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Total Factor Productivity Estimates: Some Evidence from European Regions

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Abstract

This paper analyzes the economic performance of European Regions and computes the Total Factor Productivity (TFP) using a panel cointegration approach. The main idea behind this choice is that this approach allows to directly estimate differences across economies in the production function and also to test for the presence of scale economies and market imperfections. In fact, recent studies (de la Fuente (1995, 1996b) and de la Fuente and Doménech (2000)) show that TFP differences across countries and regions are substantial and highlight the importance of TFP dynamics as crucial in the evolution of productivity.

Keywords: Total Factor Productivity, Panel Unit Root Test, Panel Cointegration, Fully Modified OLS.

JEL Classification: C23, D24, O47, O52

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1 Introduction

A common feature of many empirical studies on international comparison of Total Factor Productivity (TFP) has been the assumption of identical aggregate production function for all countries. However, the empirical evidence suggests that the production function may actually differ across countries but attempts at allowing for such differences have been limited by the fact that most of these studies have been conducted in the framework of single cross-country regressions. In this framework it is econometrically difficult to allow for differences in the production function as these are not easily measurable.

Solow (1956) develops a production function in which output growth is a function of capital, labour, and knowledge or technology. Technology is Harrod neutral and it is assumed to be exogenous and homogenous across countries. Economists use the growth accounting approach to test the neoclassical growth model, and to evaluate the effect of physical capital accumulation on output growth.

The growth accounting approach provides a breakdown of observed economic growth into components associated with changes in factor inputs and a residual that reflects technological progress and other elements. The basic of growth accounting were presented in Solow (1957).[1]

[1] Differentiation of the neoclassical production function $Y = F(A, K, L)$ with respect to time yields:

$$\frac{\dot{Y}}{Y} = g + (\frac{F_K K}{Y}) \cdot (\dot{K}/K) + (\frac{F_L L}{Y}) \cdot (\dot{L}/L) \quad (1)$$

where F_K and F_L are the factor marginal products and g is the technological progress, given by:

$$g \equiv (\frac{F_A A}{Y}) \cdot (\frac{\dot{A}}{A}) \quad (2)$$

$$g = \frac{\dot{Y}}{Y} - \frac{F_K K}{Y}) \cdot (\dot{K}/K) - (\frac{F_L L}{Y}) \cdot (\dot{L}/L) \quad (3)$$

If the technological progress is Hicks neutral then $F(A, K, L) = A \cdot \tilde{F}(K, L)$ and $g = \frac{\dot{A}}{A}$. The technological change can be calculated as a residual (*Solow residual*) from (1).

The results of the early growth accounting exercises raise questions about the large unexplained residual in Solow-model calculations. The neoclassical model emphasizes the role of factor accumulation, neglecting differences in productivity growth and technological change captured by the residual. By defining capital to include physical and human capital, Mankiw (1995) finds that the results more closely resemble the theoretical prediction of the neoclassical model. The works of Barro and Sala-i-Martin (1995), Mankiw, Romer and Weil (1992) follow a similar perspective.

Easterly and Levine (2001) suggest that growth economists should focus on TFP and its determinants rather than factor accumulation. They point out that much of the empirical evidence accumulated to date indicates that factor accumulation explains only a portion of the observed cross-country growth. Solow (1956) himself finds that income growth is explained only in little part by capital accumulation while the rest is explained by productivity growth. Easterly and Levine (2001) also observe that there exists a tendency of production factors to move to the same places, causing a concentration of economic activity. In such circumstances, to apply the neoclassical model with homogenous technology is not appropriate.

Endogenous growth theory, starting from Romer (1986) and Lucas (1988), departs from the standard neoclassical theory and considers the technological change as endogenous. The theory focuses on explaining the Solow residual.

Going back to the growth accounting approach, it is important to point out that it presents two major shortcomings: first of all, a key assumption is that prices coincide with social marginal products. If this assumption is violated, then the estimated Solow residual deviates from the true contribution of technological change to economic growth. Moreover, this approach ignores consideration on market power and returns to scale.

Hall and Jones (1996, 1997) suggest the cross-section growth accounting approach to TFP level comparisons and they follow Solow (1957) to arrive at the standard growth accounting equation. The difference with respect to Solow is that while in Solow (1957) differentiation is conducted in the direction of time t, Hall and Jones propose to apply the procedure in the cross-sectional direction, i.e. in the direction of i. But this poses a problem because the movement on i depends on the particular way the countries are ordered. Hall and Jones order the countries on the basis of an index that is a linear combination of the individual country's physical and human capital per unit of labor and its value of α, the share of physical capital in income. In order to get the country specific α, the authors make the assumption that price of capital (r) is the same across countries.

The cross-section growth accounting approach presents several advantages. First, it does not require any specific form of aggregate production function. Only constant returns to scale and differentiability are required to arrive at the growth accounting equation. Second, it allows factor income share parameters to be different across countries. However, the cross-section growth accounting approach has some weaknesses too. First, it requires prior ordering of countries and TFP measurement may be sensitive to the ordering chosen. Second, TFP indices are also sensitive to inclusion or exclusion of countries. Third, computation of α_i is made on the basis of the assumption of a uniform rate of return across countries. Finally, using capital stock data and accounting for human capital in cross-country TFP comparison, it is possible to pick up some noise.

The panel approach to international TFP comparisons arose directly from recent attempts at better explaining cross-country growth regularities. Islam (1995) takes the work of Mankiw, Romer and Weil (1992) as his starting point and examines how the results change with the adoption of the panel data approach. The main usefulness of the panel approach with respect to the single cross-country regressions lies in its ability to allow for differences in the aggregate production function across economies. This leads to results that are significantly different from those obtained from single cross-country regressions. The panel approach makes it possible to allow for differences in the aggregate production function in the form of unobservable individual "country effects". To the extent to which the "country effects" (intercepts) are correlated with the regressors, the conventional cross-section estimates of Mankiw, Romer and Weil (1992) are biased. Harrigan (1995) shows that there are systematic differences across countries in industry output. One possible explanation for this result is that technology is not the same across countries. This hypothesis has gained great attention from international economists: Trefler (1993, 1995), Dollar and Wolff (1993) and Harrigan (1997a). More recently, Harrigan (1999) compute TFP for eleven OECD countries in the 1980s and he finds large and persistent TFP differences among them.

In comparison with the cross-section growth accounting approach, the panel regression approach has some advantage. First, it does not require any prior ordering of countries. Second, it is not sensitive to inclusion or exclusion of countries. Third, the approach is flexible to the use of capital stock data or investment data and to inclusion of human capital. Finally, the econometric estimation can provide a check for the severity of noise in the relevant data. Of course, the panel approach also presents some weaknesses: it requires a specific form for aggregate production function, it imposes homogeneity of factor share parameters and, finally, it is subject to certain pitfalls of econometric estimation.[2]

The aim of this paper is to analyze the economic performance of a sample of European regions using a panel data approach. The main idea behind this choice is that this approach allows for differences across countries and regions. In fact, recent studies (de la Fuente (1995, 1996b) and de la Fuente and Doménech (2000)) show that Total Factor Productivity (TFP) differences across countries and regions are substantial and highlight the importance of TFP dynamics as crucial in the evolution of productivity. Furthermore, the empirical literature shows that regional disparities are larger when compared

[2]The cost of econometric analysis is that parameter estimation requires imposing a statistical model on the data (see Harrigan,1999)

to cross-country differences and in spite of the acceleration of the European integration, disparities has remained an open issue, especially on economic growth and employment. Therefore, the existence of large disparities among European regions justifies the choice of this paper to analyze the TFP at regional level instead that at national level. Finally, it is worth noting the fact that these large differences among regions in Europe have important implications for the economic policies of the European Union.

Le Gallo and Dall'erba (2006) analyzes the productivity structure of 145 EU regions according to the concepts of σ- and β- convergence, including spatial effects and a disaggregated analysis at a sectorial level. They detect σ- convergence in aggregate labour productivity and in the service sectors but not in other sectors. They also estimate β- convergence models and the results show that inequality in productivity levels between core and peripheral regions persist.

