45° line implies persistence properties and illustrates the position of country *i* in the distribution, which does not change from its initial location.

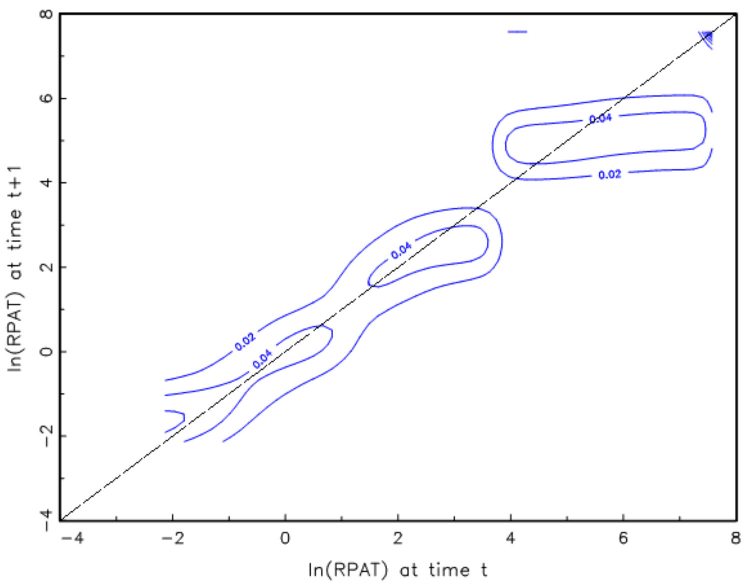

Figure 4: Contour of the conditional distribution of relative patents granted per capita.

A peak above the 45° line means that relative patents granted per capita tend to increase, while a peak below the line indicates a decrease in relative patents granted per capita. A major part of the probability mass is clustered along this line. The contour plot shows two distinct probability masses from a bird's-eye view of the surface plot. The plot indicates a stable distribution. We observe that the peaks in the upper tail of the distribution, i.e., patents granted per capita higher than 3, are somewhat different from the 45° diagonal. Additional prominent peaks can be observed, while Figure 4 also shows several portions of the density probability mass are clustered along the 45° diagonal. However, the mass for the high-level group are cluster somewhat under the 45° diagonal, something that indicate that they are relatively to the other distribution, not as dominant in in patent production.

Thus, Figure 4 displays that the distribution is stratified into roughly 3 groups, which implies that all 13 countries studied have not (as yet) converged to the same level of inventive capabilities over time, i.e., countries with low levels of inventive capabilities show little tendency to catch up with their high-level counterparts. There are local maxima in both the low and high parts of the granted-patent production range. Moreover, the low level of intra-distribution mobility (see confirmation thereof below in section 5.4) and, could indicate a move towards an EU where per-capita invention rates is rather static over time.

5.4 The γ-convergence Model

Our finding that the number of patents granted per capita in each country is rather stable across the period studied is confirmed in Figure 5, which shows the change in the γ distribution. Here, a value of 1 indicates that there has been no change in the intra-distributional ranking. If, for example, the value was 1 during the entire period in question, we would see a straight line, and this would indicate a static distribution. Similarly, in terms of their per-capita granted-patent counts, if all countries grew at the same rate, e.g. 2%, then no change would occur in the distribution pattern even though the differences among countries would increase. The results in our study showed that no years were without change in the distribution pattern, although the movements around 2003 were relatively small. Nonetheless, with a few exceptions, the value of the distribution remained at around 0.9 throughout the years of the study, indicating that less than 10% of the sample countries had changed their ranking during that time. Considering the size of the sample, this means that only two countries' per-capita granted-patent counts their counts exceeded those of other countries in the sample. Exceptions to the low movement in the distribution occurred in the years 1995 and 2009.

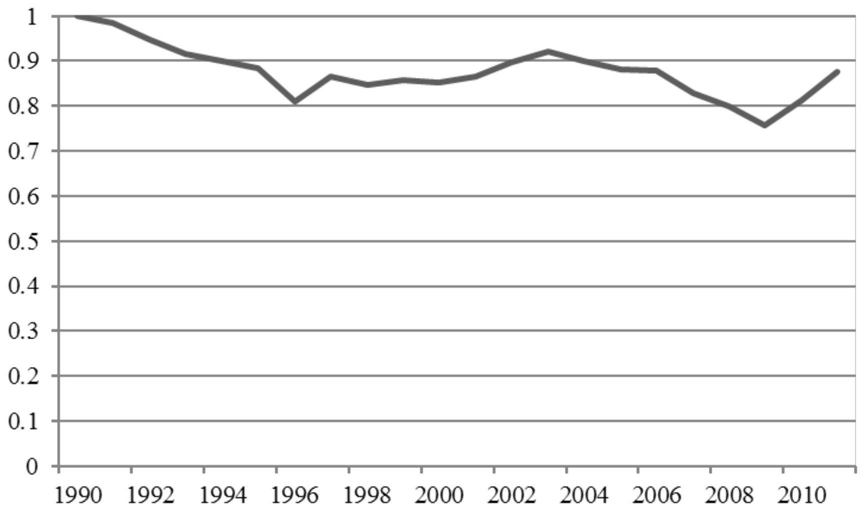

Figure 5: γ-convergence, the binary version of the non-parametric Kendall's index of rank concordance among the EU countries, 1990-2011.

