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CONVERGENCE IN R&D INTENSITY ACROSS EUROPEAN COUNTRIES: A FRACTIONAL INTEGRATION APPROACH

Amaia ALTUZARRA

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In this paper, the convergence in R&D expenditure across 21 European Union countries is examined by applying fractional integration analysis. Data are annual and cover the period 1990–2010. Results show that there is certain degree of convergence in R&D intensity. However, the speed of the convergence varies across countries. For most of the countries, the speed of convergence is higher in the R&D expenditures of governments than in the R&D expenditures of higher education institutions and businesses. Differences in the speed of convergence could be explained by differences in industry structures, in cultural trajectories, in macroeconomic conditions, or in internationalisation. The more dissimilar countries are in terms of these factors the more likely they are to have divergent paths. Furthermore, differences in R&D convergence by institutional sectors could be due to the different goals of each sector and to the relative weight of each sector in the entire economy.

Keywords: convergence, R&D, European Union, fractional integration

JEL classification indices: O32, O47, O52

1. INTRODUCTION

Convergence has been a leading issue for politicians and scholars since the beginning of the European integration process. Concerns about this matter grew with the accession of Spain and Portugal in 1986, and more recently with the enlarge-

Amaia *Altuzarra*, Professor at the Faculty of Economics and Business, University of the Basque Country, Bilbao, Spain. E-mail: amaia.altuzarra@ehu.es

ments towards the Eastern and Central European countries in 2004 and 2007, and two Balkan countries in 2013.

For a scenario of convergence to exist, it is necessary to foster competitiveness in lagging countries and this is primarily determined by innovation. Innovation is a key component and driver of economic growth since it enhances the competitive position of lagging countries, makes them less dependent on the technological developments produced in leading countries, and improves their capacity to absorb new knowledge. Innovation increases the stock of existing knowledge and facilitates the production of new products and/or processes, resulting in the expansion of existing markets and the opening of new markets. The improvement in competitiveness due to innovation will eventually be translated into increases in productivity and growth. A large number of studies have confirmed the relevance of innovation to economic growth (Romer 1986, 1990; Freeman – Soete 1997).

Within this framework, central and regional governments have designed policies aimed at promoting R&D and innovation within their territorial competencies over the last decades. This trend has been particularly true since the year of 2000 when the Lisbon Strategy was approved. The purpose of the Lisbon Agenda was transforming the EU into "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion" by 2010. In 2002, the European Council defined the objective of having 3% of GDP allocated to R&D activities, of which two-thirds should be financed from the business sector. More recently, Europe 2020, the new EU growth strategy for the present decade, renewed the idea that 3% of the EU GDP should be spent on R&D.

Currently, however, the R&D spending of the EU member states is on average below 2% of GDP. Differences among European countries are significant, not only in the total R&D spending, but also in the R&D expenditures by the institutional sector (business, government and higher education) as shown in *Figure 1.*

Despite the growing consensus regarding the crucial role of innovation and R&D as drivers of economic growth and convergence, the field of convergence in innovation and R&D itself has been little explored in the empirical literature (Jungmittag 2006; Archibugui – Fillipetti 2011). Nor has this valuable information been used to examine the economic growth or convergence, despite the significant differences in R&D investments across institutional sectors. Bilbao-Osorio –Rodriguez-Pose (2004) is one of the few studies. Using data on the EU regions, they seek to determine whether R&D investments carried out by different sectors – private, public, and higher education – have different impacts on innovation and economic growth. They find that R&D performed by the private

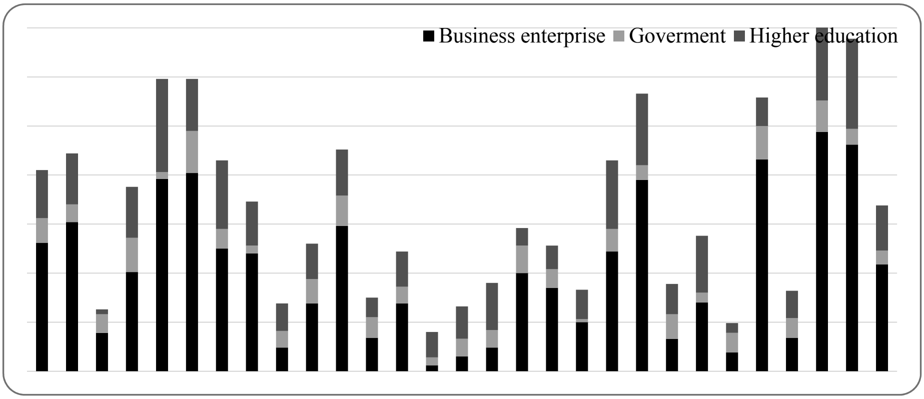

Figure 1. Structure of R&D expenditure in EU countries by institutional sector, 2012

Source: Eurostat and own elaboration.

sector has higher rates of return than research conducted by any other sector and that it is more commercially oriented. R&D conducted by public and higher education sector tends to be less applied and more basic.

This paper aims to test convergence in R&D in the European Union member states by applying fractional integration techniques. It intends to examine, on the one hand, whether *there is* convergence/divergence in total, public, private, and higher education R&D investment (over the GDP) across EU Members States, and on the other, whether *the rate* at which those R&D institutional sectors converge/diverge is different across the EU countries. The expected result is that convergence in R&D will vary according to the institutional sector and across countries. The specific institutional, social, cultural, and economic characteristics are believed to play a significant role in building the capacity of each country to produce knowledge and innovation. Also, the relative weight and the goals of each institutional sector may differ across countries. An advance in the knowledge of this issue may provide new ideas for a better understanding of the convergence process and expand the range and scope of policy intervention aimed at reducing the disparities among countries.

The rest of the paper is organised as follows. The second section contains a review of the literature on the economic growth and innovation. In the third section, the data and methodology are discussed. In the fourth section, empirical results are presented. Finally, the fifth section provides some concluding remarks.

2. REVIEW OF THE LITERATURE

There are three main approaches to address the study of economic convergence among countries and regions:[1] the traditional neoclassical theory of economic growth (Solow 1956), the endogenous growth theory (Romer 1986; Lucas 1988), and the demand-oriented approach to growth.

The neoclassical theory of economic growth is based essentially on three main assumptions: First, that labour force and technical progress grow at a constant exogenous rate. Technology is considered as a public good, accessible evenly to all countries, and determined exogenously to the model. Second, that all savings are invested. And third, that output is determined by capital and labour, where the production function has constant returns to scale, and diminishing marginal returns to the factors of production. Based on these assumptions, the theory predicts that there will be an inverse relation across countries between the capital/labour ratio and the productivity of capital. Therefore, poorer countries will have higher growth rates than the richer ones because the poorer countries will have a higher marginal productivity of capital due to a lower capital-output ratio. Thus, convergence is the rule in this growth model (Barro – Sala-i-Martin 1992).

The endogenous growth theory was developed to overcome the problems with the traditional neoclassical models. The starting point of this theory was the empirical evidence of no convergence of per capita income across countries (Baumol 1986), contrary to the prediction made by the neoclassical theory. This new growth theory argues that there are certain externalities associated with learning by doing, which outweigh the diminishing marginal returns. For instance, Romer (1986) wrote about the existence of externalities to R&D spending. Lucas (1988) focused on the presence of externalities to human capital formation and education. Grossman – Helpman (1991) concentrated on the role of technological spillovers from trade and foreign direct investment.