Marrocu, Paci e Pala (2000) estimate a complete set of long-run production functions for 20 Italian regions and 17 economic sectors. They find that regions differ considerably in the technological knowledge levels. Furthermore they find that the highest levels are those of the northern regions of Italy and the lowest are those for southern regions.

Boldrin and Canova (2001) study the disparities across the regions of EU 15. They show that neither convergence nor divergence is taking place within EU and that most regions are growing at a near uniform growth rate, with some exceptions. They also show that the evolution of TFP and labour productivity in the poorer regions are not affected by the amount of funds invested under EU programmes. Boldrin and Canova argue that most of the observed disparities in regional income levels derive from the combination of three factors: differences in TFP, differences in employment levels, and differences in the share of agriculture in regional income.

Paci, Pigliaru and Pugno (2001) study the disparities on productivity growth and unemployment across European regions, adopting a sectorial perspective, i.e. by considering the relationship between agriculture, industry and services, and their role in enhancing growth and absorbing employment. They find that regions that start from a high agricultural share are characterized by higher growth rates than average; on the contrary regions with low agricultural share are the richest and grow slowly. Furthermore, they find that convergence in aggregate productivity is strongly associated with out-migration from agriculture.

Here, I use a Cobb-Douglas specification for a sample of 115 European Regions over the period 1976-2000 and I provide estimates of TFP for each region.

This work also shows, on the basis of specific panel tests, that there is empirical evidence which suggests the presence of unit roots in the series under study. I apply, then, the panel cointegration test, proposed by Pedroni (1999), to guard against spurious regression problems.

This paper is organized as follows. Section 2 describes the model. Section 3 describes the econometric methodology. Section 4 presents the empirical results. Section 5 concludes and Section 6 describes in appendix the panel unit root test and the panel cointegration test used in this work.

2 The model

I estimate the parameters of production functions and calculate total factor productivity for a sample of European regions from Cobb-Douglas production function specifications:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{4}$$

where Y_{it} is the value added in region i at time period t, K_{it} is the stock of physical capital, L_{it} is the amount of labour used in production. A_{it} is the specification for Hicks-neutral technology and it introduces a stochastic component into the model. The knowledge production function for region i

at time period t can be defined as follows: in region i at time period t

$$A_{it} = e^{a_i + \gamma_t + \varepsilon_{it}} \tag{5}$$

where A_{it} is the level of technology in region i at time t, a_i denotes a region specific constant which captures the efficiency in technology production, γ_t is a common time effect which captures the countrywide or worldwide knowledge accumulation and ε_{it} is a random shock. The common time effect γ_t allows to take account of cross-regional dependence in the estimation of the regional production function. Rewriting equation (4) in natural logarithms yields the following:

$$\ln Y_{it} = a_i + \gamma_t + \alpha_i \ln K_{it} + \beta_i \ln L_{it} + \varepsilon_{it} \tag{6}$$

The panel model includes a regional specific effect a_i and a common time effect γ_t. The parameters α and β are the elasticities of capital and labour with respect to output, respectively. This paper estimates (6) by using a panel data of 115 European regions over the period 1976-2000. The list of the regions is given in table (1). The stock of physical capital is determined by using the Perpetual Inventory Method :

$$K_t = (1 - \delta) K_{t-1} + I_{t-1} \tag{7}$$

where δ is the depreciation rate: it is assumed constant and equal to 8%, which is consistent with OECD estimates; I is the gross fixed capital formation.[3] The initial value of K is calculate as:

$$K_0 = \frac{I_0}{g + \delta} \tag{8}$$

[3] See Machin and Van Reenen, (1998)

where g is the average annual logarithmic growth of investment expenditure and I_0 is investment expenditure in the first year for which data on investment are available.

3 Econometric methodology

Non-stationarity issues on series have been often overlooked when the panel approach has been used to estimate production functions. At the best of my knowledge, no attempt has been made to asses the non-stationarity of the series used on the estimation of production functions for European regions. Because of nonstationarity problems, first step of this work is to investigate the properties of regional time series for value added, capital stock and labour. I start applying the panel unit root test proposed by Im, Pesaran and Shin (2003, IPS hereafter), while the spurious regression problem is analyzed through the cointegration test recently proposed by Pedroni (1999).

The main theme of this paper is to analyze the economic performance of a sample of European regions. But it is worth emphasizing that only if the cointegration test provides evidence of long run dynamics in the series, although they are nostationary, it is possible to proceed with the analysis. I have in mind a particular form of normalization among variables (a production function relation) and in this case, as pointed out by Pedroni, the interest is in knowing whether the variables are cointegrated, not how many cointegrating vectors exist.

The model I use is a two error component model, with $u_{it} = a_i + \gamma_t + \varepsilon_{it}$, and ε_{it} is assumed homoskedastic. If the assumption fails, the estimates are still consistent but inefficient. It is possible to investigate about the validity of this assumption by performing a groupwise likelihood ratio heteroskedasticity test. This test is performed on the residuals of the model estimated by OLS. The test is chi-square distributed with $N-1$ degrees of freedom, where N is the number of groups in the sample.

I also control for serial correlation using the Baltagi and Li test (1995). This is LM test for serial correlation in fixed effects models. Baltagi and Li propose two versions of the test, depending on the assumption for the autocorrelation structure, namely AR(1) and MA(1). The test is asymptotically distributed as $N(0,1)$ under the null.

4 Data and empirical results

In my analysis I use a panel of 115 European regions over the period 1976-2000 (see table 1). The level of territorial disaggregation provides the maximum disaggregation possible with the data available. This level corresponds to NUTS 2 for Spain, Italy, Greece, France, Austria; NUTS 1 for Belgium, Germany, Netherlands, United Kingdom; NUTS 0 for Ireland, Denmark and Luxembourg. Annual data on value added and labour units are from Cambridge Econometrics dataset. The stock of capital is determined by using the Perpetual Inventory Method and is measured at 1995 constant prices, as value added.

There is a great disparity among regions and even across regions of the same countries. The poorest regions are those from Spain, Greece, southern regions of Italy and almost all UK regions. The richest ones are Wien, Ile de France, Hamburg and Bruxelles. The lowest rate of growth of value added is for Sterea Ellada (Greece. $0,7\%$), while the highest one is for Ireland (close to 4%) (see table 2). Extremadura (Spain) shows the lowest level of value added but its growth rate is high (over 3%). If we look at the employment performance (see table 3) over the period examined, we will see disparities again among regions and across regions of the same country. The worst performance is that for Ditiky Ellada (Greece, -1.89%); the best one is that for Ceuta y Melilla (Spain, 2.55%)