In general, Figure 5 exhibits a rather stable trend for γ over time. The γ-indicator shows that, although there were changes in the distribution, they were rather moderate. This result is much like that seen in the σ-convergence case, i.e., where countries with high and low granted-patent intensity in 1990 and are largely the same in 2011. In terms of γ-convergence, the result tells us that most countries maintained their ranking, but that some changes in distribution had occurred. A marked change would indicate that the sample countries were closer to the end of a convergence process; conversely, a low degree of change might indicate that they were beginning a long process towards convergence. Roughly speaking, from 1990 until 1996, γ tends to increase, implying higher mobility in the distribution. Similarly, γ tends to increase from 1997–2003 and around 2009. The non-parametric approaches such as distributional dynamics and γ-convergence techniques together suggest a lack of intra-distributional mobility. It should be noted, however, that although some changes have occurred, they are not large enough to be captured at a significant level by the technique applied in this study.

5.5 A Summary of the Main Findings

Table 4 summarises the overall findings from the convergence tests, and the results of the tests points towards that we have convergence in inventive capabilities cross the 13 EU countries.

Table 4: A Summary of the Main Findings by Convergence Concept

Convergence Approaches	Results

β-convergence -Absolute	Convergence
β-convergence - Conditional	Convergence
σ-convergence	Convergence
Distributional Dynamics	Convergence indication
γ-convergence	Convergence indication

6. Conclusion and Implications for Policy

The purpose of this paper was to analyse whether or not there was convergence in the national inventive capabilities of the 13 EU Member States selected in the sample for the period under study, namely 1990–2011. Specifically, this analysis was achieved by econometrically investigating, by means of parametric and non-parametric techniques, the development of patents granted per capita in the 13 countries over the period concerned. The results indicate that, overall, there are tendencies towards convergence within the EU in respect of national inventive capacities.

Neoclassical convergence is detected, firstly, via the β-convergence tests. The speed of conditional β-convergence was found to be greater than the corresponding speed for absolute β-convergence. This implies that invention activities in the countries in question are converging faster in terms of their own efficiency steady-state than in terms of a common one. On average, the half-life for conditional β-convergence is 1.5 years, compared with that for absolute β-convergence, which is equal to 25 years.

Thus, there is a slow but significant motion towards convergence but, with such a long period (25-year half-life), the final outcome is in the realm of uncertainty. Over the 21 years examined, many of the countries in our study exhibited significant and rapid technological development. However, considering the rather low output some of these countries had in terms of per-capita patent-granting outcomes, there was a great opportunity to have a fast growth rate However, because some of these countries had rather low per-capita patent-granting outputs, even a small increase in that output would constitute a relatively fast growth rate.

It should also be borne in mind that the results of all the convergence tests may reflect the period chosen. In other words, it is possible the results and, hence, our conclusions would have been different if we had investigated another period. For example, previous studies have shown that there have been periods with and without economic convergence. In times of economic crisis, there might be a tendency towards divergence (as indicated in the σ-measure) when nations with weaker R&D support temporarily decrease or even halt such input.

In our study, the rather slow convergence evidenced via the absolute β-convergence test was also borne out in the σ-convergence test. The evidence of slow convergence may be due to a mild form of so-called brain drain from less-developed countries in the south to more technologically advanced countries in the north.

The results of this paper tend to imply that, in the long run, the convergence objective established for the EU is headed in the right direction. The priorities under this objective are enhancement of human and physical capital, inventiveness, a knowledge society, the environment, and administrative efficiency. The assumed and here, to some extent, statistically supported existence of a technological gap among EU Member States could be closed via national and EU policies that encourage and enable the cross-border diffusion and spillover of technology and other knowledge. In particular, it might be necessary to promote technologically laggard Member States through a selective EU research and technology policy that would encourage the establishment of efficient national innovation systems that link up with the gradually emerging European innovation system. In this way, less-developed EU Member States could close the gap between them and their more developed counterparts.

From a policymaking perspective, the convergence findings are interesting. An EU with large differences in respect of its members' levels of technological development can result in long-term tension. Policy measures are needed, therefore, in order to promote long-lasting economic effects that aim to reduce not only the technology gap, but consequently also the economic gap between countries.