Later, a new generation of works within the endogenous growth models was developed by Romer (1990). In these new models, innovation is not considered as a pure externality, but the result of the strategic decisions of companies. Innovations, according to this current, create a temporary monopoly which can be exploited by the innovator company. In this context, the main determinant of economic growth is not capital accumulation, but R&D spending and the possibility of the appropriation of innovation rents. The policy recommendations emanating his new framework include the promotion of R&D investment and the appropriation conditions of innovation (Castellacci 2008).

[1] See Soukiazis (2001) for a survey.

Endogenous growth theory predicts that the convergence of per capita income across countries is conditional on several factors that affect economic growth such as differences in intensity of R&D expenditure, education and training, international trade, macroeconomic performance, and political stability, as opposed to the neoclassical approach of unconditional convergence associated with the diminishing returns to capital. Countries with higher spending on R&D and better-trained human capital, *inter alia,* will grow faster than countries with lower values of these factors. Under the new growth theory, convergence is not the rule. It only occurs when poor countries have improvements in the mentioned factors.

Endogenous growth models are an improvement over the neoclassical models in the sense that they attempt to explain why there is no economic convergence. However, a major criticism that can be levelled against these models is that they are supply-oriented. That is, the role of demand is not taken into account.

The demand-orientated approach to growth, meanwhile, recognises the role of demand factors as key elements for economic growth. In this stream, represented by authors such as Kaldor (1957, 1970), capital accumulation results from increases in output, which occur cumulatively due to the existence of economies of scale, particularly in manufacturing industries. Kaldor built the foundations of the so-called cumulative circular causation model of growth whose main prediction is the divergence or non-convergence in economic growth. He argued that the forces which explain convergence or divergence depend primarily on demand, where exports are a key factor. The public policy recommendations which promote the introduction of innovations or the diffusion of innovations through demand include, for instance, public procurement in certain submarkets (energy efficient technologies, healthcare, etc.), the financial support of private demand for innovative products through demand subsidies or tax reductions, or the improvement of the information of the customers on new innovations, or the quality and the functionality of the innovations (Edler 2011).

From an empirical point of view, the study of the economic convergence among countries or regions has focused on real convergence in terms of income per capita. There are three main approaches to empirically testing real economic convergence. The first approach is the so-called hypothesis of *sigma-convergence* or long-run convergence. It suggests that two countries converge in income per capita when differences in this variable diminish over time (Friedman 1992; Quah 1993). This hypothesis is consistent with the neoclassical growth theory of Solow (1956) that poor countries grow at a higher rate than rich countries, which will make convergence on the level of per capita income happen.

The second approach is known as the hypothesis of *beta-convergence* or short-run convergence. It holds that convergence occurs when countries converge not on the level of per capita income, but on the growth rate of this variable. This type of convergence occurs when there is a negative correlation between growth rate and the initial level of income. Beta-convergence may be conditional when countries differ in their long-term steady state due to differences in their structural characteristics (population, technology, etc.) or unconditional (or absolute) when such differences do not exist (Barro – Sala-i-Martin 1992). The existence of beta-convergence is a necessary, but not sufficient condition for the existence of sigma-convergence since economic shocks may cause the variable of interest in certain countries to tend to distance even when short-run convergence tends to approach.

The third approach is an alternative to the empirical models of beta- and sigma-convergence. It is based on the idea of *stochastic convergence.* This technique consists of applying root tests and cointegration analysis to time series to determine whether there is a common (deterministic and/or stochastic) trend for different countries (Bernard – Durlauf 1995). If that is the case, the convergence for a group of countries means that each country has an identical long-term trend. This definition of convergence is relatively clear for a situation of two countries, but not when the convergence is considered in a sample of more than two countries. When this occurs, researches differ as to which definition of convergence would be the most adequate (Stengos – Yazgan 2011). Some authors consider that the most appropriate measure of convergence is to consider the deviation from a reference country. Others, however, propose the deviation from the mean of a sample (Islam 2000; Jungmitag 2006).

The three previous ideas of convergence have been used in empirical research. For the case of the EU countries, some recent works are Czasonis – Quinn (2012), Monfort et al. (2013), Niebuhr (2009), Stanisic (2012), Prochniak (2013), and Tamás – Metiu (2013).[2]

[2] Czasonis – Quinn (2012) studied the income convergence in the Eurozone and found evidence of higher convergence in the 1970s and 1980s than in recent years. Monfort et al. (2013) analyse real convergence in GDP per worker in the EU member states using data from 1980 to 2009. They find different economic growth rates within Europe, which also converge to different steady states, implying some degree of divergence. Niebuhr (2009) investigates the effects of the most recent EU enlargement on convergence among countries and regions in the EU27, and finds evidence of a catching-up process in the new member states. Stanisic (2012) analyses the catching-up processes within European countries focusing on the potential growth trends and concludes that European convergence processes might slow down and stop in certain countries. Prochniak (2013) analyses the time stability of the GDP beta-convergence in two subsamples: EU27 countries during 1993–2010 and EU15 during 1972–2010. He finds that the EU27 countries converged at the rate of about 5% per annum, while the EU15 countries at a lower rate of 3%. Tamás – Metiu (2013) analyse convergence of real income per capita in the EU27 using unit roots. They find that there is no overall real per capita income convergence in the EU.

However, pioneering works preferentially used the idea of sigma- and beta-convergence using cross-sectional data (De Long 1988; Levine – Renelt 1992). This approach suffers from certain problems (Bernard – Durlauf 1995), one prominent fact among them being the alternative hypothesis that all countries converge. Therefore, this method is not suitable for analysing situations in which some countries converge while others do not. The use of time series would be desirable in order to overcome this limitation since econometric techniques based on time series permit the identification of those countries that converge and those which do not. However, time series models have a problem stemming from the strong tendency to reject the hypothesis of convergence. This occurs because most unit root tests discriminate only between processes I(0) and I(1), which produces a dichotomy between a rapid convergence and an absolute divergence. This drawback, however, can be overcome by using fractional integration techniques. Fraction integration analysis consists of estimating the fractional integration parameter (*d*), which can take values other than 0 and 1, and determines the speed of convergence between different economies.

In this research, we study the convergence among countries by means of testing the convergence in innovation in the EU countries by applying fractional integration analysis. The focus of the paper is, first, the estimation of the fractional integration parameter (*d*), that is, the parameter that determines the speed of convergence between different economies. The main finding of our paper is that the long-memory framework of analysis which we adopt is much richer than the simple I(1)/I(0) alternative that produces a simple absolute divergence and rapid convergence dichotomy.

