

# CESifo *Working Paper Series*

## PRODUCTIVITY DIFFERENCES IN OECD COUNTRIES

Antonio Garcia Pascual\*

Working Paper No. 318

July 2000

*CESifo*

*Poschingerstr. 5*

*81679 Munich*

*Germany*

*Phone: +49 (89) 9224-1410/1425*

*Fax: +49 (89) 9224-1409*

*<http://www.CESifo.de>*

---

\* I thank Yin-Wong Cheung, Kenneth Kletzer, Dalia Marin, and seminar participants at the University of California, Santa Cruz, and University of Munich for helpful comments and discussions. An earlier version of this paper was circulated as UCSC Working Paper 403. All remaining errors are mine.

## PRODUCTIVITY DIFFERENCES IN OECD COUNTRIES

### Abstract

This paper investigates cross-country productivity convergence at a sectoral level using multivariate unit-root tests. Our empirical analysis counts with three distinctive features. First, it allows all the coefficients in the panel specification to vary across countries. Second, it accounts for the presence of significant cross-country correlations found in the data. Third, when the null hypothesis of non convergence is rejected, a second test determines the number of converging countries. Based on a sample of thirteen OECD countries our results show evidence of convergence in three out of six sectors, namely, agriculture, construction, and transportation and communication services.

Keywords: Convergence, panel data, productivity

JEL Classification: O40, C32

*Antonio Garcia Pascual  
Department of Economics  
University of Munich  
Ludwigstr. 28  
80539 Munich  
Germany  
email: [antonio.pascual@lrz.uni-muenchen.de](mailto:antonio.pascual@lrz.uni-muenchen.de)*

# 1 Introduction

The convergence hypothesis, broadly defined, states that less developed countries should catch up with more advanced nations in the long-run. This hypothesis has regained a great deal of attention as a result of new developments in the theory of economic growth. The new theoretical developments emphasize the role of purposeful R&D activities as one of the main engines of long-run growth (Romer, 1990, Grossman and Helpman, 1991, and Aghion and Howitt, 1992). Further, the diffusion of new technologies towards less advanced economies, constitutes a source of growth for less technologically advanced countries (Grossman and Helpman, chapter 11, and Barro and Sala-i-Martin, 1997). Although a few OECD economies account for the largest share of the total amount of R&D undertaken in the world, empirical studies, such as Coe and Helpman (1995) and Coe, Helpman and Hoffmaister (1997), have found evidence of cross-country technological spillovers.

Whether technological spillovers provides a force towards international productivity convergence has been investigated, among others, by Bernard and Jones (1996*a*, 1996*b*). They found evidence of total factor productivity (TFP) convergence for a group of OECD countries, both at the aggregate and disaggregate level. More recent studies, however, have documented evidence against TFP convergence, when analyzing more heterogeneous groups of countries (e.g., Klenow and Rodriguez, 1997). From a theoretical viewpoint, despite of the use of common technologies in different countries, productivity differences may persist in the long run. Hall and Jones (1999) point to differences in social infrastructure, such as institutions and government policies, as the main responsible for international productivity differences. Further, Acemoglu and Zilibotti (1999) argue that international productivity differences can persist as a result of a different supply of skilled workers across countries. This fact, together with the development of skill-biased technologies by the technological leaders, results in an U-shaped relationship between productivity convergence and technological level, where high

and low-tech sectors converge, and medium-tech do not.

Our paper empirically investigates TFP convergence in OECD countries at the sectoral level. There are three main reasons for the use of disaggregated data in the study of productivity convergence. First, the use of sectoral data helps to differentiate between high and low-tech sectors versus medium-tech sectors, provided the different convergence behavior suggested by the theory.<sup>1</sup> Second, it allows to investigate the relationship between convergence and the tradability character of a sector. Third, important productivity differences across sectors have been documented by Bernard and Jones (1996*a*, 1996*b*). They find evidence of productivity convergence in most of the sectors analyzed, except in manufacturing. They argue that countries tend to specialize according to comparative advantage, therefore, there is no surprise in the lack of productivity convergence found in a highly tradable sector.

