Testing Convergence in R&D intensity across European countries: a fractional integration approach

Abstract

In this paper we examine the convergence in innovation across European Union countries applying fractional integration analysis. The variables of innovation used in are the total gross R&D expenditure as well as the total R&D expenditure broken down by institutional sector. We distinguish three institutional sectors: government, business enterprise and high education sector.

Results show that the fractional provides a more suitable framework than the traditional I(0)/I(1) scheme. The convergence/divergence in innovation across European countries depends on the variable considered. Convergence speed across countries is higher in relation to expenditure on R&D performed by higher education institutions and lower in the case of R&D expenditures by governments.

JEL: O32; O47; O52

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

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1.- Introduction

Since the beginning of the European integration process convergence in income levels has been a leading issue for politicians and academics. Concern about this matter has grown with the accession of Spain and Portugal in 1986 and more recently with the enlargement towards the Centre and Eastern European in 2004 and 2007. However, for the existence of income convergence it is necessary to boost competitiveness and this is determined by innovation.

Convergence in innovation is a primary issue since it enhances the competitive position of lagging countries, makes them less dependent on the technological developments produced in leading countries and improves on the ability of poorer countries for economic growth. Convergence in innovation, therefore, is essential for advancing in the process of both economic and political integration of the European Union. From an economic perspective, innovation contributes to reduce the risk of imbalances and divergences among countries. From a political perspective, it helps to ensure the viability of the economic development model of the European Union.

The Theory of the Economic Growth has provided the theoretical grounds for the majority of empirical research on economic convergence, the latter understood as the diminishing of income differences among countries or regions. Less attention, however, has been paid in empirical works to the critical role that innovation may play for the process of convergence to occur. Innovation increases the stock of existing knowledge and facilitates the creation of new processes and products which results in the expansion of existing markets and opening new markets. The improvement in competitiveness due to innovation will be eventually translated into increases in income levels.

Despite the consensus on the crucial role of innovation in the processes of economic convergence, the study of the convergence in innovation itself has been little explored. An advance in the knowledge of this phenomenon may provide new ideas for a better understanding of the convergence process and suggest to policymakers, further options for intervention conducive to the reduction of the disparities among countries.

This study aims to test the convergence in innovation in the European Union countries by applying fractional integration techniques. The rest of the paper is organised as follows: the second section present the theoretical framework which is based on the Economic Growth Theories and on the appropriateness of the fractional integration to study convergence processes; in the third section data and methodology are discussed. Empirical results are presented in the fourth section. Finally, the fifth section provides some conclusion remarks.

2.- Theoretical framework

Innovation is the driving force for the economic growth of countries, sectors and companies. Theories of economic growth have renewed the attention on the study of the role of the innovation in the process of economic development, underlining the interaction between investments in innovative activities, technological change and economic growth. Technology and innovation play an important role in economic growth and technology has become one of the most important factors in models of economic growth. A large number of studies have confirmed the relevance of innovation for the economic growth (Solow, 1956; Romer 1986, 1990; Lucas, 1988; Barro and Sala-i-Martin, 1997; Freeman and Soete, 1997; Archibugi and Filippetti, 2011).

The study of economic convergence among countries and regions has been extensively framed in the traditional theory of neoclassical economic growth (Solow, 1956) and endogenous growth theory (Lucas, 1988; Romer, 1986). Models based on the traditional theory have revealed the existence of convergence in income levels between countries. This means that income growth is slower in areas with higher incomes and faster in lower-income areas. Consequently long term income differences between areas tend to dissipate. The results arising from models based on endogenous growth theory show that there is a trend towards convergence in income levels due to the presence of factors such as level of education, savings or investments that affect the income levels. Countries that are in starting positions will not converge in their income over the long term.

Empirical research that has addressed the study of economic convergence has focused on real convergence in terms of income per capita and has studied this issue mainly from three different approaches. The first approach suggests that two countries converge in income per capita when differences in this variable are diminishing over time (Friedman, 1992; Quah, 1993). This occurs because poor countries grow at a higher rate than rich countries. Such convergence is also known as sigma-convergence or long run convergence.

The second approach assumes that convergence in growth rates occurs when countries converge not on the level of per capita income but on the growth rate of this variable. From the empirical viewpoint this type of convergence is tested by what is called beta-convergence or short-run convergence term. This convergence occurs when there is a negative correlation between the growth rate and the initial level of income. The 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 and Sala-i-Martin, 1991). The existence of beta-convergence is necessary but not sufficient condition for the existence of sigma-convergence since economic shocks that may exist may cause the variable of interest in certain countries tend to distance even when the 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 application of econometric techniques by using time series or panel data. Most convergence test of this group has to do with the idea of stochastic convergence (Carlino and Mills, 1993). This method consists of applying root tests and cointegration analysis to determine whether there is a common and/or deterministic trend for different countries (Bernard and 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, however, 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 in what definition of convergence would be the most adequate (Stengos and Yazgan, 2011). Some authors consider that the most appropriate measure of convergence is to consider the deviation from a reference country. Others, however, consider the deviation from the mean of a sample. (Islam, 200; Jungmitag, 2006)

The three previous measures of convergence have been used in empirical research. Pioneering work preferentially used the idea of sigma and beta convergence using cross-sectional data (De Long, 1988; Barro, 1991; Levine and Renelt, 1992). This approach suffers from certain problems (Bernard and Durlauf, 1995), among which stands out the fact that the alternative hypothesis which is considered is that all countries converge. In other words, this approach is not suitable for analyzing situations in which some countries converge while others do not. The use of time series would be desirable to overcome this limitation since econometric techniques based on time series permit identify 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 for the utilization of unit root tests that discriminate only between processes I(0) and processes I(1). This drawback can be overcome by using fractional integration techniques.

In this research we study the convergence among countries by means of testing the convergence in innovation in the UE countries applying fractional integration analysis. The focus of the paper is, first, the estimation of the fractional integration parameter (named 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 other 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 the effect will be small because 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 describe its nature. This parameter, therefore, plays a crucial role in understanding the economy and the economic planning. The size of the public intervention will depends on 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 back 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 goes back 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 are provided by Eurostat databases. The indicator selected to explore the convergence in innovation is the gross domestic expenditure on R&D as a percent of Gross Domestic Product (GDP) for each European country.