The interest in knowing whether there are values other than 0 and 1 may have remarkable implications for innovation policy. If the series are stationary, external shocks may have an impact in the short term, but their long-term effect will be small because the series will return to the mean at an exponential rate. By contrast, integrated data do not return to the mean after an external shock. The ARIMA models do not take into account the fact that data may revert to the mean and show, at the same time, the effects of shocks that have occurred in the past. By enabling d to take fractional values, data are allowed to revert to the mean and have long memory. The long-memory parameter, d, in long-memory models is what determines the presence of long memory and describes its nature. This parameter, therefore, plays a crucial role in understanding the economy and economic planning. The extent of public intervention will depend on the size of d, more specifically on whether $d < 1$ or not. It is understood that when a variable has a unit root ($d = 1$), any impact on the economic system will have a permanent effect on the variable, so that a policy intervention may be necessary to enable the variable to return to its long-term trend. On the other hand, if $d < 1$, fluctuations will be transitory, which means that the effects on the variable will dissipate and, consequently, there will be less need to implement policy actions because the series reverts to its long-term trend. Since reversion to the mean occurs only when $d < 1$, the fractional integration test can serve as a test for mean reversion.

3. DATA AND METHODOLOGY

3.1. Data

The data series used in our empirical work are provided by Eurostat databases. The indicator selected to explore the convergence in innovation is the gross domestic expenditure on R&D as a percentage of GDP.

R&D as an indicator of innovation is basically derived from the so-called linear model of innovation. The linear model of innovation suggests that innovation happens in a sequential and orderly fashion from invention to innovation to diffusion. It assumes that investment in basic research, which is mainly undertaken by universities, research institutes and laboratories, is strongly and positively correlated with innovation in the market place. R&D data may be seen as limited since it measures only an innovation input (Kleinknecht et al. 2002). However, from the empirical point of view, R&D as an indicator of innovation offers some advantages. These include the long period over which it has been collected, the detailed sub-classifications that are available in many countries, and the relatively good harmonisation across countries. In addition, many governments still set their innovation policy objectives in terms of a determined or ideal level of R&D, as is the case in the EU.

R&D data has been used extensively by the literature to examine the relationship between aggregate measures of R&D by sector or country and some measure of productivity (Griffith et al. 2004). However, most research fails to exploit the disaggregation processes that are possible with R&D data, without exploring most of the interesting details contained in the data (Smith 2005).

The data available in Eurostat regarding R&D activities are of two types: there are data on R&D expenditure as a percentage of GDP on the national level and on R&D personnel as a percentage of total employment on the national level. In this paper, we use only the former measure of R&D because it ensures greater comparability between countries and best suits the aims of this paper. Moreover, the time series available for the latter indicator are incomplete for some years in a significant number of countries.

The data on R&D spending that are available through Eurostat include, on the one hand, total spending on R&D carried out in each European country and in the

European Union as a whole. On the other, the total R&D expenditure is broken down by institutional sector. We distinguish three institutional sectors: government sector, business sector, and higher education sector (see *Figure 1*).[3]

The data series available and used in our study are annual and cover the period from 1995 to 2010. We have been forced to use this period of years because there are no previous data for all the countries of the study in Eurostat. The variables and their definitions are as follows:

a) log of the $GERD_j/GDP_j$ ratio relative to the EU average
b) log of the $BERD_j/GDP_j$ ratio relative to the EU average
c) log of the $GvERD_j/GDP_j$ ratio relative to the EU average
d) log of the $HERD_j/GDP_j$ ratio relative to the EU average

where $GERD_j$ is the Gross Expenditure on Research and Development of country j, $BERD_j$ is the Expenditure on Research and Development undertaken by businesses of country j, $GvERD_j$ is the Expenditure on Research and Development undertaken by the Government of country j, $HERD_j$ is the Expenditure by the Higher Education Systems of country j, and GDP_j is the Gross Domestic Product of country j.

The sample is made up of 21 countries of the European Union: Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, United Kingdom, and Romania. Data related to Luxemburg, Greece, Malta, Cyprus, Estonia, Croatia and Sweden are incomplete in the Eurostat database.

3.2. Methodology

The methodology used is the fractional integration, which is a widely used tool to model long memory. Long-memory models are concerned with the study of the degree of persistence in data. Granger – Ding (1996) consider that a series is long memory when the autocorrelation structure gradually decreases. This autocorrelation structure indicates that the process depends heavily on the past values of the series.

[3] The information provided by Eurostat includes a fourth sector of activity, the private non-profit sector. This sector has been omitted from the study due to the lack of data for the majority of countries and periods.

An extensive amount of recent work has emphasised the role of the persistence of data. However, most of these studies have used traditional contrasts that test for the presence of unit root (or permanent effects of a shock in the series), against the alternative of no unit root (or transient effects of a shock). These tests are sometimes complemented with stationarity tests, giving results that are often ambiguous and lead to reject both null hypotheses. This means that the rigid distinction between I(0) and I(1) processes may yield results that are excessively restrictive to study certain time series. Fractional integration can be considered a useful tool for analysing situations which fall between the I(0) and I(1) paradigms.

Fractional integration addresses a deficiency that Auto-Regressive Integrated Moving Average Models (ARIMA) present for modelling the grade and type of persistence in a time series. The ARIMA models have three parameters: *p, d,* and *q*. The parameter of the number of lags involved in the autoregressive part of the series is *p*. The parameter of the moving average lags is *q*. Finally, *d* is a dummy variable that indicates whether the series is integrated or not. If the series is integrated, *d* has a value of 1. Otherwise, *d* is equal to 0, and the model is known as an ARMA model. ARFIMA models (Autoregressive Fractionally Integrated Moving Average Models) permit *d* to take any value, not just 0 or 1. These models were introduced by Granger – Joyeus (1980) and Hosking (1981) to model the strong persistence that characterise many economic series.

An ARFIMA (*p, d, q*) process can be expressed as:

$$\Phi(L)\,(1-L)^{d}X_{t}=\Theta_{0}+\Theta(L)\,u_{t}\qquad u_{t}-(0,\sigma^{2});\ t=1,\,.......,\,T \tag{1}$$

where d is the long-memory parameter (fractional integration parameter) and shows the number of differences to be taken in series X_t to become stationary, $\Phi(L)=1-\Phi_1L-.....-\Phi_pL^p$, and $\Theta(L)=1-\Theta_1L-....-\Theta_qL^q$ are the autoregressive and moving average polynomials of p and q order, respectively, whose roots are outside the unit circle; d and Θ_0 are real numbers, and u_t are unobserved random variables that are independent and identically distributed with 0 mean and finite variance σ^2. Hosking (1981) makes the concept of factional difference $(1-L)^d$ operational by using the following expression:

$$(1-L)^{d}=\sum_{k=0}^{\infty}\binom{d}{k}(-L)^{k}=1-dL-d(1-d)\frac{L^{2}}{2!}-d(1-d)(2-d)\frac{L3}{3!}\cdots \tag{2}$$

The parameter d determines the long-run dynamic of the time series. If $0 < d < 0.5$, the series is stationary with finite variance and long memory. If $0.5 \le d < 1$, the series is not stationary with infinite variance and permanent memory, but it is mean-reverting. Finally, if $d \geq 1$, the series do not revert to the mean. Thus, for $0 < d < 1$, the process has a long memory and reverts back to the mean.