The econometric specification adopted in this paper follows a time series definition of convergence proposed by Bernard and Durlauf (1996). Their definition implies that the presence of a unit root or a deterministic component in the series of TFP differences (with respect to the most productive country) constitutes evidence against convergence. Bernard and Jones (1996*b*) extended Bernard and Durlauf's definition to a multivariate framework by using a panel data unit root to investigate productivity convergence. Overall, the advantage of the multivariate approach is that it enhances the power and efficiency of the test over the univariate counterparts. The panel data unit root tests used here counts with three

---

<sup>1</sup> Acemoglu and Zilibotti (1999) use a "North-South" type of model, therefore it could be argued that their model is not fully applicable to OECD countries. However, if one thinks of their model as a continuum of skill differences across countries, rather than a dichotomy between the North and the South, then some of their results could be extended to the group of countries analyzed here. Although skill differences across OECD countries have been narrowing between 1970 and 1991, significant variation remains (Table 7). For example, the percentage of population in the age group 25-34 which attained secondary education in Italy by 1991 is 47%, in contrast with the 86% of the US. This difference is larger for the older age group, 55-64, where the percentage in Italy is 12, whereas in the US is 74 (note that the latter age group, corresponds to the 34-43 age group in 1970).

significant improvements over previous tests employed in the study of productivity convergence, such as Bernard and Jones (1996b).

First, we implement the procedure suggested by Taylor and Sarno (1998), which allows for all the autoregressive coefficients in the panel to be country-specific. Furthermore, the lag length of the autoregressive specification is optimally chosen using an information criterion. This more general specification captures the cross-country differences in the autoregressive processes observed in the data, including differences in the lag length. Second, we also observe significant cross-country correlations in the data, which, if ignored, may lead to significant size and power distortion in the test statistics. The multivariate test employed here incorporates this information, resulting in a more efficient estimation of the relevant parameters. Third, in the event that the test rejects the joint null hypothesis of non convergence, a second testing procedure proposed by Breuer *et al.* (1999) is applied to determine the number of converging countries. The rejection of the joint null means that at least one member of the panel does not possess a unit root. This second test is implemented to determine the exact number of converging and non converging countries. Finally, in order to correct for a potential bias introduced by our limited sample size, finite sample distributions were computed for each test statistic via Monte Carlo simulation.

Our empirical results suggest that three out six major sectors analyzed converge, namely, agriculture and construction, two low-tech sectors, and transportation and communication services, a high-tech sector. This evidence seem to be consistent with the theoretical prediction of Acemoglu and Zilibotti (1999). Manufacturing, as in Bernard and Jones (1996a, 1996b), was found non converging. The tradeability character of the sector does not seem to play a central role on productivity convergence, based on our mixed convergence results in different tradable sectors.

The rest of the paper is organized as follows. Section 2 presents an stylized model of productivity convergence, and specifies the null hypotheses of interest.

In section 3, we discuss the TFP data corresponding to 13 OECD countries for six major sectors. Section 4 describes the multivariate tests for convergence and presents the empirical results. Section 5 concludes with a summary of the main results.

## 2 Empirical specification

Following Bernard and Durlauf (1996) two productivity series converge if the long-run forecast of the two series coincides, i.e.

$$\lim_{k \rightarrow \infty} E(y_{i,t+k} - y_{j,t+k} / \Theta_t) = 0,$$

where the subindexes  $i$  and  $j$  denote two different countries,  $t$  represents time, and  $\Theta_t$  is the information set at time  $t$ . It is not difficult to show that this definition implies that the presence of a unit root or a deterministic component in the series  $(y_{it} - y_{jt})$  constitutes evidence against convergence. In order to test whether TFP fulfills this definition, Bernard and Jones (1996a, 1996b) specify the following productivity catch-up model

$$\ln X_{it} = \gamma_i + \ln X_{it-1} - \lambda \ln (X_{it-1}/X_{t-1}^*) + \epsilon_{it}$$

where  $X_{it}$  indicates TFP in country  $i$  at time  $t$ , the “star” represents the productivity leader, and  $\ln (X_{it-1}/X_{t-1}^*)$  is the productivity gap between country  $i$  and the leader. If catch-up takes place then the coefficient  $\lambda$  should be positive; alternatively if there is no productivity catch-up this coefficient would be zero. This model can also be specified in productivity differences –with respect to the most productive country– as follows

$$x_{it} = \alpha_i + \rho x_{it-1} + \varepsilon_{it} \tag{1}$$

where

$$x_{it} \equiv \ln (X_{it}/X_t^*) ; \alpha_i \equiv (\gamma_i - \gamma_{i^*}) ; \rho \equiv (1 - \lambda).$$

Testing for a unit root in (1) is equivalent to testing  $\lambda = 0$ , i.e. testing non convergence.