I analyze the time series properties of my data, applying the IPS panel

Table 1: The Sample of Regions

Regions		Regions	
Belgium- NUTS1		Aquitaine (Fr)	Oost-Nederland (Nl)
Bruxelles-Brussel (Be)	Asturias (Es)	Midi-Pyrenees (Fr)	West-Nederland (Nl)
Vlaams Gewest (Be)	Cantabria (Es)	Limousin (Fr)	Zuid-Nederland (Nl)
Region Walonne (Be)	Pais Vasco (Es)	Rhone-Alpes (Fr)	Austria - NUTS 2
Denmark - NUTS 0	Navarra (Es)	Auvergne (Fr)	Burgenland (At)
Germany - NUTS 1	Rioja (Es)	Languedoc-Rouss. (Fr)	Niederosterreich (At)
Baden-Wurttemberg (De)	Aragon (Es)	Prov-Alpes-Cote d'Azur (Fr)	Wien (At)
Bayern (De)	Madrid (Es)	Corse (Fr)	Karnten (At)
Berlin (De)	Castilla-Leon (Es)	Ireland - NUTS 0	Steiermark (At)
Bremen (De)	Castilla-la Mancha (Es)	Italy - NUTS 2	Oberosterreich (At)
Hamburg (De)	Extremadura (Es)	Piemonte (It)	Salzburg (At)
Hessen (De)	Cataluna (Es)	Valle d'Aosta (It)	Tirol (At)
Niedersachsen (De)	Com. Valenciana (Es)	Liguria (It)	Vorarlberg (At)
Nordrhein-Westfalen (De)	Baleares (Es)	Lombardia (It)	United Kingdom - NUTS 1
Rheinland-Pfalz (De)	Andalucia (Es)	Trentino-Alto Adige (It)	North East (GB)
Saarland (De)	Murcia (Es)	Veneto (It)	North West (GB)
Schleswig-Holstein (De)	Ceuta y Melilla (Es)	Fr.-Venezia Giulia (It)	Yorkshire and the Humb (GB)
Greece - NUTS2	Canarias (Es)	Emilia-Romagna (It)	East Midlands (GB)
Anatoliki Makedonia (Gr)	France - NUTS 2	Toscana (It)	West Midlands (GB)
Kentriki Makedonia (Gr)	Ile de France (Fr)	Umbria (It)	Eastern (GB)
Dytiki Makedonia (Gr)	Champagne-Ard (Fr)	Marche (It)	London (GB)
Thessalia (Gr)	Picardie (Fr)	Lazio (It)	South East (GB)
Ipeiros (Gr)	Haute-Normandie (Fr)	Abruzzo (It)	South West (GB)
Ionia Nisia (Gr)	Centre (Fr)	Molise (It)	Wales (GB)
Dytiki Ellada (Gr)	BassCentre (Fr)e-Normandie (Fr)	Campania (It)	Scotland (GB)
Sterea Ellada (Gr)	Bourgogne (Fr)	Puglia (It)	Northern Ireland (GB)
Peloponnisos (Gr)	Nord-Pas de Calais (Fr)	Basilicata (It)	
Attiki (Gr)	Lorraine (Fr)	Calabria (It)	
Voreio Aigaio (Gr)	Alsace (Fr)	Sicilia (It)	
Notio Aigaio (Gr)	Franche-Comte (Fr)	Sardegna (It)	
Kriti (Gr)	Pays de la Loire (Fr)	Luxembourg - NUTS - 0	
Spain - NUTS 2	Bretagne (Fr)	Netherlands - NUTS 2	
Galicia (Es)	Poitou-Charentes (Fr)	Noord-Nederland (Nl)	

Table 2: Gross Value Added growth rate. Source: own calculations based on Cambridge Econometrics

Regions	gva-g	Regions	gva-g	Regions	gva-g	Regions	gva-g
Bruxelles-Bruxelles (Be)	1.79	Rioja (Es)	2.47	Prov-Alpes (Fr)	1.41	Salzburg (At)	2.60
Vlaams Gewest (Be)	2.31	Aragon (Es)	3.03	Corse (Fr)	1.73	Tirol (At)	2.27
Region Walonne (Be)	1.48	Madrid (Es)	3.25	Ireland	4.36	Vorarlberg (At)	2.42
Denmark - NUTS 0	1.66	Castilla-Leon (Es)	2.51	Piemonte (It)	1.73	North East (GB)	1.28
Baden-Wurttemberg (De)	1.82	Castilla-la Mancha (Es)	2.71	Valle d'Aosta (It)	1.50	North West (GB)	1.73
Bayern (De)	2.39	Extremadura (Es)	3.21	Liguria (It)	2.45	Yorkshire (GB)	1.95
Berlin (De)	0.70	Cataluna (Es)	3.12	Lombardia (It)	1.93	East Midl (GB)	2.04
Bremen (De)	1.65	Com. Valenciana (Es)	2.43	Trentino-AA (It)	2.29	West Midl (GB)	2.01
Hamburg (De)	1.90	Baleares (Es)	3.19	Veneto (It)	2.39	Eastern (GB)	2.29
Hessen (De)	2.28	Andalucia (Es)	2.47	Fr.-V Giulia (It)	2.15	London (GB)	2.27
Niedersachsen (De)	1.68	Murcia (Es)	2.21	Emilia-R(It)	1.91	South East (GB)	2.60
Nordrhein-Westfalen (De)	1.35	Ceuta y Melilla (Es)	2.94	Toscana (It)	1.91	South West (GB)	2.07
Rheinland-Pfalz (De)	1.38	Canarias (Es)	3.59	Umbria (It)	1.53	Wales (GB)	2.03
Saarland (De)	1.64	Ile de France (Fr)	2.02	Marche (It)	1.66	Scotland(GB)	2.07
Schleswig-Holstein (De)	1.57	Champagne-Ard (Fr)	1.56	Lazio (It)	2.22	Northern Ir (GB)	1.98
Anatoliki Makedonia (Gr)	1.74	Picardie (Fr)	1.24	Abruzzo (It)	1.84		
		Haute-Normandie (Fr)	1.18	Molise (It	2.18		
Kentriki Makedonia (Gr)	1.20	Centre (Fr)	1.77	Campania (It)	1.81		
Dytiki Makedonia (Gr)	0.97	BassCentre (Fr)e-Normandie (Fr)	2.11	Puglia (It)	1.60		
Thessalia (Gr)	1.25	Bourgogne (Fr)	1.82	Basilicata (It)	2.18		
Ipeiros (Gr)	0.83			Calabria (It)	2.08		
Ionia Nisia (Gr)	1.72	Nord-Pas de Calais (Fr)	1.37	Sicilia (It)	1.91		
Dytiki Ellada (Gr)	0.86	Lorraine (Fr)	1.10	Sardegna (It)	1.96		
Sterea Ellada (Gr)	0.44	Alsace (Fr)	1.67	Luxembourg	3.25		
Peloponnisos (Gr)	0.73	Franche-Comte (Fr)	1.38	Noord-Ned (Nl)	0.78		
Attiki (Gr)	0.69	Pays de la Loire (Fr)	1.93	Oost-Ned (Nl)	2.06		
Voreio Aigaio (Gr)	1.75	Bretagne (Fr)	1.93	West-Ned (Nl)	2.18		
Notio Aigaio (Gr)	2.67	Poitou-Charentes (Fr)	1.72	Zuid-Nederland (Nl)	2.60		
Kriti (Gr)	2.43	Aquitaine (Fr)	1.77	Burgenland (At)	3.36		
Galicia (Es)	2.41	Midi-Pyrenees (Fr)	2.23	Niederosterreich (At)	3.26		
Asturias (Es)	2.06	Limousin (Fr)	2.12	Wien (At)	3.01		
Cantabria (Es)	2.19	Rhone-Alpes (Fr)	1.75	Karnten (At)	2.79		
Pais Vasco (Es)	2.45	Auvergne (Fr)	1.88	Steiermark (At)	2.63		
Navarra (Es)	2.57	Languedoc-Rouss. (Fr)	1.83	Oberosterreich (At)	2.75		

Table 3: Employment growth rate. Source: own calculations based on Cambridge Econometrics