There are two main types of methods to estimate the parameter *d:* parametric and semi-parametric estimators. The former are based on maximum likelihood procedures and require the choice of the correct ARMA model. The latter is considered to be more suitable since, among other features, it does not need to specify the short-run dynamics (ARMA polynomials) in the model. In this work, the *d* parameter is computed by applying a modified form of the Geweke – Porter-Hudak (1983) estimation of the long-memory parameter proposed by Phillips (1999a,).

The fractional integration test suggested by Geweke – Porter-Hudak (1983) is based on the premise that the spectral density of X_t in Equation (1) accomplishes:

$$f_x(\omega) = \left\{ 4\sin^2\left(\frac{\omega}{2}\right) \right\}^{-d} f_y(\omega) \tag{3}$$

where $f_y(\omega)$ is the spectral density of $Y_t = (1-L)^d X_t$. Taking the logarithms in Equation (4) and rearranging them, we obtain:

$$lnf_x(\omega) = lnf_y(0) - dln\left\{ 4\sin^2\left(\frac{\omega}{2}\right) \right\} + \ln\frac{f_y(\omega)}{f_y(0)} \tag{4}$$

Given the observations X_t t = 1, …,T, the periodogram can be used to evaluate Equation (4) in the harmonic frequencies $\omega_{j,T} = \frac{2\pi_j}{T}$, obtaining:

$$lnI(\omega_{j,T}) = lnf_y(0) - dln\left\{ 4\sin^2\left(\frac{\omega_{j,T}}{2}\right) \right\} + ln\frac{f_y(\omega_{j,T})}{f_y(0)} + ln\frac{I(\omega_{j,T})}{f_x(\omega_{j,T})} \tag{5}$$

Geweke – Porter-Hudak propose the above estimation of *d* because of the similarity with a linear regression equation. $lnI(\omega_{j,T})$ is similar to the dependent variable in a linear regression, $ln\{4\sin^2(\frac{\omega_{j,T}}{2})\}$ is the explanatory variable, $\frac{\ln I(\omega_{j,T})}{f_x(\omega_{j,T})}$ is the disturbance, the slope coefficient is $-d$, and the intercept term is $lnf_y(0)$ since the term $ln\frac{f_y(\omega_{j,T})}{f_y(0)}$ is near zero in frequencies near zero and then becomes negligible. This estimator is estimated by Ordinary Least Squares (OLS). Equation (5) could be rewritten as:

$$lnI(\omega_{j,T}) = \beta_0 + \beta_1 Z_{j,T} + e_{j,T} \tag{6}$$

where j = m_1, $m_1 + 1,\ldots,$ m; $lnI(\omega_{j,T})$ is the logarithm of the periodogram in the frequency $\omega_{j,T}$; $\omega_{j,T} = \frac{2\pi j}{T}$ with T being the number of observations; β_0 is the logarithm of the spectrum zero of $(1 - L)^d X_t = u_t$; β_0 the parameter of interest; $Z_{j,T,}$ is defined by $Z_{j,T} = ln\{4\sin^2(\frac{\omega_{j,T}}{2})\}$ and the error term is $e_j = ln\left\{\frac{I(\omega_j)}{f_x(0)}\right\}$.

The GPH test allows the estimation of *d* without knowing *p* and *q* in ARFIMA (*p, d, q*). Furthermore, this method is robust to short-term dependence, as well as variance shifts and conditional heteroskedastic effects (Booth – Tse 1995). However, "distinguishing unit-root behaviour from fractional integration using this method may be problematic, given that the GPH estimator is inconsistent against d > 1 alternatives. This weakness of the GPH estimator is solved by Phillips' Modified Log Periodogram Regression estimator, in which the dependent variable is modified to reflect the distribution of *d* under the null hypothesis that *d* = 1" (Baum – Wiggins 2009). Therefore, in the implementation of the fractional integration parameter estimation method proposed by Phillips, as a correction of the Geweke – Porter-Hudak method, first a series is detrended, and the estimation method corrected to take into account density under the null hypothesis that *d* = 1.

4. EMPIRICAL RESULTS

4.1. Unit root results

Before examining long-run dependence of R&D ratios, we begin with a univariate examination of the individual series to test stationarity by using the standard unit root tests, where the most popular is the Dickey–Fuller Generalised Least Squares (DFGLS) approach of Elliott et al. (1996). This method is preferred by many econometricians to the first generation tests of Dickey – Fuller (1976) or Phillips – Perron (1988). Inferences drawn from the DFGLS test are likely to be more robust than those based on the first-generation ones (Baum 2001).

An alternative to the previous test is the KPSS test (Kwiatkowski et al. 1992). This test utilises the null hypothesis of stationarity, or I(0) instead of the DFGLS style null hypothesis of I(1) or non-stationarity in levels. The DFGLS and KPSS tests can be used complementarily to see if the results of both are consistent, so that we can accept or reject the hypothesis of the existence of a unique root with more certainty. The KPSS $\eta\tau$ test includes an intercept and linear time trend, while the KPSS $\eta\mu$ test does not. The null hypothesis for the DFGLS test is that the series has a unit root, while the null hypothesis for the KPSS test is that the series is stationary. Therefore, we can assume that a stationary series has significant DFGLS and KPSS non-significant. A series has a unit root when it has non-significant DFGLS and significant KPSS.

Even though the DGLS unit root test does not reject the null hypothesis with respect to all the countries and all four variables, when we combine the results of KPSS and DGLS tests, the verdict on the presence or absence of unit roots is contradictory at the 1% level of significance for most countries and variables. At the 5% level of significance, in the case of model with deterministic trend and in the case of model with drift, the coincidence of both tests on the diagnosis of the existence or lack of a unit root in the series tests is higher. However, there still remains a large number of cases in which the combined analysis of tests is ambiguous. This ambiguity suggests that formal estimates of *d* are useful for diagnosing the level of integration.

4.2. Fractional integration results: estimating the long-memory parameter

The results of estimating the long parameter by the method proposed by Phillips, as a correction of the Geweke – Porter-Hudak method, are presented in *Tables 1–4*. The estimation of *d* has been carried out for the bandwidth m = g(T) = T^{α}, with $\alpha = 0.50, 0.60, 0.70$, and 0.80. Simulations suggest that α should be 0.5 or higher (Geweke – Porter-Hudak 1983). However, Cheung – Lai (1993) note that a large number of α will contaminate the estimation of *d,* while very few will produce imprecise estimates of *d*. The latest results of Hurvich et al. (1998) and other authors have found that $0.6 < \alpha < 0.8$ are the most suitable values to be used.

Tables 1–4 present *d* estimates and the *p* values of the test statistics for the null hypothesis that $d = 1$ against the alternative hypothesis that $d < 1$. All comments will be referred to the case of $\alpha = 0.60$.

Table 1 shows results for variable GERD (Gross Expenditure on R&D). The fractional integration test shows evidence of a certain degree of convergence for 12 countries (Italy, Lithuania, Slovakia, United Kingdom, Czech Republic, Slovenia, Germany, Hungary, France, Bulgaria, Spain, and Belgium). Specifically, the order of integration (parameter *d*) for Lithuania, Slovakia, the United Kingdom, the Czech Republic, Slovenia, and Germany is less than 0.5, indicating that the series are stationary with long-memory processes. The order of integration for Belgium, Bulgaria, France, Hungary, and Spain is higher than 0.5, indicating slow convergence due to the existence of non-stationary mean-reverting processes in the series. Therefore, this group of countries is converging at a faster speed than the previous group of countries. For Italy, the *d* estimate is negative but non-significant.