The R&D as an indicator of innovation is basically derived from the so called linear model of innovation. The linear model of innovation basically suggests that innovation happens in a 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 and research institutes and laboratories is strongly 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, form the empirical point of view R&D as 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 harmonization across countries. In addition, many governments still set their innovation policy objectives in terms of a determined or ideal level of R&D, as it is the case of the EU administration.

The R&D data has been used by a great deal of 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 leaving without exploring most of the interesting detail contained in the data (Smith, 2005).

The data available in Eurostat regarding the R&D activities are of two types. On the one hand, there are data on R&D expenditure as a percentage of GDP at national level and on the other hand, on R&D personnel as a percentage of total employment at national level. In this paper we use only the former measure of R & D because it ensures greater comparability among 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 hand, the total R&D expenditure is broken down by institutional sector. We distinguish three institutional sectors: government sector, business sector and high education sector[1].

The data series available and used in this 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 GERDj /GDPj ratio relative to the EU27 average

b) log of the BERDj /GDPj ratio relative to the EU27 average

c) log of the GvERD /GDPj ratio relative to the EU27 average

d) log of the HERDj /GDPj ratio relative to the EU27 average

where GERDj is the Gross Expenditure on Research and Development of country j, BERDj is the Expenditure on Research and Development undertaken by businesses of country j and the GvERDj is the Expenditure on Research and Development undertaken by Government, HERDj Expenditure by the High Education Systems of country j and GDPj is the Gross Domestic Product of country j.

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

The final 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 and Sweden are incomplete in the Eurostat database.

3.2.- Methodology

The methodology used in this work is the fractional integration. Fractional integration 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 and 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.

An extensive amount of recent work has emphasized the role of persistence of data. However, most of these studies have used traditional contrasts that test for the present 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 result excessively restrictive to study certain time series. Fractional integration can be considered a useful tool for analyzing 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 and Joyeus (1980) and Hosking (1981) to model the strong persistence that present many economic series.

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

$$\Phi(L)\ (1\text{-}L)^d Y_t = \Theta(L)\varepsilon_t,\ \varepsilon_t\text{-}\ (0,\sigma^2)$$

where, d is the long memory parameter (fractional integration) d and shows the number of differences to be taken in the series Y_t to become stationary, Φ (L) and Θ (L) are autoregressive and moving average polynomials whose roots are outside the unit circle. If $0<d<0.5$ the series is stationary with finite variance and long memory. If $0.5\leq d<1$ 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. Table 1 summarizes the different situations that can be found.

Table 1. Parameter values of fractional integration

d	Variance	Shock duration	Stationarity
d=0	Finite	Long lived	Stationary
0<d<0.5	Finite	Long lived	Stationary
0.5<d<1	Infinite	Long lived	Non-estationary
d=1	Infinite	Infinite	Non-estationary
d>1	Infinite	Infinite	Non-estationary

Source: Tkacz (2001)

There are different methods to estimate the parameter d. 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, 1999b).

The fractional integration test suggested by Geweke and Porter-Hudak (GPH) is based on the following OLS estimation:

$$\mathrm{Ln}\ (I(\omega j)) = \beta 0 + \beta 1\ \ln(4\sin 2(\omega j/2)) + \delta t, \qquad j=1,\ldots.n$$

with $\beta 1$ =-d, where I (ωj) is the periodogram of a series in the frequency ωj $\omega j = 2\pi j$ / T (j = 1, ... T-1). The ordinal number of low frequency (n) used in this test is $n = T^{\alpha}$ where T is the number of observations.

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 and 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 and Wiggins, 2009). Therefore, in the implementation of the fractional integration parameter estimation method proposed by Phillips, as a correction of the Geweke and 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 the 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, Rothenberg and Stock (1996). This method is preferred by many econometricians to the first–generation tests of Dickey and Fuller (Dickley and Fuller, 1976) or Phillips and Perron (Phillips and Perron, 1988). Inferences drawn from the DF–GLS 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, Phillips, Schmidt and Shin, 1992). This test utilizes 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 existence of 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.

Table 2 shows the results of multiple test of stationarity. We can note that the DGLS unit-root test does not reject the null hypothesis with respect to all the countries and all four variables. However, when we combine the results of KPSS and DGLS tests we observe that the verdict on the presence or not of unit roots is contradictory at the level of significance of 1% for all countries and for all the variables except for United Kingdom in the GvERD variable (the series is stationary with deterministic trend) and Netherlands and Slovakia in the HERD variable (the series are stationary with drift in both cases and with deterministic trend in the case of Netherlands).

Table 2 also presents, combining the results of both tests, a diagnosis on the existence or not of unit-root in the series tests at the level of 5% of significance in the case of model with deterministic trend and in the case of model with drift. We can note that at this level of significance the agreement in the results of both tests is higher. However, it still remains a large number of cases in which the combined analysis of tests is ambiguous.

These results suggest that formal estimates of d became useful to diagnose 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 and Porter-Hudak method, are presented in Tables 3-6. The estimation of d has been carry out for the bandwidth m= g(T) = T^{α}, with α= 0.50, 0.60, 0.70 and 0.80. Simulations suggest that α should be 0.5 or higher (Geweke and Porter-Hudak; 1983). However, the work of Cheung and Lai (1993) notes 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.

Table 3-6 present d estimates, standard errors and two p-values of the test statistics for the null hypothesis d=0 and d=1 since the method that we have applied allow us to obtain the T and z-statistics for d=0 and d=1 hypothesis, respectively. Tables also show one conclusion for the case of α= 0.60. All comments on the results will be based on this power.

We find that in all four variables, we obtain estimated parameters that are quiet robust to the choice of the number of frequencies for some of the countries, however, for other countries the parameters show more sensibility.