Regions	emp-g	Regions	emp-g	Regions	emp-g	Regions	emp-g
Bruxelles-Bruxelles (Be)	-0.41	Rioja (Es)	0.33	Prov-Alpes (Fr)	0.48	Salzburg (At)	0.92
Vlaams Gewest (Be)	0.47	Aragon (Es)	0.41	Corse (Fr)	0.81	Tirol (At)	1.06
Region Walonne (Be)	-0.14	Madrid (Es)	1.53	Ireland	1.65	Vorarlberg (At)	0.60
Denmark - NUTS 0	0.43	Castilla-Leon (Es)	-0.07	Piemonte (It)	0.14	North East (GB)	-0.49
Baden-Wurttemberg (De)	0.74	Castilla-la Mancha (Es)	0.61	Valle d'Aosta (It)	0.50	North West (GB)	-0.13
Bayern (De)	0.80	Extremadura (Es)	0.20	Liguria (It)	-0.07	Yorkshire (GB)	0.06
Berlin (De)	0.62	Cataluna (Es)	0.90	Lombardia (It)	0.59	East Midl (GB)	0.37
Bremen (De)	-0.06	Com. Valenciana (Es)	1.15	Trentino-AA (It)	0.97	West Midl (GB)	0.15
Hamburg (De)	0.28	Baleares (Es)	1.46	Veneto (It)	0.87	Eastern (GB)	0.86
Hessen (De)	0.60	Andalucia (Es)	0.73	Fr.-V Giulia (It)	0.20	London (GB)	0.16
Niedersachsen (De)	0.57	Murcia (Es)	1.40	Emilia-R(It)	0.11	South East (GB)	1.16
Nordrhein-Westfalen (De)	0.55	Ceuta y Melilla (Es)	2.55	Toscana (It)	0.29	South West (GB)	1.00
Rheinland-Pfalz (De)	0.39	Canarias (Es)	1.36	Umbria (It)	0.12	Wales (GB)	0
Saarland (De)	0.34	Ile de France (Fr)	0.28	Marche (It)	0.16	Scotland(GB)	-0.07
Schleswig-Holstein (De)	0.63	Champagne-Ard (Fr)	-0.19	Lazio (It)	0.82	Northern Ir (GB)	0.94
Anatoliki Makedonia (Gr)	0.77	Picardie (Fr)	-0.01	Abruzzo (It)	0.22		
		Haute-Normandie (Fr)	-0.01	Molise (It	-0.51		
Kentriki Makedonia (Gr)	0.85	Centre (Fr)	0.12	Campania (It)	0.04		
Dytiki Makedonia (Gr)	0	BassCentre (Fr)e-Normandie (Fr)	0.03	Puglia (It)	-0.57		
Thessalia (Gr)	-0.45	Bourgogne (Fr)	-0.19	Basilicata (It)	-0.31		
Ipeiros (Gr)	-1.62			Calabria (It)	-0.05		
Ionia Nisia (Gr)	0.62	Nord-Pas de Calais (Fr)	-0.10	Sicilia (It)	0.33		
Dytiki Ellada (Gr)	-1.89	Lorraine (Fr)	-0.25	Sardegna (It)	0.49		
Sterea Ellada (Gr)	-1.33	Alsace (Fr)	0.55	Luxembourg	1.98		
Peloponnisos (Gr)	-0.26	Franche-Comte (Fr)	-0.13	Noord-Ned (Nl)	0.96		
Attiki (Gr)	1.68	Pays de la Loire (Fr)	0.41	Oost-Ned (Nl)	1.70		
Voreio Aigaio (Gr)	-0.96	Bretagne (Fr)	0.40	West-Ned (Nl)	1.11		
Notio Aigaio (Gr)	1.07	Poitou-Charentes (Fr)	-0.12	Zuid-Nederland (Nl)	1.32		
Kriti (Gr)	0.99	Aquitaine (Fr)	0.51	Burgenland (At)	1.12		
Galicia (Es)	-0.20	Midi-Pyrenees (Fr)	0.73	Niederosterreich (At)	0.76		
Asturias (Es)	-0.53	Limousin (Fr)	-0.46	Wien (At)	0		
Cantabria (Es)	-0.23	Rhone-Alpes (Fr)	0.62	Karnten (At)	0.52		
Pais Vasco (Es)	0.24	Auvergne (Fr)	-0.42	Steiermark (At)	0.43		
Navarra (Es)	0.68	Languedoc-Rouss. (Fr)	1.13	Oberosterreich (At)	0.73		

Table 4: Capital growth rate. Source: own calculations based on Cambridge Econometrics

Regions	K-g	Regions	K-g	Regions	K-g	Regions	K-g
Bruxelles-Bruxelles (Be)	1.16	Rioja (Es)	0.65	Prov-Alpes (Fr)	3.14	Salzburg (At)	3.44
Vlaams Gewest (Be)	2.92	Aragon (Es)	0.73	Corse (Fr)	2.62	Tirol (At)	2.70
Region Walonne (Be)	2.29	Madrid (Es)	1.74	Ireland	5.03	Vorarlberg (At)	3.26
Denmark - NUTS 0	4.37	Castilla-Leon (Es)	0.00	Piemonte (It)	0.06	North East (GB)	2.22
Baden-Wurttemberg (De)	2.63	Castilla-la Mancha (Es)	0.47	Valle d'Aosta (It)	0.13	North West (GB)	1.79
Bayern (De)	3.15	Extremadura (Es)	1.01	Liguria (It)	0.42	Yorkshire (GB)	2.00
Berlin (De)	2.02	Cataluna (Es)	1.17	Lombardia (It)	0.77	East Midl (GB)	2.28
Bremen (De)	1.72	Com. Valenciana (Es)	0.83	Trentino-AA (It)	1.26	West Midl (GB)	1.31
Hamburg (De)	1.56	Baleares (Es)	2.28	Veneto (It)	1.04	Eastern (GB)	2.87
Hessen (De)	3.08	Andalucia (Es)	0.98	Fr.-V Giulia (It)	0.33	London (GB)	1.14
Niedersachsen (De)	2.74	Murcia (Es)	0.73	Emilia-R(It)	0.55	South East (GB)	2.91
Nordrhein-Westfalen (De)	1.70	Ceuta y Melilla (Es)	-1.61	Toscana (It)	0.53	South West (GB)	2.74
Rheinland-Pfalz (De)	2.23	Canarias (Es)	2.58	Umbria (It)	0.28	Wales (GB)	2.57
Saarland (De)	1.88	Ile de France (Fr)	1.99	Marche (It)	0.39	Scotland(GB)	2.14
Schleswig-Holstein (De)	1.75	Champagne-Ard (Fr)	1.86	Lazio (It)	1.00	Northern Ir (GB)	0.82
Anatoliki Makedonia (Gr)	3.99	Picardie (Fr)	2.11	Abruzzo (It)	0.41		
		Haute-Normandie (Fr)	3.04	Molise (It	0.93		
Kentriki Makedonia (Gr)	2.58	Centre (Fr)	2.79	Campania (It)	0.69		
Dytiki Makedonia (Gr)	2.70	BassCentre (Fr)e-Normandie (Fr)	2.75	Puglia (It)	0.40		
Thessalia (Gr)	3.68	Bourgogne (Fr)	2.54	Basilicata (It)	0.81		
Ipeiros (Gr)	3.96			Calabria (It)	0.63		
Ionia Nisia (Gr)	4.20	Nord-Pas de Calais (Fr)	1.50	Sicilia (It)	0.72		
Dytiki Ellada (Gr)	3.38	Lorraine (Fr)	1.23	Sardegna (It)	0.81		
Sterea Ellada (Gr)	3.22	Alsace (Fr)	2.33	Luxembourg	-0.20		
Peloponnisos (Gr)	3.66	Franche-Comte (Fr)	2.35	Noord-Ned (Nl)	0.50		
Attiki (Gr)	1.84	Pays de la Loire (Fr)	2.11	Oost-Ned (Nl)	-0.98		
Voreio Aigaio (Gr)	3.20	Bretagne (Fr)	1.85	West-Ned (Nl)	-1.34		
Notio Aigaio (Gr)	5.21	Poitou-Charentes (Fr)	1.68	Zuid-Nederland (Nl)	-0.51		
Kriti (Gr)	5.03	Aquitaine (Fr)	2.94	Burgenland (At)	2.86		
Galicia (Es)	0.12	Midi-Pyrenees (Fr)	2.77	Niederosterreich (At)	3.32		
Asturias (Es)	-0.57	Limousin (Fr)	2.28	Wien (At)	2.70		
Cantabria (Es)	0.15	Rhone-Alpes (Fr)	2.18	Karnten (At)	0.92		
Pais Vasco (Es)	-0.11	Auvergne (Fr)	2.02	Steiermark (At)	2.13		
Navarra (Es)	0.70	Languedoc-Rouss. (Fr)	2.56	Oberosterreich (At)	2.68		

Table 5: Panel Unit Root Test

Variables	$t-bar$	$t-bar^{*}$
Y	0.95 (0.83)	−1.20 (0.12)
K	0.43 (0.67)	1.45 (0.93)
L	0.27 (0.61)	−4.07 (0.00)
ΔY	−8.87 (0.00)	−4.82 (0.00)
ΔK	−2.43 (0.01)	−1.77 (0.04)
ΔL	−8.48 (0.00)	−2.63 (0.00)

Notes: p-values are in brackets. All variables are in logs.
The test statistics are asymptotically distributed as N(0,1) under
the null hypothesis of non-stationarity.

root test[4] to control for stationarity of the three variables included in the panel used to estimate the production function. Table 5 reports the results of the test for the logarithm of value added (Y), capital stock (K) and labour (L). The test is performed both on levels and first differences ($\Delta Y, \Delta K, \Delta L$) of the variables. The null hypothesis refers to non-stationarity behavior of the time series. Under the null of non-stationarity. the test is distributed as $N(0,1)$, so that large negative numbers indicate stationarity.