Table 1. Estimation of *d* for GERD

	α = 0.50		α = 0.60		α = 0.70		α = 0.80		
Power	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	Conclusion based on α = 0.60
Austria	2.79	0.00	1.34	0.23	0.93	0.80	0.42	0.01	Divergence
Belgium	0.81	0.61	0.96	0.89	0.87	0.63	1.06	0.80	Mean-reverting
Bulgaria	0.08	0.01	0.81	0.51	0.90	0.70	0.75	0.26	Mean-reverting
Czech Rep.	0.14	0.02	0.47	0.06	0.50	0.06	0.92	0.73	Long-memory stationary
Denmark	0.54	0.21	1.56	0.05	1.48	0.07	1.44	0.05	Divergence
Finland	1.33	0.37	1.06	0.84	1.16	0.54	1.15	0.51	Divergence
France	0.03	0.01	0.79	0.46	0.66	0.20	0.73	0.24	Mean-reverting
Germany	0.77	0.53	0.49	0.08	0.83	0.52	0.97	0.88	Long-memory stationary
Hungary	–0.06	0.00	0.54	0.11	0.60	0.13	0.74	0.25	Mean-reverting
Ireland	1.92	0.01	1.24	0.40	1.03	0.90	0.81	0.40	Divergence
Italy	–0.81	0.00	–0.12	0.00	0.21	0.00	0.27	0.00	Stationary
Latvia	0.57	0.25	1.00	0.99	0.75	0.35	0.61	0.09	Divergence
Lithuania	0.39	0.10	0.22	0.01	0.90	0.70	0.98	0.94	Long-memory stationary
Netherlands	0.80	0.59	1.08	0.77	1.02	0.94	0.76	0.29	Divergence
Poland	1.47	0.20	1.09	0.75	0.77	0.39	0.65	0.12	Divergence
Portugal	1.61	0.10	1.39	0.17	1.11	0.68	1.21	0.35	Divergence
Slovakia	0.32	0.07	0.22	0.01	0.73	0.30	0.79	0.35	Long-memory stationary
Slovenia	0.44	0.13	0.47	0.07	0.57	0.10	0.50	0.03	Long-memory stationary
Spain	1.71	0.06	0.90	0.72	0.64	0.17	0.64	0.11	Mean-reverting
U. K.	0.64	0.33	0.27	0.01	0.68	0.23	0.46	0.02	Long-memory stationary
Romania	1.52	0.16	1.14	0.63	1.04	0.87	1.20	0.37	Divergence

Notes: α is the frequencies band used in the log-periodogram regression. The MODLPR test (Phillips, 1999b) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: Tpower ordinates are included.

For the remaining 9 countries (Latvia, Finland, Netherlands, Poland, Romania, Ireland, Austria, Portugal and Denmark), the estimates of *d* are higher than 1, meaning that the series contain a unit root and are not reverting toward the mean. Indeed, this means that the series are explosive. There is no convergence in these countries. The first four countries mentioned are among the countries with the highest innovative profile in Europe.

Table 2 shows results for BERD (Expenditure on R&D conducted by Businesses). The values of parameter *d* imply, again, a certain degree of convergence in BERD for 12 countries (Slovakia, Lithuania, Spain, Germany, Czech Republic, Latvia, Hungary, United Kingdom, Italy, Slovenia, Finland, and Bulgaria). The fractional integration parameter *d* for Slovakia is negative, indicating a stationary and rapid convergence to the EU average. The parameter *d* varies between 0 and 0.5 for Lithuania, Spain, and Germany, indicating a higher degree of convergence because the series are mean-reverting processes. For the Czech Republic, Latvia, Hungary, the United Kingdom, Italy, Slovenia, Finland, and Bulgaria, the parameter *d* is higher than 0.5, implying that these countries experience slower convergence.

For the remaining 8 countries (Belgium, France, Ireland, Romania, Denmark, Austria, Portugal, and Poland), the estimates of *d* are higher than 1, the series contain a unit root and are not reverting toward the mean. There is no convergence, but divergence from the EU average.

Table 3 shows results for GvERD (Expenditure in R&D performed by the Government). There is some degree of convergence in 17 countries (United Kingdom, Czech Republic, Netherlands, Germany, Austria, Bulgaria, Slovenia, Ireland, Poland, Spain, France, Finland, Italy, Denmark, Slovakia, Romania, and Lithuania). The parameter *d* is below 0 for the cases of the United Kingdom, and the Czech Republic, indicating that the series are stationary and therefore there is convergence. For the Netherlands and Germany, the fractional integration parameter is lower than 0.5, implying a certain degree of convergence because the series are long-memory stationary processes. The parameter *d* is higher than 0.5 (but lower than 1) for Austria, Bulgaria, Slovenia, Ireland, Poland, Spain, France, Finland, Italy, Denmark, Slovakia, Romania, and Lithuania, indicating a slower convergence than the previous group of countries. The government spending on R&D in these countries is non-stationary but mean-reverting.

The remaining 4 countries (Latvia, Hungary, Belgium, and Portugal) exhibit estimates of *d* higher than 1, which means that there is no reversion to the mean in the series and therefore these countries diverge from the EU average.

Finally, *Table 4* shows the results for HERD (Expenditure in R&D by Higher Education Institutions). In this case, there are some convergence processes in 13 countries (Belgium, Bulgaria, Romania, Austria, United Kingdom, Germany,

Table 2. Estimation of *d* for BERD

	α = 0.50		α = 0.60		α = 0.70		α = 0.80		
Power	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	Conclusion based on α = 0.60
Austria	2.25	0.00	1.39	0.18	1.04	0.89	0.56	0.05	Divergence
Belgium	0.38	0.09	1.00	0.99	0.78	0.40	0.75	0.26	Divergence
Bulgaria	1.31	0.41	0.94	0.84	1.09	0.74	0.88	0.61	Mean-reverting
Czech Rep.	0.89	0.77	0.57	0.13	0.59	0.12	0.73	0.24	Mean-reverting
Denmark	0.66	0.35	1.28	0.33	1.14	0.60	1.28	0.21	Divergence
Finland	1.36	0.33	0.87	0.64	0.98	0.94	1.08	0.71	Mean-reverting
France	–0.14	0.00	1.09	0.76	0.70	0.25	0.76	0.30	Divergence
Germany	0.54	0.22	0.49	0.07	0.79	0.42	0.74	0.25	Long-memory stationary
Hungary	0.15	0.02	0.60	0.16	0.93	0.78	1.44	0.05	Mean-reverting
Ireland	1.64	0.09	1.18	0.54	0.91	0.74	0.71	0.21	Divergence
Italy	1.15	0.69	0.74	0.36	0.85	0.56	0.86	0.54	Mean-reverting
Latvia	0.02	0.01	0.59	0.16	0.53	0.07	0.33	0.00	Mean-reverting
Lithuania	0.07	0.01	0.41	0.04	0.67	0.21	0.68	0.16	Long-memory stationary
Nether-lands	1.02	0.97	1.28	0.32	1.33	0.21	1.00	1.00	Divergence
Poland	0.73	0.46	1.63	0.03	1.15	0.58	0.88	0.59	Divergence
Portugal	0.57	0.25	1.43	0.13	1.45	0.09	1.37	0.10	Divergence
Slovakia	0.25	0.04	–0.31	0.00	0.19	0.00	0.48	0.02	Stationary
Slovenia	0.64	0.33	0.86	0.63	0.47	0.05	0.20	0.00	Mean-reverting
Spain	1.10	0.78	0.41	0.04	0.26	0.01	0.28	0.00	Long-memory stationary
U. K.	1.64	0.09	0.72	0.34	0.62	0.14	0.41	0.01	Mean-reverting
Romania	0.96	0.90	1.19	0.51	1.31	0.24	1.39	0.09	Divergence

Notes: α is the frequencies band used in the log-periodogram regression. The MODLPR test (Phillips. 1999b) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: Tpower ordinates are included.