This paper has tried to answer the question of what is currently happening on a technological development front in the EU, and it has revealed that a slow converging process is emerging in this regard. A matter to be investigated via another platform would be to explain why this convergence is occurring.

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Appendix A

Table A1: Parameter estimates for the conditional convergence model different specifications and with a 5% and a 15% depreciation rate to the R&D-based knowledge stock.

Coefficients	Estimates	Estimates	Estimates	Estimates	Estimates
β_c Convergence parameter	-0.362	-0.324***	-0.359***	-0.363***	-0.363***
	(0.062)	(0.62)	(0.065)	(0.062)	(0.063)
β_1 Research personnel	-0.133	-0.162***	-0.161**	-0.174***	-0.203***
		(0.117)	(0.05)	(0.049)	(0.05)
β_2 Stock of public R&D in the country 5 %		-0.0599		-0.009	
		(0.118)		(0.167)	
β_3 Stock of public R&D in the country 10 %	-0.055				
	(0.06)				
β_3 Stock of public R&D in the country 15 %			-0.006		0.076
			(0.201)		(0.092)
β_3 Government final consumption expenditure per capita				0.08	0.104
				(0.123)	(0.140)
β_5 GDP per capita				-0.131	-0.235
				(0.212)	0.216
Country dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of observations	260	260	260	260	260
Number of countries	13	13	13	13	13
Number of years	21	21	21	21	21
λ	0.196	0.182	0.191	0.197	0.197
	(0.047)***	(0.047)***	(0.048)***	(0.047)***	(0.047)***
Half-Life	1.54	1.63	1.55	1.53	1.53
	(0.851)***	(0.852)***	(0.845)***	(0.852)***	(0.852)***
Speed of convergence	0.48	0.51	0.47	0.47	0.47
Iterations	200	200	200	200	200

Appendix B

Table B1: Descriptive statistics for the change in granted patents, by country

Country	Mean	S.D.	Min	Max
Austria	1.04	0.08	0.92	1.29
Belgium	1.04	0.12	0.78	1.29
Denmark	1.06	0.08	0.91	1.24
Finland	1.06	0.10	0.87	1.23
France	1.02	0.04	0.93	1.11
Germany	1.03	0.07	0.81	1.19
Ireland	1.07	0.14	0.82	1.34
Italy	1.02	0.07	0.85	1.13
Netherlands	1.03	0.10	0.84	1.20
Portugal	1.18	0.35	0.59	1.80
Spain	1.09	0.10	0.95	1.27
Sweden	1.04	0.08	0.87	1.18
United Kingdom	1.01	0.06	0.89	1.11
Total	1.05	0.13	0.59	1.80

Table B2: Descriptive statistics for the total number of granted patents, by country

Country	Mean	S.D	Min	Max
Austria	1121.8	404.6	616.6	1785
Belgium	1134.8	349.3	493.1	1581.4
Denmark	824.4	345.3	323.7	1373.7
Finland	1027.8	388.1	401.6	1504.84
France	6734.5	1513.2	4679.5	8759.8
Germany	18503.4	5155	10600.7	24687.7
Ireland	192.1	100.2	61.8	346
Italy	3559.6	1010.8	2136.3	5088.5
Portugal	48.6	39.2	5.2	125.1
Spain	812.8	441.7	252	1555.8
Sweden	1919.3	637.7	908.3	2861.6
The Netherlands	2688.6	960.7	1463.4	4056.4
United Kingdom	4800.7	1032.5	3225.2	6177.4
Total	3336	5018	5.25	24687.7

Table B3: Descriptive statistics of granted patents per million inhabitants

Country	Mean	S.D.	Min	Max
Austria	137.87	46.81	77.99	215.04
Belgium	109.01	31.99	49.29	149.72
Denmark	152.972	61.56	62.97	250.05
Finland	197.16	72.71	80.55	290.06
France	112.3	22.25	81.42	140.60
Germany	225.81	61.58	132.48	300.09
Ireland	47.28	21.82	17.50	78.068
Italy	61.29	16.63	37.63	85.70
Portugal	4.651	3.69	0.525	11.87
Spain	19.09	9.36	6.48	33.77
Sweden	213.48	68.15	105.40	310.38
The Netherlands	167.69	56.42	96.38	247.62
United Kingdom	81.093	16.83	50.96	104.50
Total	117.66	82.33	0.52	310.38

Appendix C

Table C1: Correlation matrix

	Research personnel	Stock of public R&D in the country	Final government consumption expenditure per capita	GDP per capita
Research personnel	1.00			
Stock of public R&D in the country	0.75	1.00		
Final government consumption expenditure per capita	0.52	0.36	1.00	
GDP per capita	0.13	0.27	-0.28	1.00