The test is performed with constant but not trend ($t-bar$), constant and heterogeneous trend ($t-bar^{*}$) in the test regression. I introduce up to five lags of the dependent variable for serial correlation in the errors.

Table 5 shows the $t-bar$ and the $t-bar^{*}$statistics values. The $t-bar$

[4]See Appendix for a description of IPS test

test (see the first column of table 5) shows that variables are integrated of order one or $I(1)$ process: they are nonstationary in levels but are stationary in first differences.[5]

Because of non-stationarity of the series, next step of this work is to determine if all three variables are cointegrated in order to avoid the spurious regression problem.[6]

The cointegrating regression that I estimate is

$$\ln Y_{it} = a_i + \gamma_t + \alpha_i \ln K_{it} + \beta_i \ln L_{it} + \varepsilon_{it} \tag{9}$$

so that each region has its own relationship among Y_{it}, gross value added, K_{it}, capital stock, and L_{it}, total employment. The variable ε_{it} represents a stationary error term. Table (6) presents the results of cointegration test on (9) with a lag length of up to 5 years in order to check the robustness of results with respect to different dynamic structures. The slopes (α_i, β_i) of the cointegrating relationship are allowed to vary across regions. The common time factor γ_t, captures any common effects that would tend to cause the individual region variables to move together over time. These may be short term business cycle effects or longer run effects. All reported values are *normally distributed* under the null of no cointegration. Panel statistics are weighted by long run variances. Under the alternative hypothesis, the panel variance statistic diverges to positive infinity, and consequently large positive values imply that the null of no cointegration is rejected. To the contrary, the other six statistics diverge to negative infinity under the alternative hypothesis and large negative values imply that the null of cointegration is rejected.

The results suggest that the null of no cointegration is rejected by five out of seven statistics: only panel rho and group rho statistics do not reject the null hypothesis. Except for panel rho and group rho statistics, it is worth

[5] The exact critical values of the t-bar statistic are given in IPS (2003)
[6] See appendix for a description of Pedroni Panel Cointegration Test.

Table 6: Panel Cointegration Test

lags	1	2	3	4	5
panel v-stat	2.20**	2.20**	2.20**	2.20**	2.20**
panel rho-stat	−0.20	−0.20	−0.20	−0.20	−0.20
panel pp-stat	−2.76*	−2.76*	−2.76*	−2.76*	−2.76*
panel adf-stat	−4.08*	−4.10*	−4.15*	−3.38*	−3.43*
group rho-stat	2.84	2.84	2.84	2.84	2.84
group pp-stat	−1.88**	−1.88**	−1.88**	−1.88**	−1.88**
group adf-stat	−5.33*	−6.28*	−6.34*	−5.11*	−5.65*

The test statistics are distributed as N(0,1) under the null hypothesis of no co-integration. *and ** represent the rejection of null hypothesis at 1% and 5% significance level. The critical values for 1% and 5% level are -2.328 and -1.645, respectively.

Table 7: Test for groupwise heteroskedasticity

GH Test	$\chi^2_{(114)} = 18037.50$
P-value	0.00

Groupwise likelihood ratio heteroskedasticity test.
The test is χ^2 distributed with $N-1$ degrees of freedom
The null hypothesis of homoskedasticity is rejected

noting that the statistics are highly significant even at lower lags. Test results provide evidence in favour of a long-run production function relationship.

Table (7) presents a groupwise likelihood ratio heteroskedasticity test performed on the residuals of the production function estimates by fixed effects (see equation 6). The test is chi-square distributed with $N-1$ degrees of freedom, where N is the number of groups in the sample (115 in my case). The null hypothesis of homoskedasticity is rejected.

Table (8) presents the two versions of the Baltagi and Li (1995) test for serial correlation in fixed effects models. The test presents two alternative specifications for autocorrelation in the errors: $AR(1)$ and $MA(1)$. Under both assumptions, the null hypothesis of no serial correlation is rejected.

Test results justify the adoption of a GLS fixed effect estimator, in order to control for region unobservable and to correct for heteroskedasticity across regions and residual serial correlation. However, in this study the GLS method contains important shortcomings. The panel cointegration test has shown that the variables of the production function are cointegrated and this implies that the point estimates for panel GLS based method will be superconsistent. But the key problem is that standard errors, and consequently any confidence intervals and test statistics computed from GLS, are not consistent.

The panel cointegration literature has evolved methods to account for this issue. The most popular of these are known as group mean fully modified OLS (FMOLS) and group mean dynamic OLS (DOLS) methods developed

Table 8: Test for serial correlation

LM Test, AR(1) $v_{it}=\rho v_{it-1}+\varepsilon_{it}$ $H_0 : \rho = 0$	$\chi^2_{(1)} = 2038.19$ $(p\text{-}value \simeq 0.000)$
LM_5Test, MA(1) $v_{it}=\varepsilon_{it}+\lambda\varepsilon_{it-1}$ $H_0 : \lambda = 0$	$N(0,1) = 45.15$ $(p\text{-}value \simeq 0.000)$

Baltagi and Li test for serial correlation in fixed effects models. The test presents two alternative specifications: AR(1) and MA(1). Under both assumptions the null hypothesis of no serial correlation is rejected.

in Pedroni (2000) and Pedroni (2001) respectively. These methods correct for the second order of bias that endogeneity creates under cointegration so as to ensure that the standard errors are consistently estimated and to conduct valid inference.. I estimate the equation (6) for the whole the sample. I do not impose the assumption of constant returns to scale: the production function can display increasing, constant, or decreasing returns to scale as $\alpha + \beta$ is greater than, equal to, or less than one, respectively. Table (9), presents the results of a two-dimension panel where individuals are represented by 115 European Regions over the period 1976-2000. The equation ($\ln Y_{it} = a_i + \gamma_t + \alpha_i \ln K_{it} + \beta_i \ln L_{it} + \varepsilon_{it}$) has been estimated using the group mean FMOLS developed in Pedroni (2000) in order to obtain valid standard errors. The method modifies least squares to account for serial correlation effects and the endogeneity in the regressors that results from the existence of cointegrating relationship. Time dummies are included in the specification to capture disturbances which may be shared across the different regions. These may be business cycle effects or long run effects such as changes in technology. Evidence of decreasing returns to scale is found when common time effects are included in the model. Low coefficients on capital stock were expected given the characteristics of the data. Table (9) also presents the results for

Table 9: Production Function Estimate

	1	2	3	4
Dependent Variable: Y_{it}	$GLS_{(*)}$	$GLS_{(**)}$	$FMOLS_{(*)}$	$FMOLS_{(**)}$
α	0.66	0.25	0.90	0.12
	80.66	18.80	69.65	10.60
β	0.45	0.64	0.64	0.57
	31.30	38.44	30.83	43.15
Year Dummies	no	yes	no	yes
Fixed Effects	115	115	115	115
N.obs	2875	2875	2875	2875

*No time dummies; **including time dummies. The estimation takes account for heteroskedasticity and serial correlation. t-statistics are in brackets.

GLS estimates.

From the estimated fixed effects I calculate the antilogarithms, which represents the parameter of technological efficiency for each region. As a residual, TFP incorporates also the effects of changes in the degree of factor utilization, innovation or measurement errors. Furthermore TFP reflects better capital goods or an improvement in the educational attainment and skills of the labour force (see table 10).

The results show remarkable differences among regions in the technological knowledge levels. The lowest level is that for Ionia Nisia (Greece). Ile de France (France) and Nordrhein (Germany) exibit the highest levels of TFP (2.70 and 2.56, respectively). On the other hand, the lowest parameters are those of regions of Greece, Spain and United Kingdom. In spite of the acceleration of the economic integration of European economies, which should imply that the labor productivity of one following region would catch up to the technological level of the leading region, TFP estimates do not show a convergence of technological levels of all developed regions. Differences among regions persist over the period examined.