Table 3. Estimation of *d* for GvERD

	α = 0.50		α = 0.60		α = 0.70		α = 0.80		
Power	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	Conclusion based on α = 0.60
Austria	0.48	0.16	0.56	0.12	0.23	0.00	0.35	0.00	Mean-reverting
Belgium	1.54	0.15	1.24	0.40	1.18	0.49	1.05	0.82	Divergence
Bulgaria	0.27	0.05	0.58	0.14	0.58	0.11	0.60	0.08	Mean-reverting
Czech Rep.	–0.17	0.00	0.06	0.00	0.59	0.11	0.42	0.01	Long-memory stationary
Denmark	0.83	0.66	0.75	0.38	0.64	0.17	0.94	0.81	Mean-reverting
Finland	1.54	0.15	0.73	0.34	0.40	0.02	0.20	0.00	Mean-reverting
France	1.62	0.09	0.71	0.32	0.99	0.98	0.69	0.17	Mean-reverting
Germany	0.36	0.08	0.48	0.07	0.59	0.12	0.42	0.01	Long-memory stationary
Hungary	1.80	0.03	1.14	0.63	1.11	0.66	0.97	0.89	Divergence
Ireland	0.46	0.14	0.67	0.26	0.46	0.04	0.48	0.02	Mean-reverting
Italy	1.74	0.05	0.73	0.34	0.79	0.42	0.65	0.12	Mean-reverting
Latvia	1.77	0.04	1.07	0.80	0.83	0.52	0.70	0.19	Divergence
Lithuania	1.04	0.92	0.81	0.51	0.60	0.13	0.88	0.59	Mean-reverting
Netherlands	–1.07	0.00	0.18	0.00	0.05	0.00	0.17	0.00	Long-memory stationary
Poland	0.69	0.41	0.63	0.20	0.48	0.05	0.21	0.00	Mean-reverting
Portugal	0.93	0.85	1.29	0.00	1.78	0.00	1.71	0.00	Divergence
Slovakia	1.16	0.66	0.76	0.41	0.69	0.24	0.92	0.72	Mean-reverting
Slovenia	0.14	0.02	0.59	0.15	0.99	0.96	1.01	0.96	Mean-reverting
Spain	2.25	0.00	0.68	0.27	0.62	0.15	0.77	0.32	Mean-reverting
U. K.	–0.59	0.00	–0.24	0.00	–0.10	0.00	0.15	0.00	Stationary
Romania	1.16	0.67	0.77	0.42	0.62	0.14	0.87	0.56	Mean–reverting

Notes: α is the frequencies band used in the log–periodogram regression. The MODLPR test (Phillips 1999b) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: Tpower ordinates are included.

Table 4. Estimation of *d* for HERD

	α = 0.50		α = 0.60		α = 0.70		α = 0.80		
Power	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	*d*	P > |z| z(H0:*d* = 1)	Conclusion based on α = 0.60
Austria	0.22	0.03	0.24	0.01	0.55	0.09	0.72	0.21	Long-memory stationary
Belgium	–0.48	0.00	–0.19	0.00	–0.10	0.00	–0.10	0.00	Stationary
Bulgaria	–0.69	0.00	0.00	0.00	0.52	0.07	0.83	0.46	Stationary
Czech Rep.	0.42	0.12	1.93	0.00	1.78	0.00	1.49	0.03	Divergence
Denmark	1.00	1.00	1.15	0.60	0.94	0.83	0.68	0.16	Divergence
Finland	0.85	0.68	1.43	0.14	1.05	0.84	1.34	0.13	Divergence
France	0.12	0.02	0.71	0.31	0.56	0.09	0.78	0.33	Mean-reverting
Germany	1.58	0.12	0.39	0.03	0.16	0.00	0.03	0.00	Long-memory stationary
Hungary	0.52	0.20	0.62	0.19	0.55	0.09	0.96	0.87	Mean-reverting
Ireland	1.59	0.11	1.57	0.05	1.29	0.27	1.28	0.22	Divergence
Italy	0.09	0.01	0.69	0.28	0.98	0.93	0.96	0.86	Mean-reverting
Latvia	0.81	0.61	0.74	0.36	0.46	0.04	0.38	0.01	Mean-reverting
Lithuania	0.68	0.38	1.75	0.01	1.33	0.21	1.00	0.99	Divergence
Netherland	0.73	0.47	1.01	0.96	0.94	0.81	0.98	0.91	Divergence
Poland	2.32	0.00	0.99	0.98	0.68	0.22	0.43	0.01	Divergence
Portugal	1.29	0.44	0.78	0.45	0.66	0.19	0.89	0.63	Mean-reverting
Slovakia	0.42	0.12	0.82	0.52	0.96	0.89	0.76	0.28	Mean-reverting
Slovenia	0.09	0.01	0.50	0.08	0.79	0.42	1.38	0.10	Long-memory stationary
Spain	2.29	0.00	1.61	0.03	0.86	0.59	0.66	0.13	Divergence
U. K.	0.29	0.06	0.25	0.01	0.61	0.14	0.66	0.13	Long-memory stationary
Romania	–0.17	0.00	0.12	0.00	0.20	0.00	0.41	0.01	Long-memory stationary

Notes: α is the frequencies band used in the log-periodogram regression. The MODLPR test (Phillips 1999b) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: Tpower ordinates are included.

Slovenia, Hungary, Italy, France, Latvia, Portugal, and Slovakia). There is convergence in Belgium and Bulgaria where the parameter d is lower than 0. The fractional parameter is lower than 0.5 in Romania, Austria, the United Kingdom, Germany, and Slovenia where convergence seems to happen at a higher speed than in the case of Hungary, Italy, France, Latvia, Portugal, and Slovakia. In these latter countries, the parameter d is higher than 0.5.

For 8 countries (Poland, Netherlands, Denmark, Finland, Ireland, Spain, Lithuania, and Czech Republic), the estimates of d are higher than 1, meaning that there is no convergence at all.

Figure 2 summarises the d estimates for the four variables when $\alpha = 0.60$.