Table 2. Unit Root and Stationary tests

	GERD						BERD					
	DFGLS	**DFGLS**	**KPSS**	**KPSS**	Diagnosis at 5% of significance		**DFGLS**	**DFGLS**	**KPSS**	**KPSS**	Diagnosis at 5% of significance	
	Model a	Model b	ητ.	ημ	With trend	With drift	Model a	Model b	ητ.	ημ	With trend	With drift
Austria	-0,498	-0,399	0,135	0,598 **	Contradictory	Unit Root	-0,44	-0,324	0,137	0,6 **	Contradictory	Unit Root
Belgium	-0,428	-0,773	0,143	0,143	Contradictory	Contradictory	-0,076	-0,121	0,133	0,273	Contradictory	Contradictory
Bulgaria	-1,612	-0,336	0,135	0,54 **	Contradictory	Unit Root	-0,581	-2,255 **	0,16 **	0,232	Unit Root	Stationary
Czech Repub	-3,034 **	-0,695	0,065	0,553 **	Stacionary	Unit Root	-1,616	-0,241	0,0726	0,505 **	Contradictory	Unit Root
Denmark	-1,978	0,398	0,13	0,585 **	Contradictory	Unit Root	-1,518	0,334	0,147 **	0,579 **	Unit Root	Unit Root
Finland	-0,708	0,816	0,159 **	0,549 **	Unit Root	Unit Root	-0,451	1,578	0,161 **	0,575 **	Unit Root	Unit Root
France	-0,917	0,291	0,088	0,56 **	Contradictory	Unit Root	-0,918	1,425	0,0843	0,486 **	Contradictory	Unit Root
Germany	-0,82	-0,055	0,158 **	0,601 **	Unit Root	Unit Root	-0,946	0,538	0,154 **	0,596 **	Unit Root	Unit Root
Hungary	-1,603	0,245	0,087	0,531 **	Contradictory	Unit Root	-0,259	0,646	0,145	0,549 **	Contradictory	Unit Root
Ireland	-0,372	-0,286	0,16 **	0,218	Unit Root	Contradictory	-0,286	-0,406	0,159 **	0,16	Unit Root	Contradictory
Italy	-0,686	-0,306	0,073	0,577 **	Contradictory	Unit Root	-0,506	-0,079	0,154 **	0,35	Unit Root	Contradictory
Latvia	-1,807	-1,665	0,097	0,284	Contradictory	Contradictory	-0,657	-0,104	0,0857	0,352	Contradictory	Contradictory
Lithuania	-0,894	0,283	0,122	0,589 **	Contradictory	Unit Root	-0,253	0,089	0,111	0,504 **	Contradictory	Unit Root
Netherlands	-3,229	-0,143	0,077	0,398	Contradictory	Contradictory	0,162	-0,467	0,1	0,501 **	Contradictory	Unit Root
Poland	-0,98	-1,114	0,118	0,384	Contradictory	Contradictory	-3,553 **	-0,9	0,108	0,378	Stacionary	Contradictory
Portugal	-0,029	-0,706	0,131	0,548 **	Contradictory	Unit Root	-0,476	-0,939	0,125	0,582 **	Contradictory	Unit Root
Slovakia	-0,408	0,0029	0,126	0,56 **	Contradictory	Unit Root	-1,227	0,257	0,0685	0,562 **	Contradictory	Unit Root
Slovenia	-0,537	-0,52	0,152 **	0,347	Unit Root	Contradictory	-1,908	0,375	0,13	0,593 **	Contradictory	Unit Root
Spain	-1,461	-0,707	0,126	0,581 **	Contradictory	Unit Root	-1,547	-0,759	0,0913	0,585 **	Contradictory	Unit Root
U. Kingdom	-1,158	0,06	0,146 **	0,547 **	Unit Root	Unit Root	-0,534	0,14	0,16 **	0,565 **	Unit Root	Unit Root
Romania	-0,313	-0,028	0,153 **	0,25	Unit Root	Contradictory	-1,409	0,74	0,148 **	0,541 **	Unit Root	Unit Root

	GvERD						HERD					
	DFGLS	**DFGLS**	**KPSS**	**KPSS**	Diagnosis at 5% of significance		**DFGLS**	**DFGLS**	**KPSS**	**KPSS**	Diagnosis at 5% of significance	
	Model a	Model b	ητ.	ημ	With trend	With drift	Model a	Model b	ητ.	ημ	With trend	With drift
Austria	**-0,4**	-0,379	0,178 **	0,596 **	Unit Root	Unit Root	-1,135	-1,063	0,0652	0,107	Contradictory	Contradictory
Belgium	-1,261	1,731	0,174 **	0,579 **	Unit Root	Unit Root	-1,14	-0,115	0,102	0,489 **	Contradictory	Unit Root
Bulgaria	-1,003	-2,074	0,137	0,154	Contradictory	Contradictory	-1,398	-1,506	0,0666	0,095	Contradictory	Contradictory
Czech Repub	-3,408 **	0,697	0,124	0,537 **	Stacionary	Unit Root	-1,186	0,092	0,135	0,552 **	Contradictory	Unit Root
Denmark	-1,36	0,008	0,151 **	0,523 **	Unit Root	Unit Root	-0,539	2,163	0,132	0,559 **	Contradictory	Unit Root
Finland	-1,677	-1,509	0,152 **	0,251	Unit Root	Contradictory	-1,027	-0,325	0,145	0,309	Contradictory	Contradictory
France	-0,59	0,513	0,096	0,483 **	Contradictory	Unit Root	-1,814	0,466	0,123	0,509 **	Contradictory	Unit Root
Germany	-1,785	1,034	0,123	0,595 **	Contradictory	Unit Root	-0,122	-0,38	0,146	0,501 **	Contradictory	Unit Root
Hungary	-1,832	-2,897 ***	0,157 **	0,361	Unit Root	Stacionary	-1,467	-0,663	0,119	0,288	Contradictory	Contradictory
Ireland	-1,164	-0,208	0,078	0,081	Contradictory	Contradictory	-2,069	-0,629	0,155 **	0,43	Unit Root	Contradictory
Italy	-0,966	-0,976	0,16 **	0,177	Unit Root	Contradictory	-1,629	-1,442	0,141	0,263	Contradictory	Contradictory
Latvia	-1,582	-1,458	0,149 **	0,184	Unit Root	Contradictory	-1,818	-0,133	0,0665	0,306	Contradictory	Contradictory
Lithuania	-1,179	-0,354	0,097	0,514 **	Contradictory	Unit Root	-0,569	0,069	0,122	0,57 **	Contradictory	Unit Root
Netherlands	-2,933 **	0,377	0,062	0,522 **	Stacionary	Unit Root	-4,077 ***	-3,689 ***	0,111	0,163	Stationary	Stacionary
Poland	-1,909	-1,955	0,138	0,377	Contradictory	Contradictory	-1,07	-1,09	0,1	0,238	Contradictory	Contradictory
Portugal	-1,792	-0,768	0,121	0,274	Contradictory	Contradictory	-1,026	-0,031	0,115	0,474 **	Contradictory	Unit Root
Slovakia	-1,814	-0,12	0,136	0,41	Contradictory	Contradictory	-4,107 ***	-1,278	0,0794	0,429	Stationary	Contradictory
Slovenia	-2,715	-2,501 **	0,074	0,137	Stacionary	Stacionary	-0,671	-0,437	0,139	0,405	Contradictory	Contradictory
Spain	-0,525	-1,475	0,162 **	0,582 **	Unit Root	Unit Root	-2,65	0,096	0,105	0,565 **	Contradictory	Unit Root
U. Kingdom	-7,102 ***	0,38	0,08	0,571 **	Stacionary	Unit Root	-1,121	-0,314	0,0846	0,437	Contradictory	Contradictory
Romania	-1,498	-0,022	0,131	0,381	Contradictory	Contradictory	-2,476	-0,501	0,0727	0,554 **	Contradictory	Unit Root