Table 10: TFP estimates - mean of i region/mean of all sample

Regions	tfp	Regions	tfp	Regions	tfp	Regions	tfp
Bruxelles-Bruxelles (Be)	1.33	Rioja (Es)	0.39	Prov-Alpes (Fr)	1.57	Salzburg (At)	0.90
Vlaams Gewest (Be)	1.72	Aragon (Es)	0.62	Corse (Fr)	0.57	Tirol (At)	0.94
Region Walonne (Be)	1.24	Madrid (Es)	1.14	Ireland	1.01	Vorarlberg (At)	0.75
Denmark - NUTS 0	1.73	Castilla-Leon (Es)	0.72	Piemonte (It)	1.37	North East (GB)	0.73
Baden-Wurttemberg (De)	2.15	Castilla-la Mancha (Es)	0.59	Valle d'Aosta (It)	0.47	North West (GB)	1.02
Bayern (De)	2.19	Extremadura (Es)	0.43	Liguria (It)	0.95	Yorkshire (GB)	0.92
Berlin (De)	1.20	Cataluna (Es)	1.13	Lombardia (It)	1.84	East Midl (GB)	0.87
Bremen (De)	0.98	Com. Valenciana (Es)	0.86	Trentino-AA (It)	0.87	West Midl (GB)	0.92
Hamburg (De)	1.55	Baleares (Es)	0.59	Veneto (It)	1.31	Eastern (GB)	1.14
Hessen (De)	1.89	Andalucia (Es)	0.94	Fr.-V Giulia (It)	0.84	London (GB)	1.22
Niedersachsen (De)	1.78	Murcia (Es)	0.53	Emilia-R(It)	1.32	South East (GB)	1.22
Nordrhein-Westfalen (De)	2.56	Ceuta y Melilla (Es)	0.28	Toscana (It)	1.20	South West (GB)	0.92
Rheinland-Pfalz (De)	1.48	Canarias (Es)	0.64	Umbria(It)	0.72	Wales (GB)	0.75
Saarland (De)	0.97	Ile de France (Fr)	2.70	Marche (It)	0.84	Scotland(GB)	1.00
Schleswig-Holstein (De)	1.29	Champagne-Ard (Fr)	1.02	Lazio (It)	1.39	Northern Ir (GB)	0.61
Anatoliki Makedonia (Gr)	0.37	Picardie (Fr)	1.13	Abruzzo (It)	0.74		
		Haute-Normandie (Fr)	1.18	Molise (It	0.46		
Kentriki Makedonia (Gr)	0.60	Centre (Fr)	1.22	Campania (It)	1.05		
Dytiki Makedonia (Gr)	0.36	BassCentre (Fr)e-Normandie (Fr)	0.93	Puglia (It)	0.91		
Thessalia (Gr)	0.41	Bourgogne (Fr)	1.08	Basilicata (It)	0.54		
Ipeiros (Gr)	0.28			Calabria (It)	0.73		
Ionia Nisia (Gr)	0.25	Nord-Pas de Calais (Fr)	1.39	Sicilia (It)	1.09		
Dytiki Ellada (Gr)	0.37	Lorraine (Fr)	1.22	Sardegna (It)	0.78		
Sterea Ellada (Gr)	0.66	Alsace (Fr)	1.25	Luxembourg	0.89		
Peloponnisos (Gr)	0.41	Franche-Comte (Fr)	0.96	Noord-Ned (Nl)	1.35		
Attiki (Gr)	0.83	Pays de la Loire (Fr)	1.26	Oost-Ned (Nl)	1.21		
Voreio Aigaio (Gr)	0.29	Bretagne (Fr)	1.17	West-Ned (Nl)	1.86		
Notio Aigaio (Gr)	0.37	Poitou-Charentes (Fr)	1.00	Zuid-Nederland (Nl)	1.33		
Kriti (Gr)	0.39	Aquitaine (Fr)	1.28	Burgenland (At)	0.55		
Galicia (Es)	0.62	Midi-Pyrenees (Fr)	1.17	Niederosterreich (At)	1.05		
Asturias (Es)	0.57	Limousin (Fr)	0.74	Wien (At)	1.43		
Cantabria (Es)	0.46	Rhone-Alpes (Fr)	1.69	Karnten (At)	0.75		
Pais Vasco (Es)	0.85	Auvergne (Fr)	0.93	Steiermark (At)	0.98		
Navarra (Es)	0.56	Languedoc-Rouss. (Fr)	1.10	Oberosterreich (At)	1.10		

It is also interesting to look at the rate of growth of TFP (see table 11).[7]In fact an increase in TFP growth means more output can be produced with a given level of labor and capital inputs, indicating that a more efficient utilization of resources, inputs and materials. One region shows a decrease in TFP growth over the period (Attiki (Greece)); Ireland is the region with the highest value of the sample. The TFP growth rate is over 2% for all of the Spanish regions. Dytiki Ellada is the greek region with the highest rate of TFP growth (2.56%). In Italy, Molise is the region with the highest rate of TFP growth (2.82%), while Piemonte shows the lowest rate (1.26%). In France, Lorraine is the region in which TFP has grown less (1.03%) and Basse Centre and Normandie shows the highest rate (2.01%). In Germany, Berlin is the region with the highest rate of TFP growth and South East for United Kingdom. In conclusion, looking at TFP growth rates there is no evidence of a convergence process among regions in the technological levels. Only for some regions, which have a low level of TFP, the growth rate of TFP is high (all Spanish regions, some Greek regions, Molise for Italy, Corse for France, Northern Ireland for Great Britain).

5 Conclusion

This paper has analyzed the economic performance of a sample of European Regions. It has provided estimates of Cobb-Douglas production functions over the period 1976-2000. The sample was composed by 115 European Regions of 12 Countries: Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Spain, United Kingdom. Great attention has been devoted to the estimation procedures. Because problems of nonstationarity may arise when panel data approach is used to estimate the production function, the first step of this work has been

[7] I calulate TFP as residual from the estimation of equation (1.6). TFP growth is calculated as growth of TFP level. Numbers in tables (10, 11) correspond to sample means.