In sum, the results show that divergence and long-memory stationary convergence are the most widespread processes in the EU countries in the variable GERD, while divergence and mean-reverting non-stationary convergence in R&D are the most common processes in the rest of the variables (GvERD, BERD, and HERD). These results suggest that convergence in R&D, when it exists, is slow for most of the countries, particularly in the latter variables. As noted before, in countries in which a long-memory stationary process is identified, convergence occurs at a faster speed than in those countries in which a mean-reverting non-stationary process is detected. Furthermore, our findings show that the process of convergence for a given country depends on the variable that we are considering (that is, on the type of the institutional sector that allocates R&D resources), as not all the countries converge at the same rate in all R&D variables under study.

It seems reasonable to assume that the process of convergence/divergence to the EU average of R&D intensity (in total, as well as by institutional sector) does not mean the same in leading countries as in lagging countries. If we interpret our results considering the convergence in those countries which are considered to be the least competitive ones (the so-called convergence countries[4]), our results show that there is no convergence *sensu stricto* for the majority of the variables and countries, as we only find stationarity in very few cases. However, we do find varying degrees of convergence in lagging countries. Divergence processes are also present in this group of countries.

Several factors may contribute to explaining the differences in the pace of convergence in R&D intensity across countries and institutional sectors. Firstly, the rhythm of convergence may differ because of differences in industry structures across countries. In countries with a greater relative weight of traditional industries, companies and/or public institutions may have less necessity to spend in

4 Convergence countries are eligible for the Cohesion Fund. They are countries that acceded to the EU in 2004 and 2007, along with Spain and Portugal. Ireland is not eligible since 2004 and Greece is not included in the study due to the lack of information.

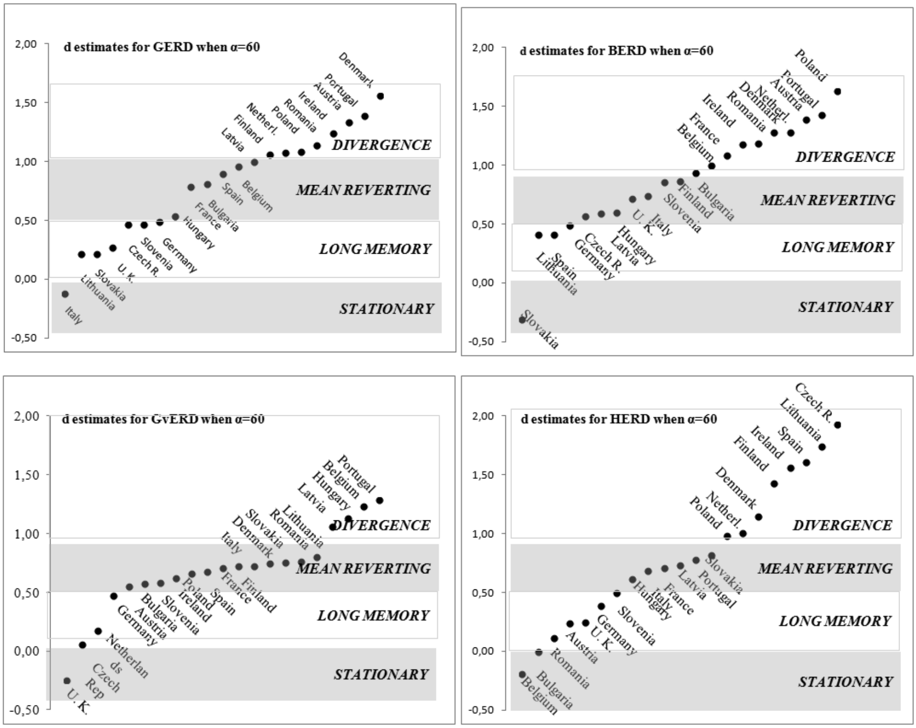

Figure 2. d estimates when α = 60

R&D since their innovation does not depend as much on R&D as on other sources of knowledge. When this is the case, changes in the productive specialisation might accelerate the pace of convergence. Secondly, the rate of convergence may differ as a result of cultural factors. R&D investments are path-dependent decisions. Lagging countries in which decisive policy interventions in favour of R&D are implemented would be in better condition for convergence. Thirdly, there are linkages between R&D and internationalisation, so that countries in which firms and/or higher education are more internationalised allocate more resources to R&D. Differences in the intensity of internationalisation may also explain differences in the R&D intensity convergence pace.

The results are consistent to some extent with the scarce studies that have investigated the convergence in terms of innovation across countries. Archibugi – Filippetti (2011) study the convergence in innovation performance across Europe using the Innobarometer and the European Innovation Scoreboard as innovation indicators during the period 2004–2008. They find a certain degree of convergence in lagging countries. Jungmittag (2006) studies the stochastic convergence in patents in the EU15 during the period 1967–1998 using panel data techniques. He also found that there are converging developments within the EU, although the convergence behaviour of the individual countries differs significantly.

5. CONCLUSIONS

In this research, we study the convergence among countries by means of testing the convergence in innovation in the EU countries applying fractional integration analysis in different measures of R&D intensity (total R&D and government, business and higher education R&D). The long-memory framework of analysis yields results much richer than the simple I(1)/I(0) alternative, which produces a simple divergence/rapid convergence dichotomy. We have estimated the fractional integration parameter (*d*), which determines the speed of convergence across EU countries. The estimation of the parameter *d* has been computed by the method of Phillips, which is a correction of the Geweke – Porter-Hudak method.

Results show that there was a certain degree of convergence in R&D intensity across countries between 1990 and 2010. However, the speed of convergence varied. For most of the countries, the speed of convergence was higher in the R&D expenditures of governments than in the R&D expenditures of higher education institutions and businesses. Differences in the speed of convergence across countries could be explained by differences in industry structures, in cultural trajectories, in macroeconomic conditions, or in internationalisation. The more dissimilar countries are in terms of these factors, the more likely they are to have divergent paths. Further, differences in R&D convergence by institutional sectors could be due to the different goals of each sector and to the relative weight of each sector in the total economy.

A better understanding of how the process of convergence in innovation works is an essential issue for economic and political integration. Furthermore, knowing whether there are values other than 0 and 1 may have remarkable implications for innovation policy. If series are stationary, external shocks may have an impact in the short term, but their long-term effect will be small because series will return to the mean. By contrast, series with an order of integration higher than 0 do not return easily to the mean after an external shock. An active public policy intervention would be needed in order to reach higher convergence levels.

REFERENCES

Archibugi, D. – Filippetti, A. (2011): Is the Economic Crisis Impairing Convergence in Innovation Performance across Europe? *Journal of Common Market Studies,* 49(6): 1153–1182.

Barro, R. J. – Sala-i-Martin, X. (1991): Convergence across States and Regions. *Journal of Political Economy,* 100(2): 223–251.

Baum, Ch. F. (2001): Stata: The Language of Choice for Time Series Analysis? *The Stata Journal*, 1: 1–16.

Baum, Ch. F. – Wiggins, V. (2006): MODLPR: Stata Module to Estimate Long Memory in a Time Series. http://EconPapers.repec.org/RePEc:boc:bocode:s411002.

Baumol, W. (1986): Productivity Growth, Convergence and Welfare: What the Long-Data Show. *American Economic Review,* 71(213): 116–131.