The numbers of lags of DFGLS has been selected in accordance with the AIC criterion. Model "a" refers to the Model with constant and trend and Model "b"to the Model with constant. In the KPSS test **, *** indicate a unit root at 5% and 1% level under critical values of 0.146 and 0.216 for the model with trend and 0.463 and 0.739 for the model without trend (Kwiatkowski et al, 1992). ητ and ημ refer to the test statistics with and without trend, respectively. The maximum lags for the test is chosen by Schwartz criterion

Table 3 shows results for variable GERD (Gross Expenditure on R&D). We can note that for the cases of Belgium, Finland, Ireland, Latvia, Netherlands, Poland, Portugal, Spain and Romania, hypothesis that d=0 is rejected against the alternative hypothesis that d>0.

For most of countries the hypothesis that d=1 cannot be rejected against the alternative hypothesis that d<1 (it is rejected for Czech Republic, Denmark, Italy, Lithuania, Slovakia, and United Kingdom. The d estimates have varying values. For Belgium, Bulgaria, France, Hungary and Spain values are higher than 0.5. This result indicates that these countries are nonestationary but mean reverting; for Czech Republic, Lithuania, Slovakia, Slovenia, United Kingdom lower than 0.5, though for Lithuania and United Kingdom are non-significant. This finding means that the latter new EU member countries are converging at a faster speed than the previous group of countries. For Italy, d estimates are negative but non-significant.

For Austria, Denmark, Finland, Netherlands, Ireland Latvia, Poland, Portugal and Romania, d estimates is higher than 1 which technically means that data are explosive. The first ones are among the countries with the highest innovative profile in Europe.

Table 4 shows results for BERD (Expenditure on R&D carried out by businesses). In countries as Austria, Bulgaria, Denmark, Finland, Ireland, Lithuania, Netherlands, Portugal and Romania, hypothesis that d=0 is rejected against the alternative hypothesis that d>0. Again, for many countries the hypothesis that d=1 is not rejected against the alternative hypothesis that d<1 (it is rejected for Lithuania, Poland, Slovakia and Spain). The d estimates are higher than 0.5 (but lower than 1) in the cases of Bulgaria, Czech Republic, Finland, Hungary, Italy, Latvia, Slovenia and United Kingdom meaning that these countries are non-stationary but mean reverting. For Germany, Lithuania and Spain, the d estimates are lower than 0.5, though in the Spanish case the parameter is non-significant statistically. This finding means that regarding BERD the accessing new countries to the UE such as Bulgaria, Czech Republic, Hungary, Latvia and Slovenia are converging to the UE average at a lower speed than Lithuania, for example. For Slovakia, d estimates are negative whose interpretation is not clear. For Belgium, d estimates are 1 what means that there is no convergence to the EU average. In Austria, Denmark, France, Ireland, Netherlands, Poland, Portugal and Romania, the estimates are is higher than 1 which technically means that data are explosive.

Table 5 shows results for GvERD (Expenditure in R&D performed by the Government). For countries such as Bulgaria, Denmark, Germany, Hungary, Ireland, Latvia, Poland, Portugal and Romania the hypothesis that d=0 is rejected. In most countries the hypothesis that d=1 cannot be rejected, though it is rejected in the cases of Czech Republic, Germany, Netherlands, Portugal and United Kingdom. In a large number of countries (Austria, Bulgaria, Denmark, Finland, France, Ireland, Italy, Lithuania, Poland, Slovakia, Slovenia, Spain, and Romania) d estimates are higher than 0.5 (but lower than 1). The government spending on R&D in these countries is non-stationary but mean reverting; in Germany, Czech Republic and Netherlands the d estimates are lower than 0.5, though statistically non-significant for the former two. This result suggests that most countries are converging to the EU average at a slower speed than Germany, for example.