Table 11: TFP growth rate - sample means

Regions	tfp-g	Regions	tfp-g	Regions	tfp-g	Regions	tfp-g
Bruxelles-Bruxelles (Be)	1.60	Rioja (Es)	2.69	Prov-Alpes (Fr)	1.50	Salzburg (At)	2.31
Vlaams Gewest (Be)	1.94	Aragon (Es)	2.86	Corse (Fr)	1.43	Tirol (At)	1.81
Region Walonne (Be)	1.50	Madrid (Es)	2.76	Ireland	3.36	Vorarlberg (At)	2.19
Denmark - NUTS 0	1.01	Castilla-Leon (Es)	2.60	Piemonte (It)	1.26	North East (GB)	1.22
Baden-Wurttemberg (De)	1.67	Castilla-la Mancha (Es)	2.62	Valle d'Aosta (It)	1.62	North West (GB)	1.53
Bayern (De)	2.02	Extremadura (Es)	3.24	Liguria (It)	1.93	Yorkshire (GB)	1.82
Berlin (De)	2.39	Cataluna (Es)	2.85	Lombardia (It)	1.43	East Midl (GB)	1.97
Bremen (De)	1.24	Com. Valenciana (Es)	2.34	Trentino-AA (It)	2.14	West Midl (GB)	1.92
Hamburg (De)	1.61	Baleares (Es)	2.93	Veneto (It)	1.85	Eastern (GB)	2.10
Hessen (De)	1.95	Andalucia (Es)	2.84	Fr.-V Giulia (It)	1.80	London (GB)	2.06
Niedersachsen (De)	1.40	Murcia (Es)	2.33	Emilia-R(It)	1.99	South East (GB)	2.12
Nordrhein-Westfalen (De)	1.05	Ceuta y Melilla (Es)	2.51	Toscana (It)	1.75	South West (GB)	1.76
Rheinland-Pfalz (De)	1.30	Canarias (Es)	3.41	Umbria (It)	1.66	Wales (GB)	1.88
Saarland (De)	1.16	Ile de France (Fr)	1.99	Marche (It)	1.57	Scotland(GB)	1.81
Schleswig-Holstein (De)	1.29	Champagne-Ard (Fr)	1.42	Lazio (It)	1.88	Northern Ir (GB)	1.71
Anatoliki Makedonia (Gr)	0.88	Picardie (Fr)	1.35	Abruzzo (It)	1.99		
		Haute-Normandie (Fr)	1.22	Molise (It	2.82		
Kentriki Makedonia (Gr)	1.06	Centre (Fr)	1.78	Campania (It)	1.99		
Dytiki Makedonia (Gr)	1.03	BassCentre (Fr)e-Normandie (Fr)	2.01	Puglia (It)	2.55		
Thessalia (Gr)	1.62	Bourgogne (Fr)	1.65	Basilicata (It)	2.04		
Ipeiros (Gr)	2.13			Calabria (It)	1.73		
Ionia Nisia (Gr)	1.42	Nord-Pas de Calais (Fr)	1.30	Sicilia (It)	1.89		
Dytiki Ellada (Gr)	2.56	Lorraine (Fr)	1.03	Sardegna (It)	1.68		
Sterea Ellada (Gr)	1.84	Alsace (Fr)	1.53	Luxembourg	2.91		
Peloponnisos (Gr)	1,08	Franche-Comte (Fr)	1.30	Noord-Ned (Nl)	0.58		
Attiki (Gr)	-0.20	Pays de la Loire (Fr)	1.98	Oost-Ned (Nl)	2.05		
Voreio Aigaio (Gr)	1.89	Bretagne (Fr)	1.85	West-Ned (Nl)	2.20		
Notio Aigaio (Gr)	2.52	Poitou-Charentes (Fr)	1.76	Zuid-Nederland (Nl)	2.48		
Kriti (Gr)	1.96	Aquitaine (Fr)	1.57	Burgenland (At)	2.28		
Galicia (Es)	2.54	Midi-Pyrenees (Fr)	1.88	Niederosterreich (At)	2.63		
Asturias (Es)	2.45	Limousin (Fr)	1.86	Wien (At)	2.73		
Cantabria (Es)	2.80	Rhone-Alpes (Fr)	1.76	Karnten (At)	2.57		
Pais Vasco (Es)	2.31	Auvergne (Fr)	1.72	Steiermark (At)	2.09		
Navarra (Es)	2.55	Languedoc-Rouss. (Fr)	1.73	Oberosterreich (At)	2.26		

to investigate the properties of regional time series for value added, capital stock and labour. The presence of unit roots in the series has been found and, consequently, I applied panel cointegration tests to guard against the spurious regression problem. It has been clearly shown that in the given panel all the variables share a long-run relationship and this implies evidence in favour of a long-run production function relationship.

I have reported results for a fixed effects GLS estimator and group mean FMOLS estimator.

The results show remarkable differences among regions in the technological knowledge levels. The lowest level is that for Ionia Nisia (Greece). Ile de France (France) and Nordrhein (Germany) exhibit the highest levels of TFP (2.70 and 2.56, respectively). On the other hand, the lowest parameters are those of regions of Greece, Spain and United Kingdom. It is also interesting to look at the rate of growth of TFP over the period examined (see table 11).[8]In fact an increase in TFP growth means more output can be produced with a given level of labour and capital inputs, indicating that a more efficient utilization of resources, inputs and materials. One region shows a decrease in TFP growth over the period (Attiki (Greece)); Ireland is the region with the highest value of the sample. The TFP growth rate is over 2% for all of the Spanish regions. Dytiki Ellada is the greek region with the highest rate of TFP growth (2.56%). In Italy, Molise is the region with the highest rate of TFP growth (2.82%), while Piemonte shows the lowest rate (1.26%). In France, Lorraine is the region in which TFP has grown less (1.03%) and Basse Centre e Normandie shows the highest rate (2.01%). In Germany, Berlin is the region with the highest rate of TFP growth and South East for United Kingdom.

The existence of large disparities among European regions has justified the choice of this paper to analyze the TFP at regional level instead that at

[8]I calulate TFP as residual from the estimation of equation (1.6). TFP growth is calculated as growth of TFP level. Numbers in tables (11, 12) correspond to sample means.

national level. It is worth noting the fact that these large differences among regions in Europe have important implications for the economic policies of the European Union. In fact, in my study the process of economic integration of European economies should imply that the labor productivity of one following region would catch up to the technological level of the leading region. This mechanism leads to a convergence of technological levels of all developed regions. However, if we look at TFP level estimates we can see that differences persist among regions over the period examined. Furthermore, looking at the TFP growth rates we can see that only for some regions, which have a low level of TFP, the growth rate of TFP is high (all Spanish regions, some Greek regions, Molise for Italy, Corse for France, Northern Ireland for Great Britain).

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6 Appendix : Panel Unit Root test and Panel Cointegration test

6.1 Panel unit root tests

Over the past decade a number of important panel data set covering different countries, regions or industries over long time spans have become available. This raises the issue of the plausibility of the dynamic homogeneity assumption that characterizes the traditional analysis of panel data models. The inconsistency of pooled estimators in dynamic heterogeneous panel models has been demonstrated by Pesaran and Smith (1995), and Pesaran et al.(1996).

Panel based unit root tests have been advanced by Quah (1990, 1994), Breitung and Meyer (1991), Levin and Lin (1992), Phillips and Moon (1999), Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003), among others. Quah (1990, 1994) uses the random field methods to analyze a panel with i.i.d. disturbances, and demonstrates that the Dickey-Fuller test statistic has a standard normal limiting distribution as both cross-section and time series dimensions grow arbitrarily large. Unfortunately, the random field method does not allow for individual specific effects. Breitung and Meyer (1991) approach allows for time specific effects and higher-order serial correlation, but cannot be extended to panel with heterogeneous errors. Levin and Lin test allows for heterogeneity only in the intercept and is based on the following model

$$\Delta y_{it} = \beta y_{i,t-1} + \alpha_{mi} d_{mt} + u_{it} \tag{10}$$

$i = 1, ..., N$; $t = 1, ...T$; $m = 1, 2, 3$, where d_{mt} contains deterministic variables; $d_{1t} = \{0\}, d_{2t} = \{1\}, d_{3t} = \{1, t\}$. The Levin and Lin test requires the strong condition $N/T \to 0$ for its asymptotic validity. A revised version of Levin and Lin's (1992) earlier work is proposed by Levin, Lin and Chu (2002). The panel-based unit root test proposed in this paper allows for individual-specific intercepts, the degree of persistence in individual regression error and trend coefficient to vary freely across individuals. This test is relevant for panels of moderate size. However, this test has its limitations. First, there are some cases in which contemporaneous correlations cannot be removed by simply subtracting cross-sectional averages. Secondly, the assumption that all individuals are identical with respect to the presence or absence of a unit root is, in some sense, restrictive.

Im, Pesaran and Shin (2003) propose unit root tests for dynamic heterogeneous panels based on the mean of individual unit root test statistics. In particular they propose a standardized t-bar test statistic based on the (augmented) Dickey-Fuller statistics averaged across the groups.

Consider a sample of N cross-section observed over T time periods. IPS suppose that the stochastic process, y_{it}, is generated by the first-order autoregressive process:

$$y_{it} = (1 - \phi_i)\mu_i + \phi_i y_{i,t-1} + \xi_{it} \tag{11}$$

$i = 1, ..., N$, $t = 1, ..., T$, where initial values, y_{i0}, are given. The null hypothesis of unit roots $\phi_i = 1$ can be expressed as

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \xi_{it} \tag{12}$$

where $\alpha_i = (1 - \phi_i)\mu_i$, $\beta_i = -(1 - \phi_i)$ and $\Delta y_{it} = (y_{it} - y_{i,t-1)}$. The null hypothesis of unit roots then becomes

$$H_0 : \beta_i = 0 \tag{13}$$

for all i, against the alternatives

$H_1 : \beta_i < 0$, $i = 1, ..., N_1$, $\beta_i = 0$, $i = N_1 + 1, N_2 + 1, ..., N$.

This formulation of the alternative hypothesis allows for β_i to differ across groups, and is more general than the homogeneous alternative hypothesis, namely $\beta_i = \beta < 0$ for all i, which is implicit in the testing approaches of

Quah and Levin-Lin.