There are two ways in which this model specification can be improved upon. The first one, is to allow for further lags of productivity differences in (1). The reason for that is clear: productivity catch-up as a result of technological diffusion might be extended over several periods. The speed of acquiring and absorbing knowledge is a function of the existing knowledge in the country, among other variables. Countries lagging far behind the technological leader are the ones for which the implementation of the new technologies takes longer. Allowing for more lags in the equation above we obtain the following expression (in first differences):

$$\Delta x_{it} = \alpha_i + b_{0,i}x_{it-1} + \sum_{j=1}^{p_i-1} b_{j,i}\Delta x_{it-j} + \varepsilon_{it} .$$

A second improvement in our testing framework is to allow for cross country correlations in a panel specification. Each *TFP* differentials series is expressed with respect to the leader's productivity, i.e.  $(x_{it} - x_t^*)$ . Therefore every series includes a common component,  $x^*$ , which introduces cross-country correlation in the panel. Moreover, from a technological viewpoint, country  $i$  may have high levels of bilateral exchanges of goods and factors with countries, other than the leader. In this case, country  $i$  may also receive knowledge spillovers from these third countries. A simple way to incorporate the cross-country spillovers is through a panel specification

$$\Delta x_{it} = \alpha_i + b_{0,i}x_{it-1} + \sum_{j=1}^{p_i-1} b_{j,i}\Delta x_{it-j} + \varepsilon_{it}, \quad i = 1, \dots, N \quad (2)$$

where  $N$  denotes the number of countries in the panel, and the error term has the following variance-covariance matrix

$$E(\varepsilon\varepsilon') = \begin{pmatrix} \Omega_{11} & \Omega_{12} & \cdots & \Omega_{1N} \\ \Omega_{21} & \Omega_{22} & \cdots & \Omega_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \Omega_{N1} & \Omega_{N2} & \cdots & \Omega_{NN} \end{pmatrix}_{NT \times NT}$$

with  $\Omega_{ij}$  denoting the covariance matrix ( $T \times T$ ) between country  $i$  and  $j$ , which captures the cross country spillovers. This model specification would require the estimation of too many parameters (a  $NT \times NT$  covariance matrix), thus, we simplify the problem by assuming that the adoption of technologies from countries, other than the leader, occurs more rapidly, since a less pronounced knowledge gap between countries results in a faster diffusion and absorption of technologies. Furthermore, the technologies developed by countries other than the leader would potentially be more adequate to the needs of the lagging economies, constituting an additional force for a more rapid implementation. Under this simplification the covariance matrix can be expressed as

$$E(\varepsilon\varepsilon') = \begin{pmatrix} \sigma_{11}I & \sigma_{12}I & \cdots & \sigma_{1N}I \\ \sigma_{21}I & \sigma_{22}I & \cdots & \sigma_{2N}I \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1}I & \sigma_{N2}I & \cdots & \sigma_{NN}I \end{pmatrix}_{NT \times NT}$$

with

$$\sigma_{ij} = Cov(\varepsilon_{it}, \varepsilon_{js}) \quad \text{if} \quad t = s \text{ (0 otherwise),}$$

where  $I$  is the identity matrix of size  $T$ .

Given the presence of cross-country correlation, an appropriate estimation method for (2) would be seemingly unrelated equations (SUR), which is a particular case of feasible generalized least squares estimation (FGLS, hereafter). On the one hand, this procedure provides more efficient estimates of the parameters and test statistics than ordinary least squares. On the other hand, the exact distribution of the relevant test statistics are unknown. Thus, in order to do hypothesis testing we will have to compute the finite sample distribution of the test statistics through Monte Carlo simulation.



### 3 TFP data

The definition of productivity used in this empirical application corresponds to a Hicks neutral measure of technological progress. In particular, assuming a Cobb-Douglas aggregate production function  $Y = AL^wK^{(1-w)}$ , our measure of TFP corresponds to an estimate of  $A$ , the Solow residual. The data on TFP are obtained from the OECD International Sectoral database (1998 version). The TFP-index series used in this study were constructed according to the following equation:

$$TFP = \left[ \frac{Y}{L^w K^{1-w}} \right] \frac{1}{TFP_0}$$

where  $Y$  represents gross value added at 1990 US prices. The labor share,  $w$ , is estimated as the product of *compensation to employees* times *total employment* divided by *value added at current prices*. For most of the sectors the labor share is close to 70%, the only exception being “Electricity, gas and water”, where the labor share is 33%.  $L$  denotes total employment, and  $K$  represents gross capital stock, i.e. the total volume of physical capital assets valued at 1990 US prices. When actual data were not available for  $K$ , estimates were provided according to  $\sum_j I_j g_j$ , where  $I$  is the gross fixed capital formation at constant prices and  $g$  represents the amount of capital formation of a given vintage (for further details on the estimates of  $g_j$  see Meyer zu Schlochtern, 1994).  $TFP_0$  is TFP in the base year, 1990.<sup>2</sup>