Table 3. Estimation of d for GERD

power	α= 0.50			α= 0.60			α= 0.70			α= 0.80			Conclusion
	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	
Austria	2,79	0,00	0,10	1,34	0,23	0,18	0,93	0,80	0,27	0,42	0,01	0,55	Divergence
s.e.	1,18			0,85			0,77			0,67			
Belgium	0,81	0,61	0,30	0,96	0,89	0,06	0,87	0,63	0,04	1,06	0,80	0,00	Mean-reverting convergence
s.e.	0,66			0,40			0,32			0,27			
Bulgaria	0,08	0,01	0,87	0,81	0,51	0,18	0,90	0,70	0,07	0,75	0,26	0,05	Mean-reverting convergence
s.e.	0,45			0,52			0,41			0,31			
Czech Repub	0,14	0,02	0,88	0,47	0,06	0,29	0,50	0,06	0,15	0,92	0,73	0,04	Long memory stationary
s.e.	0,89			0,39			0,30			0,38			
Denmark	0,54	0,21	0,05	1,56	0,05	0,11	1,48	0,07	0,05	1,44	0,05	0,01	Divergence
s.e.	0,16			0,79			0,62			0,44			
Finland	1,33	0,37	0,00	1,06	0,84	0,00	1,16	0,54	0,00	1,15	0,51	0,00	Divergence
s.e.	0,09			0,17			0,16			0,12			
France	0,03	0,01	0,97	0,79	0,46	0,24	0,66	0,20	0,21	0,73	0,24	0,06	Mean-reverting convergence
s.e.	0,63			0,59			0,47			0,34			
Germany	0,77	0,53	0,49	0,49	0,08	0,31	0,83	0,52	0,13	0,97	0,88	0,03	Long memory stationary
s.e.	0,98			0,43			0,47			0,35			
Hungary	-0,06	0,00	0,86	0,54	0,11	0,25	0,60	0,13	0,11	0,74	0,25	0,02	Mean-reverting convergence
s.e.	0,31			0,42			0,33			0,25			
Ireland	1,92	0,01	0,07	1,24	0,40	0,04	1,03	0,90	0,04	0,81	0,40	0,04	Divergence
s.e.	0,71			0,43			0,39			0,32			
Italy	-0,81	0,00	0,63	-0,12	0,00	0,86	0,21	0,00	0,74	0,27	0,00	0,55	Stationary
s.e.	1,53			0,68			0,61			0,44			
Latvia	0,57	0,25	0,50	1,00	0,99	0,04	0,75	0,35	0,08	0,61	0,09	0,06	Divergence
s.e.	0,75			0,36			0,36			0,28			
Lithuania	0,39	0,10	0,64	0,22	0,01	0,49	0,90	0,70	0,25	0,98	0,94	0,09	Long memory stationary
s.e.	0,76			0,30			0,70			0,50			
Netherlands	0,80	0,59	0,55	1,08	0,77	0,08	1,02	0,94	0,04	0,76	0,29	0,06	Divergence
s.e.	1,19			0,50			0,39			0,34			
Poland	1,47	0,20	0,04	1,09	0,75	0,01	0,77	0,39	0,09	0,65	0,12	0,05	Divergence
s.e.	0,41			0,28			0,38			0,29			
Portugal	1,61	0,10	0,02	1,39	0,17	0,00	1,11	0,68	0,01	1,21	0,35	0,00	Divergence
s.e.	0,36			0,18			0,31			0,23			
Slovakia	0,32	0,07	0,02	0,22	0,01	0,05	0,73	0,30	0,20	0,79	0,35	0,06	Long memory stationary
s.e.	0,07			0,09			0,50			0,36			
Slovenia	0,44	0,13	0,55	0,47	0,07	0,26	0,57	0,10	0,11	0,50	0,03	0,05	Long memory stationary
s.e.	0,66			0,37			0,30			0,22			
Spain	1,71	0,06	0,00	0,90	0,72	0,08	0,64	0,17	0,16	0,64	0,11	0,06	Mean-reverting convergence
s.e.	0,12			0,41			0,40			0,29			
U. Kingdom	0,64	0,33	0,78	0,27	0,01	0,76	0,68	0,23	0,40	0,46	0,02	0,44	Long memory stationary
s.e.	2,05			0,82			0,75			0,56			
Romania	1,52	0,16	0,20	1,14	0,63	0,04	1,04	0,87	0,02	1,20	0,37	0,00	Divergence
s.e.	0,93			0,42			0,33			0,27			

α is the frequencies band used in the log-peridogram regression The MODLPR test (Phillips, 1999) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: T^{power} ordinates are included. S.E are standard errors

Table 4. Estimation of d for BERD

power	α= 0.50			α= 0.60			α= 0.70			α= 0.80			
	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	Conclusion
Austria	2,25	0,00	0,13	1,39	0,18	0,09	1,04	0,89	0,26	0,56	0,05	0,35	Divergence
s.e.	1,08			0,66			0,62			0,56			
Belgium	0,38	0,09	0,36	1,00	0,99	0,12	0,78	0,40	0,09	0,75	0,26	0,06	Divergence
s.e.	0,35			0,54			0,47			0,33			
Bulgaria	1,31	0,41	0,00	0,94	0,84	0,01	1,09	0,74	0,01	0,88	0,61	0,01	Mean-reverting convergence
s.e.	0,09			0,25			0,24			0,23			
Czech Repub	0,89	0,77	0,47	0,57	0,13	0,26	0,59	0,12	0,06	0,73	0,24	0,03	Mean-reverting convergence
s.e.	1,07			0,45			0,34			0,27			
Denmark	0,66	0,35	0,25	1,28	0,33	0,06	1,14	0,60	0,01	1,28	0,21	0,00	Divergence
s.e.	0,46			0,52			0,42			0,32			
Finland	1,36	0,33	0,00	0,87	0,64	0,02	0,98	0,94	0,00	1,08	0,71	0,00	Mean-reverting convergence
s.e.	0,01			0,25			0,22			0,18			
France	-0,14	0,00	0,88	1,09	0,76	0,33	0,70	0,25	0,33	0,76	0,30	0,25	Divergence
s.e.	0,83			1,00			0,86			0,62			
Germany	0,54	0,22	0,61	0,49	0,07	0,24	0,79	0,42	0,06	0,74	0,25	0,04	Long memory stationary
s.e.	0,95			0,37			0,41			0,30			
Hungary	0,15	0,02	0,89	0,60	0,16	0,27	0,93	0,78	0,05	1,44	0,05	0,02	Mean-reverting convergence
s.e.	0,99			0,48			0,49			0,52			
Ireland	1,64	0,09	0,01	1,18	0,54	0,01	0,91	0,74	0,04	0,71	0,21	0,04	Divergence
s.e.	0,29			0,29			0,34			0,28			
Italy	1,15	0,69	0,44	0,74	0,36	0,22	0,85	0,56	0,04	0,86	0,54	0,02	Mean-reverting convergence
s.e.	1,28			0,53			0,42			0,30			
Latvia	0,02	0,01	0,99	0,59	0,16	0,46	0,53	0,07	0,44	0,33	0,00	0,47	Mean-reverting convergence
s.e.	1,51			0,73			0,57			0,43			
Lithuania	0,07	0,01	0,80	0,41	0,04	0,10	0,67	0,21	0,03	0,68	0,16	0,01	Long memory stationary
s.e.	0,24			0,20			0,30			0,22			
Netherlands	1,02	0,97	0,24	1,28	0,32	0,01	1,33	0,21	0,01	1,00	1,00	0,01	Divergence
s.e.	0,68			0,33			0,26			0,31			
Poland	0,73	0,46	0,27	1,63	0,03	0,12	1,15	0,58	0,21	0,88	0,59	0,19	Divergence
s.e.	0,53			0,87			0,82			0,62			
Portugal	0,57	0,25	0,00	1,43	0,13	0,04	1,45	0,09	0,00	1,37	0,10	0,00	Divergence
s.e.	0,01			0,51			0,39			0,29			
Slovakia	0,25	0,04	0,85	-0,31	0,00	0,61	0,19	0,00	0,54	0,48	0,02	0,38	Stationary
s.e.	1,22			0,57			0,66			0,52			
Slovenia	0,64	0,33	0,43	0,86	0,63	0,19	0,47	0,05	0,57	0,20	0,00	0,67	Mean-reverting convergence
s.e.	0,70			0,56			0,57			0,46			
Spain	1,10	0,78	0,06	0,41	0,04	0,33	0,26	0,01	0,35	0,28	0,00	0,27	Long memory stationary
s.e.	0,38			0,38			0,33			0,24			
U. Kingdom	1,64	0,09	0,10	0,72	0,34	0,23	0,62	0,14	0,23	0,41	0,01	0,25	Mean-reverting convergence
s.e.	0,68			0,53			0,42			0,34			
Romania	0,96	0,90	0,00	1,19	0,51	0,01	1,31	0,24	0,00	1,39	0,09	0,00	Divergence
s.e.	0,10			0,28			0,24			0,18			