The IPS group-mean t-bar statistic is given by:

$$t - bar_{NT} = N^{-1} \sum_{i=1}^{N} t_{iT_i}(p_i) \tag{14}$$

where t_{iT_i} is the individual t statistic for time series with different lag lengths.

6.2 Panel cointegration test

Methods for nonstationary panels have been gaining increased acceptance in recent empirical research. Initial theoretical work on nonstationary panels focused on testing for unit roots in univariate panels.[9] However, many applications involve multi-variate relationships and a researcher is interested to know whether or not a particular set of variables is cointegrated. Pedroni (1999) proposes a method to implement tests for the null of cointegration for the case with multiple regressors. The tests allow for a considerable heterogeneity among individual members of the panel.[10]

6.2.1 Testing for cointegration in heterogeneous panels: the multivariate case

Here I provide a complete description of the test proposed by Pedroni. The first step is to compute the regression residuals from the hypothesized cointegrating regression. The general case is:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} X_{1_{it}} + \beta_{2i} X_{2_{it}} + ... + \beta_{Mi} X_{M_{it}} + e_{it} \tag{15}$$

for $t = 1, ..., T$; $m = 1, ..., M$, where T refers to the number of observation over time, N refers to the number of individual members in the panel, and

[9] See for instance, Levin and Lin (1993) and Quah (1994).

[10] Pedroni cointegration tests include heterogeneity in both the long run cointegrating vectors as well as in the dynamics associated with short run deviations from these one.

M refers to the number of variables. The parameter α_i is the fixed effects parameter and β_{1i}, β_{2i},..., β_{Mi} are the slope coefficients. Both the fixed effects parameter and slope coefficients are allowed to vary across individual members. $\delta_i t$ represents a deterministic time trend, which might be included in some applications.

To capture disturbances, which may be shared across the different members of the panel, common time dummies can be included.

Pedroni derives the asymptotic distributions of seven different statistics: four are based on pooling along the within-dimension, and three are based on pooling along the between-dimension. Pedroni calls the within-dimension based statistics as panel cointegration statistics, and the between-dimension based statistics as group mean panel cointegration statistics. The first of the panel cointegration statistics is a type of nonparametric variance ratio statistic. The second is a panel version of nonparametric statistic analogous to the Phillips and Perron rho-statistic. The third statistic is also nonparametric and analogous to the Phillips and Perron t-statistic. The fourth of the panel cointegration statistics is a parametric statistic analogous to the augmented Dickey-Fuller t-statistic.

The other three statistics are based on a group mean approach. The first and the second ones are analogous to the Phillips and Perron rho and t-statistic respectively, while the third one is analogous to the augmented Dickey-Fuller t-statistic.

Table (12) presents the seven statistics.

Pedroni panel cointegration test computes the seven statistics following a procedure in steps:

1. Estimate the panel cointegration regression (15) and collect residuals $\hat{e}_{it}$;

2. Estimate (15) in differences and collect residuals (η_{it});

3. Compute the long run variance of $\hat{\eta}_{it}$ using a kernel estimator, such as

Table 12: Panel Cointegration Statistics

Panel Statistics (within)	
v	$T^2 N^{3/2} Z_{\hat{v}_{NT}} \equiv T^2 N^{3/2} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{it-1}^2 \right)^{-1}$
ρ	$T\sqrt{N} Z_{\rho_{NT}-1} \equiv T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{it-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} (\hat{e}_{it-1} \Delta\hat{e}_{it} - \hat{\lambda}_i)$
t nonparametric	$Z_{t_{NT}} \equiv \left(\tilde{\sigma}_{NT}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{it-1}^2 \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} (\hat{e}_{it-1} \Delta\hat{e}_{it} - \hat{\lambda}_i)$
t (parametric)	$Z_{t_{NT}}^* \equiv \left(\tilde{s}_{NT}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{it-1}^{*} \Delta\hat{e}_{it}^{*}$
Group Statistics (between)	
ρ	$TN^{-1/2} Z_{\hat{\rho}_{NT-1}} \equiv TN^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{it-1}^2 \right)^{-1} \sum_{t=1}^{T} (\hat{e}_{it-1} \Delta\hat{e}_{it} - \hat{\lambda}_i)$
t (nonparametric)	$N^{-1/2} \tilde{Z}_{t_{NT}}^* \equiv N^{-1/2} \sum_{i=1}^{N} \left(\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{e}_{it-1}^2 \right)^{-1/2} \sum_{t=1}^{T} (\hat{e}_{it-1} \Delta\hat{e}_{it} - \hat{\lambda}_i)$
t (parametric)	$N^{-1/2} \tilde{Z}_{t_{NT}}^* \equiv N^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{s}_i^{*2} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} \hat{e}_{it-1}^{*} \Delta\hat{e}_{it}^{*}$

where $\hat{\lambda}_i = \frac{1}{T} \sum_{s=1}^{k_i} (1 - \frac{s}{k_i+1}) \sum_{t=s+1}^{T} \hat{\mu}_{it} \hat{\mu}_{it-s}$,
$\hat{s}_i^2 \equiv \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it}^2$,
$\hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i$,
$\tilde{\sigma}_{NT}^2 \equiv \frac{1}{N} \sum_{i=1}^{N} \hat{L}_{11i}^{-2} \hat{\sigma}_i^2$,
$\hat{s}_i^{*2} \equiv \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it}^{*2}$,
$\tilde{s}_{NT}^{*2} \equiv \frac{1}{N} \sum_{i=1}^{N} \hat{s}_i^{*2}$,
$\hat{L}_{11i}^{-2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\eta}_{it}^2 + \frac{2}{T} \sum_{s=1}^{k_i} (1 - \frac{s}{k_i+1}) \sum_{t=s+1}^{T} \hat{\eta}_{it} \hat{\eta}_{it-s}$
and where $\hat{\mu}_{it}$, $\hat{\mu}_{it}^*$ and $\hat{\eta}_{it}$ are obtained from the following regressions:
$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \hat{u}_{it}$, $\quad \hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{ik} \Delta\hat{e}_{it-k} + \hat{u}_{it}^*$,
$\Delta y_{it} = \sum_{m=1}^{M} \hat{b}_{mit} \Delta X_{mit} + \hat{\eta}_{it}$

the Newey-West (1987) estimator, and calculate $\hat{L}_{11i}^{-2}$;

4. Use the residuals $\hat{e}_{it}$ and :

   a) compute the non parametric statistics estimating the following regression:

   $$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \hat{u}_{it}$$

   The residuals $(\hat{u}_{it})$ are used to calculate the long run variance, denoted by $\hat{\sigma}_i^2$, while $\hat{s}_i^2$ is the simple variance of $\hat{u}_{it}$ and the term λ_i is calculated as $\lambda_i = \frac{1}{2}(\hat{\sigma}_i^2 - \hat{s}_i^2)$;

   b) compute the parametric statistics estimating the following regression:

   $$\hat{e}_{it} = \hat{\rho}_i \hat{e}_{it-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{ik} \Delta \hat{e}_{it-k} + \hat{u}_{it}^*$$

   and use the residuals $(\hat{u}_{it}^*)$ to compute the simple variance $\hat{s}_i^{*2}$.

Pedroni (1995, 1997a) shows that each of the seven statistics presented in table (12) will be distributed as standard normal after an appropriate standardization. This standardization depends only on the moments of certain Brownian motion functionals.[11] In Pedroni (1999) the moments of the vector of Brownian motion functionals are computed by Monte Carlo simulation for the case of multiple regressors.

The asymptotic distributions for each of the seven panel and group mean statistics can be expressed in the form

$$\frac{\varkappa_{NT} - \mu\sqrt{N}}{\sqrt{\nu}} \rightarrow N(0,1)$$

[11] A Brownian motion is a continuous-time stochastic process with three important properties. First, it is a Markov process and it means that the probabilty distribution for all future values of the process depends only on its current value. Second, the Brownian process has indipendent increments. Finally, changes in the process over any finite interval of time are normally distributed.

where $\varkappa_{NT}$ is the standardized form of the statistics as described in table (12), and the value for μ and ν are functions of the moments of Brownian motion functionals.