The annual data set, from 1970 to 1991, corresponds to the following thirteen OECD countries.<sup>3</sup> Australia (AUS), Belgium (BEL), Canada (CAN), Den-

---

<sup>2</sup> Bernard and Jones (1996a) proposed a more appropriate measure of factor productivity,  $TTP$ , defined as:

$$\ln TTP_{it} = \ln TFP_{it} + (1 - w_{it}) \ln K_0 + w_{it} \ln L_0$$

where  $K_0$  and  $L_0$  are constant across time and country sector. This measure has the advantage of accounting for changes over time in the labor share,  $w$ . Despite of the improved productivity measure used by these authors, their study shows no major qualitative differences in the convergence results with respect to the results when using the  $TFP$  series. This is also the case for our data.

<sup>3</sup> We use the maximum number of periods and countries for which we could construct ho-

mark (DNK), Finland (FIN), France (FRA), Germany (GER), Italy (ITA), Japan (JPN), Norway (NOR), Sweden (SWE), United Kingdom (UK), and United States (USA). Table 1 below presents the sectors analyzed in the empirical section and the abbreviations used hereafter:

**Table 1** : Major sectors

Agriculture	AGR
Construction	CST
Utilities: electricity, gas and water	EGW
Manufacturing	MAN
Community, social and personal services	SOC
Transportation and communication services	TRS
Total industries	TIN

The first important feature of the disaggregated data is the dissimilar behavior of productivity across sectors, illustrated in Figure 1 in the Appendix. Each plot represents the natural logarithm of the level of TFP from 1970 to 1991 for a particular sector. We also present the standard deviation of the log of TFP across countries for each sector. The latter constitutes a rough measure of productivity convergence (see the definition of  $\sigma$  – *convergence* in Sala-i-Martin, 1990).

All the countries have experienced productivity gains in AGR, although productivity differences seem to remain by 1991. However, most countries in CST show no significant productivity changes. In MAN productivity has experienced a clear upward trend in all countries. In EGW we observe an increase in TFP for the lagging countries, however, a substantial difference with respect to the leader remains by the end of the sample. SOC shows hardly any productivity changes. Finally, TRS displays clear productivity gains for all the countries, with the high

---

mogenous panels. As a result, two major sectors, mining and retail trading, were excluded from the sample due to lack of data for some countries (and periods) of interest. The inclusion of a different set of countries in each panel would invalidate the comparison across sectors of the convergence results.

productivity countries growing at a lower pace. Some evidence of productivity catch up can be observed, with the standard deviation falling from 0.14 to 0.10.

Another feature of the data is the presence of significant cross-country contemporaneous correlations in every sector (Table 5). The correlations are computed from the residuals of the OLS estimation of (2). The average correlations range from 0.35, in SOC, to 0.56, in CST. Testing for the significance of the correlation matrices shows clear evidence of cross-country dependence: the Likelihood Ratio test statistic rejects the null of cross-country independence at the 1% level in each sector.

## 4 Test description and empirical results

The first step was to estimate autoregressive univariate models for each country in order to determine the country-specific optimal lag length to be used in the multivariate tests. The Akaike and Schwarz information criteria shown that different countries had longer autoregressive models than others, varying between 1 and 4. We employed an univariate Augmented Dickey-Fuller test, where the critical values were adequately corrected for the number of lagged variables in the equation specification following Cheung and Lai (1995). The test results, overall, could not reject the null of non convergence.<sup>4</sup>

Given our limited sample size, 22 observations for each country and sector, the univariate analysis of the long-run properties of time series, such as stationarity, should be interpreted with caution. The use of more powerful multivariate unit root tests together with the computation of the finite sample distributions for the relevant test statistics help to alleviate the statistical problems caused by small samples. Moreover, the multivariate approach takes advantage of the additional information in the cross-sectional correlations, which turn out to be statistically significant for every sector analyzed. Hence, the panel estimation of (2) through

---

<sup>4</sup> The univariate unit root results are available from the author upon request.

FGLS provides a more efficient estimation as it incorporates the information contained in the cross-country correlations.