α is the frequencies band used in the log-peridogram regression The MODLPR test (Phillips, 1999) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: T^{power} ordinates are included. S.E are standard errors

Table 5. Estimation of d for GvERD

power	α= 0.50			α= 0.60			α= 0.70			α= 0.80			Conclusion
	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	
Austria	0,48	0,16	0,81	0,56	0,12	0,49	0,23	0,00	0,73	0,35	0,00	0,49	Mean-reverting convergence
s.e.	1,82			0,74			0,65			0,47			
Belgium	1,54	0,15	0,00	1,24	0,40	0,10	1,18	0,49	0,05	1,05	0,82	0,02	Divergence
s.e.	0,03			0,61			0,47			0,35			
Bulgaria	0,27	0,05	0,53	0,58	0,14	0,04	0,58	0,11	0,01	0,60	0,08	0,00	Mean-reverting convergence
s.e.	0,37			0,21			0,17			0,12			
Czech Repub	-0,17	0,00	0,00	0,06	0,00	0,85	0,59	0,11	0,34	0,42	0,01	0,35	Long memory stationary
s.e.	0,01			0,29			0,56			0,42			
Denmark	0,83	0,66	0,26	0,75	0,38	0,04	0,64	0,17	0,03	0,94	0,81	0,01	Mean-reverting convergence
s.e.	0,60			0,26			0,23			0,28			
Finland	1,54	0,15	0,00	0,73	0,34	0,41	0,40	0,02	0,59	0,20	0,00	0,71	Mean-reverting convergence
s.e.	0,19			0,80			0,70			0,52			
France	1,62	0,09	0,08	0,71	0,32	0,22	0,99	0,98	0,09	0,69	0,17	0,14	Mean-reverting convergence
s.e.	0,64			0,51			0,48			0,41			
Germany	0,36	0,08	0,45	0,48	0,07	0,09	0,59	0,12	0,03	0,42	0,01	0,06	Long memory stationary
s.e.	0,41			0,22			0,20			0,19			
Hungary	1,80	0,03	0,00	1,14	0,63	0,04	1,11	0,66	0,01	0,97	0,89	0,01	Divergence
s.e.	0,06			0,42			0,32			0,26			
Ireland	0,46	0,14	0,12	0,67	0,26	0,01	0,46	0,04	0,10	0,48	0,02	0,02	Mean-reverting convergence
s.e.	0,21			0,15			0,24			0,17			
Italy	1,74	0,05	0,07	0,73	0,34	0,25	0,79	0,42	0,12	0,65	0,12	0,09	Mean-reverting convergence
s.e.	0,62			0,56			0,43			0,33			
Latvia	1,77	0,04	0,06	1,07	0,80	0,06	0,83	0,52	0,09	0,70	0,19	0,05	Divergence
s.e.	0,59			0,43			0,41			0,31			
Lithuania	1,04	0,92	0,09	0,81	0,51	0,14	0,60	0,13	0,20	0,88	0,59	0,04	Mean-reverting convergence
s.e.	0,42			0,46			0,41			0,36			
Netherlands	-1,07	0,00	0,14	0,18	0,00	0,79	0,05	0,00	0,93	0,17	0,00	0,68	Long memory stationary
s.e.	0,54			0,66			0,52			0,38			
Poland	0,69	0,41	0,18	0,63	0,20	0,02	0,48	0,05	0,05	0,21	0,00	0,41	Mean-reverting convergence
s.e.	0,40			0,18			0,20			0,24			
Portugal	0,93	0,85	0,25	1,29	0,00	0,04	1,78	0,00	0,07	1,71	0,00	0,02	Divergence
s.e.	0,65			0,81			0,80			0,57			
Slovakia	1,16	0,66	0,08	0,76	0,41	0,18	0,69	0,24	0,12	0,92	0,72	0,02	Mean-reverting convergence
s.e.	0,44			0,49			0,39			0,32			
Slovenia	0,14	0,02	0,92	0,59	0,15	0,49	0,99	0,96	0,22	1,01	0,96	0,09	Mean-reverting convergence
s.e.	1,33			0,79			0,72			0,52			
Spain	2,25	0,00	0,12	0,68	0,27	0,47	0,62	0,15	0,40	0,77	0,32	0,16	Mean-reverting convergence
s.e.	1,04			0,88			0,68			0,50			
U. Kingdom	-0,59	0,00	0,14	-0,24	0,00	0,35	-0,10	0,00	0,68	0,15	0,00	0,56	Stationary
s.e.	0,30			0,23			0,22			0,24			
Romania	1,16	0,67	0,00	0,77	0,42	0,04	0,62	0,14	0,05	0,87	0,56	0,01	Mean-reverting convergence
s.e.	0,03			0,27			0,26			0,26			