Bernard, A. B. – Durlauf, S. N. (1995): Convergence in International Output. *Journal of Applied Economics,* 10(2): 97–108.

Bilbao-Osorio, B. – Rodríguez-Pose, A. (2004): From R&D to Innovation and Economic Growth in the EU. *Growth and Change,* 35(4): 434–455.

Booth, G. G. – Tse, Y. (1995): Long Memory in Interest Rate Futures Markets: A Fractional Cointegration Analysis. *Journal of Futures Markets,* 15(5): 573–584.

Borsi, T. M. – Metiu, N. (2013): The Evolution of Economic Convergence in the European Union. *Deutsche Bundesbank Discussion paper,* 28/2013.

Castellacci, F. (2008): Innovation and the Competitiveness of Industries: Comparing the Mainstream and the Evolutionary Approaches. *Technological Forecasting and Social Change*, 75(8): 984–1006.

Cheung, Y. – Lai, K. (1993): A Fractional Cointegration Analysis of Purchasing Power Parity. *Journal of Business and Economic Statistics,* 11(1): 103–112.

Czasonis, M. – Quinn, M. A. (2012): Income Convergence in Europe: Catching up or Falling Behind? *Acta Oeconomica,* 62(2): 183–204.

De Long, B. J. (1988): Productivity Growth, Convergence and Welfare: A Comment. *American Economic Review,* 78(5): 1138–1154.

Dickey, D. A. – Fuller, W. A. (1979): Distribution of Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association,* 74(366): 427–431.

Edler, J. (2011): Innovation in EU CEE: The Role of Demand-Based Policy. In: Radosevic, S. – Kaderabkova, A. (eds): *Challenges for European Innovation Policy: Cohesion and Excellence from a Schumpeterian Perspective.* Cheltenham: Edward Elgar, pp. 177–208.

Elliott, G. – Rothenberg, T. J. – Stock, J. H. (1996): Efficient Tests for an Autoregressive Unit Root. *Econometrica,* 64(4): 813–836.

Freeman, Ch. – Soete, L. (1997): *The Economics of Industrial Innovation.* 3rd Edition. Cambridge, MA.: MIT Press, Volume 1.

Friedman, M. (1992): Do Old Fallacies Ever Die? *Journal of Economic Literature,* 30(4): 2129–2132.

Geweke, J. – Porter-Hudak, S. (1983): The Estimation and Application of Long Memory Time Series Models. *Journal of Time Series Analysis,* 4(4): 221–238.

Granger, C. W. J. – Ding, Z. (1996): Varieties of Long Memory Models. *Journal of Econometrics,* 73(1): 61–78.

Granger, C. W. J. – Joyeux, F. (1980): An Introduction to Long-Memory Time Series Models and Fractional Differencing. *Journal of Time Series Analysis,* 1(1): 15–29.

Griffith, R. – Redding, S. – Van Reenen, J. (2004): Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries. *The Review of Economics and Statistics,* 86(4): 883–895.

Grossman, G. M. – Helpman, E. (1991): *Innovation and Growth in the Global Economy.* Cambridge, MA: MIT Press.

Hosking, J. R. M. (1981): Fractional Differencing. *Biometrika,* 68(1): 165–176.

Hurvich, C. M. – Deo, R. – Brodsky, J. (1998): The Mean Squared Error of Geweke and Porter Hudak's Estimator of a Long Memory Time Series. *Journal of Time Series Analysis,* 19(1): 19–46.

Islam, N. (2003): What have We Learnt from the Convergence Debate? *Journal of Economic Surveys,* 17(3): 309–362.

Jungmittag, A. (2006): Innovation Dynamics in the EU: Convergence or Divergence? A Cross-Country Panel Data. *Empirical Economics,* 31(2): 313–331.

Kaldor, N. (1957): A Model of Economic Growth. *Economic Journal,* 67(268): 591–629.

Kaldor, N. (1970): The Case for Regional Policies. *Scottish Journal of Political Economy,* 17(3): 337–348.

Kleinknecht, A. – Montfort, K. V. – Brouwer, E. (2002): The Non-Trivial Choice between Innovation Indicators. *Economics of Innovation and New Technology,* 11(2): 109–121.

Kwiatkowski, D. – Phillips, P. C. B – Schmidt, P. – Shin, Y. (1992): Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure are We that Economic Time Series have a Unit Root? *Journal of Econometrics,* 54: 159–178.

Levine, R. – Renelt, D. (1992): A Sensitivity Analysis of Cross-Country Growth Regressions. *American Economic Review,* 82(4): 942–963.

Lucas, R. (1988): On the Mechanics of Economic Development. *Journal of Monetary Economics,* 22(1): 3–42.

Monfort, M. – Cuestas, J. C. – Ordóñez, J. (2013): Real Convergence in Europe: A Cluster Analysis. *Economic Modelling,* 33: 689–694.

Niebuhr, A. – Schlitte, F. (2009): EU Enlargement and Convergence: Does Market Access Matter? *Eastern European Economics,* 47(3): 28–56.

Phillips, P. C. B. (1999a): Discrete Fourier Transforms of Fractional Processes. *Working paper* 1243, Cowles Foundation for Research in Economics, Yale University. http://cowles.econ.yale.edu/P/cd/d12a/d1243.pdf

Phillips, P. C. B. (1999b): Unit Root Log Periodogram Regression. *Unpublished Working Paper* 1244, Cowles Foundation for Research in Economics, Yale University. http://cowles.econ.yale.edu/P/cd/d12a/d1244.pdf

Phillips, P. C. B. – Perron, P. (1988): Testing for Unit Roots in Time Series Regression. *Biometrika,* 75: 335–346.

Próchniak, M. – Witkowski, B. (2013): Time Stability of the Beta Convergence among EU Countries: Bayesian Model Averaging Perspective. *Economic Modelling,* 30: 322–333.

Quah, D. T. (1993): Galton's Fallacy and Tests of the Convergence Hypothesis. *Scandinavian Journal of Economics,* 95: 427–443.

Romer, P. M. (1986): Increasing Returns and Long-Run Growth. *Journal of Political Economics,* 94: 1002–1037.

Romer, P. M. (1990): Endogenous Technological Change. *Journal of Political Economics,* 98: S71–S102.

Sass, M. – Szalavetz, A. (2014): R&D-Based Integration and Upgrading in Hungary. *Acta Oeconomica,* 64(S1): 153–180.

Smith, K. H. (2005): Measuring Innovation. In: *The Oxford Handbook of Innovation.* New York: Oxford University Press, pp. 148–177.

Solow, R. M. (1956): A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics,* 70: 65–94.

Soukiazis, E. (2001): The Cumulative Growth Model as an Alternative Approach to the Convergence Process: Some Theoretical and Empirical Considerations. *Notas Económicas,* FEUC, 15(October): 19–39.

Staňisić, N. (2012): The Effects of the Economic Crisis on Income Convergence in the European Union. *Acta Oeconomica,* 62(2): 161–182.

Stengos, T. – Yazgan, M. E. (2011): Persistence in Convergence. *Working Paper Series* 34-11. The Rimini Centre for Economic Analysis.