The multivariate unit root test applied here is based on previous panel data unit root tests developed by Levin and Lin (1992, 1993), Quah (1994), and Taylor and Sarno (1998), among others. Taylor and Sarno's procedure improves upon Levin and Lin's, and Quah's tests, since the autoregressive coefficients,  $b$ , are allowed to differ across the elements of the panel. Their test also corrects for the presence of cross-sectional correlation by applying seemingly unrelated estimation, using the contemporaneous cross-sectional correlations of the residuals from OLS estimation. Our test builds upon Taylor and Sarno's approach, by allowing the lag order of the autoregressive process of each country in (2) to be optimally chosen, following the Akaike and Schwarz information criteria.

The null hypothesis of interest is the presence of a unit root in all the countries of the panel, i.e.

$$H_0 : b_{0,1} = b_{0,2} = \dots = b_{0,N} = 0. \quad (3)$$

The appropriate statistic to conduct this test is the standard Wald criterion

$$W = \hat{b}' R' [R \text{Var}(\hat{b}) R']^{-1} R \hat{b} \quad (4)$$

where  $\hat{b}$  is the matrix of FGLS coefficient estimates of (2);  $R$  is a matrix that contains the coefficients for the  $N$  linear constraints in (3); and  $\text{Var}(\hat{b})$  is the estimated variance of  $\hat{b}$

$$\text{Var}(\hat{b}) = [X' (\text{Var}(\hat{\varepsilon}))^{-1} X]^{-1}$$

where  $X$  are the right hand side variables and  $\hat{\varepsilon}$  are the residuals of the FGLS estimation of (2). The use of the standard  $\chi^2(N)$  distribution to draw inferences is not possible in this context. For the general model specification adopted here the distribution of the Wald statistic is non standard. Instead, the finite sample distribution of (4) is calculated through Monte Carlo simulation.

The Monte Carlo simulations were based on data generation processes (dgp) similar to those estimated from the data. The steps involved in the generation of the finite sample critical values can be briefly summarized as follows. First, the dgp was built from the FGLS estimates of (2), where country specific time trends were included in the estimation. Each artificial data set was generated under the null of a unit root, i.e. the coefficients  $b_{0,i}$ ,  $\forall i = 1, \dots, N$ , were set equal to zero. The error term, was drawn from a Gaussian distribution with zero mean and covariance matrix equal to the covariance of the FGLS residuals. With this dgp, an artificial panel of size  $N \times T$  was created, and the Wald statistic was estimated. This process was repeated 5,000 times—with equal pseudo random numbers for each simulation—and the resulting 5,000 statistics were ordered to compute the 1%, 5% and 10% critical values.

The test results are reported in tables 2a and 2b. The first column denotes the sector for which the joint null hypothesis of non convergence is being tested. The second column displays “the most productive country”: in Table 2a, the most productive country corresponds to the country with the highest sample average TFP; in Table 2b, it corresponds to the country with the highest TFP level at the beginning of the sample. In the third and fourth columns the Wald statistic and the corresponding p-values are shown. The last three columns are the finite sample critical values, computed through Monte Carlo simulation. For Table 2a the p-values indicate that, at a standard 5% significance level, only AGR and TRS show evidence of productivity convergence. For the other four sectors, CST, EGW, MAN, and SOC, the multivariate test fails to reject the null of non convergence. For the TFP aggregate (TIN) the test also fails to reject the null. The results shown in Table 2b (i.e., based on the most productive country at the beginning of the sample) only differ qualitatively for CST, which is also found to converge. For the rest of the sectors we find similar results as in Table 2a (i.e., based on the average most productive country).

The rejection of the null hypothesis in AGR, CST and TRS, however, does

not provide information about the number of countries in the panel that converge. In fact, from the rejection of the joint null hypothesis we can only infer that at least one country in the panel does not converge. In order to determine the precise number of converging countries in a particular sector, a test proposed by Breuer *et al.* (1999) was implemented for those sectors where the joint null of non stationarity was rejected. Using again FGLS estimates of (2), we tested the separate null of non stationarity for each member of the panel, i.e.

$$\begin{aligned}
 H_0 & : b_{0,1} = 0 \\
 H_0 & : b_{0,2} = 0 \\
 & \vdots \\
 H_0 & : b_{0,N} = 0.
 \end{aligned}$$

This procedure allows to determine which particular members of the panel converge and which ones do not. This test statistic also follows a nonstandard distribution that needs to be computed by Monte Carlo simulation.