α is the frequencies band used in the log-peridogram regression The MODLPR test (Phillips, 1999) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: T^{power} ordinates are included. S.E are standard errors

Table 6. Estimation of d for HERD

power	α= 0.50			α= 0.60			α= 0.70			α= 0.80			Conclusion
	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	d	P>|z| z(H0:d=1 against H1:d<1)	P>|t| t(H0:d=0 against H1:d>0)	
Austria	0,22	0,03	0,57	0,24	0,01	0,35	0,55	0,09	0,17	0,72	0,21	0,04	Long memory stationary
s.e.	0,34			0,23			0,35			0,28			
Belgium	-0,48	0,00	0,60	-0,19	0,00	0,61	-0,10	0,00	0,75	-0,10	0,00	0,70	Stationary
s.e.	0,82			0,35			0,29			0,21			
Bulgaria	-0,69	0,00	0,38	0,00	0,00	1,00	0,52	0,07	0,43	0,83	0,46	0,13	Stationary
s.e.	0,67			0,45			0,62			0,50			
Czech Repub	0,42	0,12	0,20	1,93	0,00	0,08	1,78	0,00	0,05	1,49	0,03	0,03	Divergence
s.e.	0,26			0,89			0,70			0,55			
Denmark	1,00	1,00	0,40	1,15	0,60	0,05	0,94	0,83	0,06	0,68	0,16	0,09	Divergence
s.e.	1,03			0,46			0,41			0,35			
Finland	0,85	0,68	0,01	1,43	0,14	0,02	1,05	0,84	0,07	1,34	0,13	0,01	Divergence
s.e.	0,15			0,39			0,47			0,40			
France	0,12	0,02	0,60	0,71	0,31	0,16	0,56	0,09	0,17	0,78	0,33	0,03	Mean-reverting convergence
s.e.	0,21			0,42			0,36			0,30			
Germany	1,58	0,12	0,08	0,39	0,03	0,57	0,16	0,00	0,78	0,03	0,00	0,94	Long memory stationary
s.e.	0,60			0,65			0,55			0,40			
Hungary	0,52	0,20	0,11	0,62	0,19	0,00	0,55	0,09	0,00	0,96	0,87	0,02	Mean-reverting convergence
s.e.	0,23			0,12			0,11			0,31			
Ireland	1,59	0,11	0,12	1,57	0,05	0,01	1,29	0,27	0,02	1,28	0,22	0,00	Divergence
s.e.	0,73			0,39			0,41			0,29			
Italy	0,09	0,01	0,91	0,69	0,28	0,17	0,98	0,93	0,07	0,96	0,86	0,02	Mean-reverting convergence
s.e.	0,78			0,44			0,44			0,31			
Latvia	0,81	0,61	0,64	0,74	0,36	0,28	0,46	0,04	0,43	0,38	0,01	0,36	Mean-reverting convergence
s.e.	1,54			0,61			0,54			0,39			
Lithuania	0,68	0,38	0,11	1,75	0,01	0,03	1,33	0,21	0,07	1,00	0,99	0,08	Divergence
s.e.	0,30			0,56			0,60			0,49			
Netherlands	0,73	0,47	0,29	1,01	0,96	0,05	0,94	0,81	0,02	0,98	0,91	0,00	Divergence
s.e.	0,57			0,39			0,31			0,22			
Poland	2,32	0,00	0,05	0,99	0,98	0,27	0,68	0,22	0,36	0,43	0,01	0,44	Divergence
s.e.	0,70			0,80			0,69			0,53			
Portugal	1,29	0,44	0,00	0,78	0,45	0,03	0,66	0,19	0,03	0,89	0,63	0,01	Mean-reverting convergence
s.e.	0,08			0,26			0,23			0,24			
Slovakia	0,42	0,12	0,71	0,82	0,52	0,28	0,96	0,89	0,12	0,76	0,28	0,10	Mean-reverting convergence
s.e.	1,02			0,67			0,53			0,41			
Slovenia	0,09	0,01	0,94	0,50	0,08	0,34	0,79	0,42	0,14	1,38	0,10	0,04	Long memory stationary
s.e.	1,10			0,47			0,46			0,55			
Spain	2,29	0,00	0,29	1,61	0,03	0,09	0,86	0,59	0,40	0,66	0,13	0,37	Divergence
s.e.	1,79			0,76			0,94			0,69			
U. Kingdom	0,29	0,06	0,87	0,25	0,01	0,72	0,61	0,14	0,36	0,66	0,13	0,17	Long memory stationary
s.e.	1,69			0,64			0,61			0,44			
Romania	-0,17	0,00	0,84	0,12	0,00	0,74	0,20	0,00	0,49	0,41	0,01	0,14	Long memory stationary
s.e.	0,73			0,33			0,27			0,25			