The country-specific test results for AGR, CST, and TRS are presented in tables 3-5, respectively. The first column indicates the country for which the null of non convergence is tested. The rest of the columns are organized in a similar fashion as in tables 2a and 2b. In the AGR sector, the null of non convergence is rejected for 5 countries at the 5% level: AUS, ITA, NOR, SWE and UK (at the 10% level, we also find evidence of convergence for DNK, FRA and JPN). In the CST sector we find evidence of convergence at the 5% level in DNK, GER, JPN and UK. Finally, for the TRS sector, the test rejects the null at a 5% level for AUS, CAN, FRA and NOR (at the 10% level, GER also shows evidence of productivity convergence).

The evidence in favor of convergence found in AGR, CST and TRS seems to be consistent with the theoretical prediction of Acemoglu and Zilibotti (1999). Their model argues that new technologies developed by the leading countries tend to be tailored to the needs of the leader. New technologies are, thus, skill-biased

and might not be equally appropriate for other countries with different levels of skills and technologies. As new technologies tend to be imported from the leader, only those sectors with equally skilled workers in the leading and following countries should display evidence of productivity convergence. Specifically, productivity should converge in low-tech sectors (AGR and CST), where both the leader and follower use low skilled labor. High-tech sectors (TRS), which employed the highest skilled workers should also display similar productivity across countries. However, productivity gaps can appear in medium-tech sectors (EGW, MAN and SOC), where more skilled workers in the leading country can be more easily substituted for less skilled workers in the following country. As technology is developed by the leader to fit the skills of its labor force, the following countries will not be able to reach the higher productivity level of the leader.

In contrast to our results, previous studies by Bernard and Jones (1996*a*, 1996*b*) found evidence of convergence in all sectors, except manufacturing. They argued that international trade leads to non convergence since countries tend to specialize according to the law of comparative advantage. However, this argument does not seem satisfactory to explain the evidence in favor of convergence found in transportation and communication services. This is a high-tech and highly tradable sector subject to rapid technological changes which are readily diffused across countries. An alternative explanation for the lack of convergence in the manufacturing sector could be the following. Manufacturing includes varied industries with potentially different levels of technology, therefore, looking at the manufacturing aggregate might hide a diverse industrial behavior. This argument seems to be consistent with the empirical studies at the aggregate (country) level, where evidence of non convergence in TFP has been documented, for example Klenow and Rodriguez (1997) and Hall and Jones (1999).

## 5 Conclusions

This paper has investigated productivity convergence in 6 major sectors across 13 OECD countries. We apply a multivariate unit root test, where the null of non stationarity can be interpreted as non convergence. Our approach counts with three important advantages over previous tests for convergence. First, the equation specification allows for different coefficients and lag length in each autoregressive equation of the panel. Second, it accounts for the presence of significant cross-country correlations found in the data. Third, in case of rejection of the joint-null hypothesis of non convergence, a second test is then implemented to determine the exact number of countries which show evidence of convergence. This two-stage procedure provides individual information on the convergence or non convergence result for each country, while taking advantage of the efficiency gain from the panel estimation.

The empirical evidence suggests that TFP does not converge in 3 out of 6 major sectors analyzed. Specifically, evidence of convergence is found in agriculture, construction, and transportation and communication services; whereas non convergence is found in utilities, manufacturing, and social, community and personal services. We further investigated those sectors showing evidence of convergence to determine which particular countries converge. Overall, our results seem to be consistent with the theoretical predictions of Acemoglu and Zilibotti (1999), who argue that convergence should be observed in high and low-tech sectors, and non convergence in the medium-tech sectors. However, the finding of both convergence and non convergence in different tradable sectors, suggests that the tradeability character of a sector does not play a key role on productivity convergence.



## References

- Acemoglu, D., and F. Zilibotti, 1999. *Productivity differences*, NBER Working paper 6879.
- Aghion, P., and P. Howitt, 1992. *A model of growth with creative destruction*, **Econometrica** **60**, 323-351.
- Barro, R.J., and X. Sala-i-Martin, 1997. *Technological diffusion, convergence, and growth*, **Journal of Economic Growth** **1**, 1-27.
- Bernard, A.B., and S.N. Durlauf., 1996. *Interpreting tests of the convergence hypothesis*, **Journal of Econometrics** **71**, 161-173.
- Bernard, A.B., and C.I. Jones, 1996a. *Comparing apples and oranges: productivity convergence and measurement across industries and countries*, **American Economic Review** **86**, 1216-1238.
- \_\_\_\_ 1996b, *Productivity across industries and countries: time series theory and evidence*, **The Review of Economics and Statistics** **78**, 135-146.
- Breuer J.B., McNown R., and M. Wallace, 1999. Series-specific tests for a unit root in a panel setting with an application to real exchange rates. Mimeo.
- Cheung, Y.W., and K.S. Lai, 1995. Lag order and critical values of the augmented Dickey-Fuller test, **Journal of Business and Economic Statistics** **13**, 227-280.
- Coe, D.T., and E. Helpman, 1995. *International R&D spillovers*, **European Economic Review** **39**, 859-887.
- Coe, D.T., Helpman, E., and, A. Hoffmaister, 1997. *North-South R&D spillovers*, **Economic Journal** **107**, 134-149.
- Grossman, G.M., and E. Helpman, 1991. **Innovation and Growth in the Global Economy**, The MIT Press, Cambridge, MA.
- Hall, R., and C.I. Jones, 1999. *Why do some countries produce so much more output per worker than others?*, **Quarterly Journal of Economics** **CXIV**, 83-116.
- Klenow, P., and A. Rodriguez, 1997. *The neoclassical revival in growth economics: has it gone too far?*, **NBER Macroeconomics Annual**, 35-78.
- Levin, A., and C.F. Lin, 1992. *Unit root in panel data : asymptotic and finite-sample properties*, University of California, San Diego Working Paper 92-63.

\_\_\_\_\_, 1993. *Unit root tests in panel data : new results*, University of California, San Diego Working Paper 93-56.

Meyer zu Schlochtern, Jeroen, 1994. *An international sectoral data base for fourteen OECD countries*, OECD Economic Department Working Papers, No. 145.

Quah, D., 1994. *Exploiting cross-section variations for unit root inference in dynamic data*, **Economic Letters** **44**, 9-19.

Romer, P., 1990. *Endogenous technical change*, **Journal of Political Economy** **98**, 71-102.

Sala-i-Martin, X., 1990. *On Growth and States*, Ph.D. Dissertation, Harvard University.

Taylor, M., and L. Sarno, 1998. *The behavior of real exchange rates during the post-Bretton Woods period*, **Journal of International Economics** **46**, 281-312.

## Appendix : Tables and figures

**Table 2a** : Multivariate test results ( $H_0 : b_{0,1} = \dots = b_{0,N} = 0$ )

Sector	Country	Statistic	p-value	FSCV		
				1%	5%	10%
AGR	BEL	195.40	0.0006	144.82	121.48	109.62
CST	CAN	71.078	0.6600	163.69	134.11	119.37
EGW	ITA	75.918	0.5566	146.09	121.45	110.80
MAN	DNK	84.898	0.4622	162.49	133.37	120.08
SOC	ITA	89.493	0.2540	148.31	119.70	108.52
TRS	USA	99.422	0.0146	104.47	79.817	69.029
TIN	USA	95.176	0.2338	159.64	126.85	112.47

**Note** : This table shows the Wald test results for the joint null of a unit root. The equation estimated though FGLS corresponds to (2). The first column indicates the sector; the second column shows the average most productive country; the third column is the Wald statistic; the fourth column is the p-value; the last three columns are the finite sample critical values computed through Monte Carlo simulation.

**Table 2b** : Multivariate test results ( $H_0 : b_{0,1} = \dots = b_{0,N} = 0$ )

Sector	Country	Statistic	p-value	FSCV		
				1%	5%	10%
AGR	USA	152.04	0.017	162.22	129.38	119.03
CST	USA	124.16	0.001	96.859	78.203	68.644
EGW	ITA	75.918	0.557	146.09	121.45	110.80
MAN	USA	84.898	0.483	162.69	131.72	121.22
SOC	ITA	89.493	0.254	148.31	119.70	108.52
TRS	BEL	129.89	0.003	121.14	100.78	89.298
TIN	USA	95.176	0.234	159.64	126.85	112.47

**Note** : The most productive country (column 2) is computed as the country with the highest productivity level in 1970. Similar comments as in Table 2a apply.