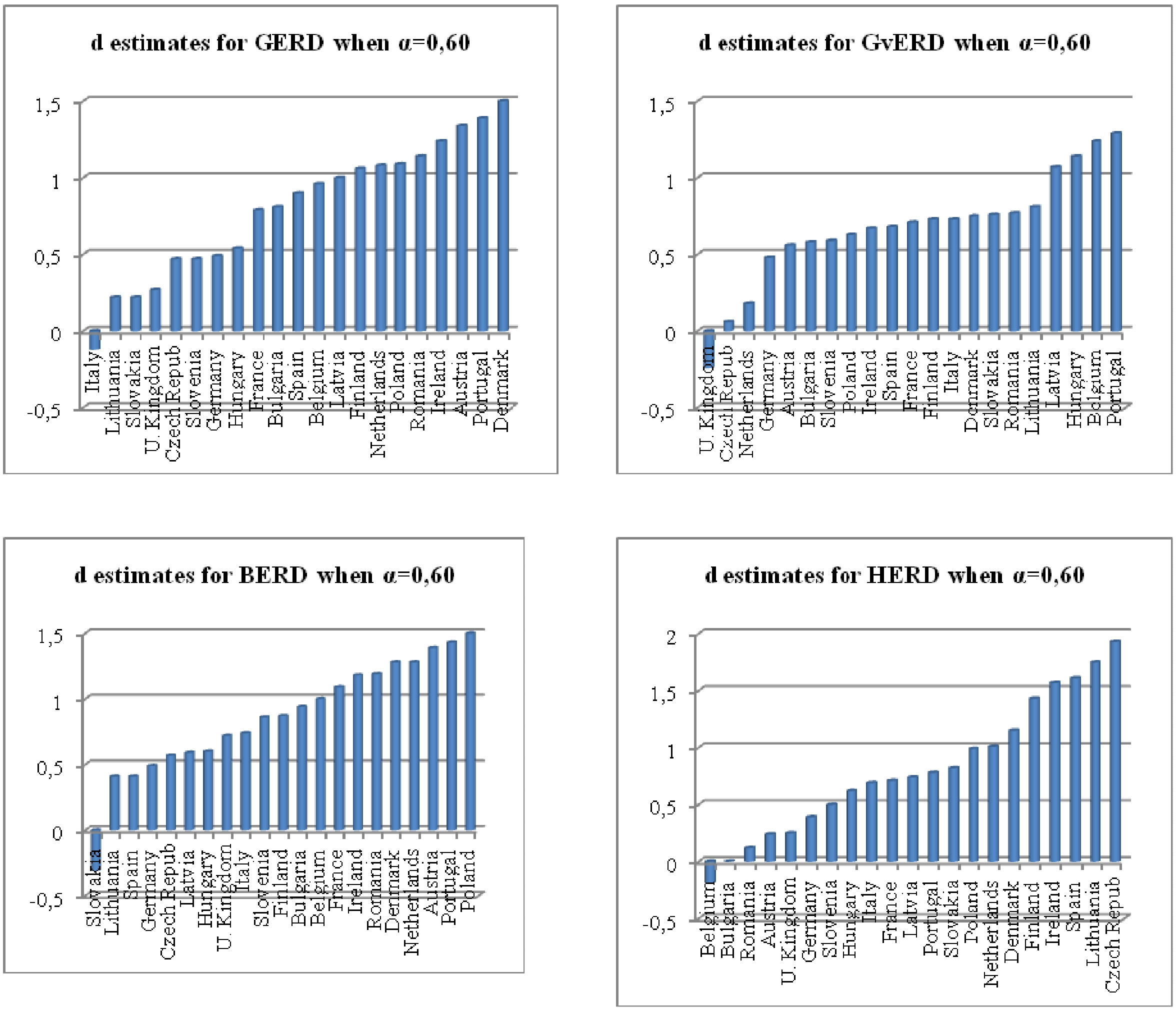
α is the frequencies band used in the log-peridogram regression The MODLPR test (Phillips, 1999) is applied to the levels of the series after removal of a liner trend. Power indicates the sample used: T^{power} ordinates are included. S.E are standard errors

Finally, Table 6 shows results for HERD (expenditure in R&D by High Education Institutions). In this case, we note that countries as Czech Republic, Denmark, Finland, Hungary, Ireland, Lithuania, Netherlands, Portugal and Spain the hypothesis that d=0 is rejected. For various countries the hypothesis that d=1 cannot be rejected (it is rejected for Belgium, Bulgaria, Czech Republic, Germany, Ireland, Lithuania, Slovakia, Spain, United Kingdom and Romania).

The d estimates have varying values. For France, Hungary, Italy, Latvia, Poland, Portugal and Slovakia the d parameter is higher than 0.5 though lower than the unit. This result indicates that in these countries the variable HERD is non-stationary but mean reverting; for Austria, Germany, Slovenia, United Kingdom and Romania the d estimates are lower than 0.5 though non-significant statistically.

Figure 1 summarizes the d estimates for the four variables when α= 0.60.

Figure 1. d estimates



We can note that in the variable GERD, o countries are stationary with long memory while 5 countries are not stationary but mean reverting. 8 countries are not stationary. In the variable BERD, only 3 countries are stationary with long memory while 9 countries are not stationary but mean reversion and 8 are not stationary. In the case of variable GvERD, 3 countries are stationary with long memory, while 13 countries are non-stationary but mean reversion and 3 member states non-stationary. In the case of variable HERD, 6 countries are stationary with long memory, 8 are not stationary but mean reverting and 6 countries are non-stationary. Therefore, we can observe that non-stationarity is more widespread in the case of R&D expenditures by governments. The stationarity with long memory is more widespread in relation to expenditure on R&D performed by higher education institutions. Convergence in R&D in European countries, therefore, depends on the variable that we are considering. Not all countries converge at the same rate in each variable under study.

4.- Conclusions

In this research we study the convergence among countries by means of testing the convergence in innovation in the UE countries applying fractional integration analysis in different measures of R&D intensity time series. The long memory framework of analysis is much richer than the simple I(1)/I(0) alternative that produces a simple absolute divergence and rapid convergence dichotomy. We have estimated the fractional integration parameter (d), that is, the parameter that determines the speed of convergence between different economies. The estimation of the integration parameter has been computed by the method of Phillips which is a correction of the Geweke and Porter-Hudak method.

Results show that convergence to the EU average R&D intensity across countries depends on the variable that it is considered. Not all countries converge at the same rate in each variable under study. Convergence speed is higher in relation to expenditures on R&D performed by higher education institutions while convergence advances at a slower speed in the case of R&D expenditures carried out by governments. The speed of convergence (divergence) captured by the estimated parameter d could be explained by differences in physical and human capital as well as fiscal characteristics of the economic policies pursued by different countries. The more dissimilar countries are in terms of these factors the more likely they are to have divergent paths.

A better understanding of how the process of convergence in innovation among European countries occurs is an essential issue for the economic and political integration in EU. Knowing whether there are other 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 the effect will be small because series will return to the mean at an exponential rate. By contrast, integrated data do not return to the mean after an external shock.

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