**Table 3** : Multivariate test results for AGR ( $H_0 : b_{0,i} = 0$ )

Country	Statistic	p-value	FSCV		
			1%	5%	10%
AUS	-5.4341	0.0198	-6.3864	-4.2970	-3.2312
CAN	-3.6951	0.4946	-8.2767	-6.5932	-5.8103
DNK	-5.8192	0.0866	-8.0991	-6.3741	-5.6622
FIN	-4.2028	0.3698	-8.2211	-6.5552	-5.7808
FRA	-6.1203	0.0604	-8.2060	-6.3055	-5.5395
GER	-4.2613	0.2412	-7.7801	-6.0629	-5.3230
ITA	-7.4002	0.0252	-8.4422	-6.6685	-5.9146
JPN	-6.1389	0.0794	-8.1341	-6.5806	-5.8685
NOR	-6.3554	0.0418	-7.6827	-6.2043	-5.4417
SWE	-6.5359	0.0498	-8.3469	-6.5221	-5.7430
UK	-8.4803	0.0054	-7.9251	-6.3050	-5.6211
USA	-4.3748	0.3328	-8.3652	-6.6804	-5.8773

**Note** : This table shows the test results for the null of non convergence for each country in the panel. The columns are organized in a similar fashion as in Tables 2a and 2b.

**Table 4** : Multivariate test results for CST ( $H_0 : b_{0,i} = 0$ )

Country	Statistic	p-value	FSCV		
			1%	5%	10%
AUS	-1.6349	0.916	-7.5753	-6.0583	-5.4764
BEL	-5.0040	0.157	-7.7659	-6.2414	-5.5307
CAN	-1.7015	0.843	-7.7287	-6.5170	-5.7859
DNK	-5.1994	0.001	-0.1725	1.1995	1.7011
FIN	-3.6960	0.431	-7.8297	-6.2193	-5.5990
FRA	-4.4232	0.238	-8.1412	-6.1528	-5.4664
GER	-5.6944	0.099	-8.2883	-6.5228	-5.6857
ITA	-7.8170	0.015	-8.3280	-6.4041	-5.4674
JPN	-6.0323	0.003	-0.8037	1.1129	1.7576
NOR	-5.5865	0.109	-7.9920	-6.5609	-5.6978
SWE	0.1952	0.992	-8.5852	-6.4504	-5.7111
UK	-9.1136	0.004	-7.6525	-6.2383	-5.5063

**Note** : Similar comments as in Table 3 apply.

**Table 5** : Multivariate test results for TRS ( $H_0 : b_{0,i} = 0$ )

Country	Statistic	p-value	FSCV		
			1%	5%	10%
AUS	-5.3964	0.0016	-2.5889	0.52506	1.4395
BEL	-2.0997	0.7940	-7.8425	-6.0087	-5.3205
CAN	-6.7900	0.0288	-7.8019	-6.1890	-5.4705
DNK	-2.4019	0.5158	-7.9150	-5.9204	-5.1739
FIN	-2.8010	0.5818	-7.4069	-5.8720	-5.2165
FRA	-6.3068	0.0002	-0.19106	1.1584	1.7829
GER	-5.8678	0.0522	-7.9532	-5.9172	-5.0798
ITA	-5.3866	0.1120	-8.0187	-6.2932	-5.5243
JPN	-1.0118	0.9240	-8.0642	-6.0981	-5.3088
NOR	-7.2649	0.0158	-7.7481	-6.0832	-5.3052
SWE	-3.6133	0.4164	-8.2816	-6.2044	-5.4472
UK	-2.0937	0.7992	-7.9577	-6.0624	-5.3174

**Note** : Similar comments as in Table 3 apply.

**Table 6** : Cross-country correlations

Sector	Avg	L.R.	p-value
AGR	0.4238	143.95	$9.9746 \times 10^{-8}$
CST	0.5589	222.71	$7.2248 \times 10^{-19}$
EGW	0.4209	160.31	$8.1487 \times 10^{-10}$
MAN	0.4213	194.92	$1.1618 \times 10^{-14}$
SOC	0.3463	142.65	$1.4389 \times 10^{-7}$
TRS	0.3810	138.07	$5.1315 \times 10^{-7}$
TIN	0.3079	138.43	$4.6474 \times 10^{-7}$

**Note** : This table shows the Likelihood Ratio test for the null of cross-country independence of the error term of equation (2). The first column shows the sector; the second column presents the average correlations in each sector; the third column presents the L.R. statistic; the last column shows the p-values for the test statistics corresponding to a  $\chi^2(66)$ .



**Table 7:** Percentage of population having attained  
at least upper secondary education, 1991.

Country	Age groups			
	25-34	35-44	45-54	55-64
AUS	57	56	51	42
BEL	60	51	38	24
CAN	81	78	65	49
DNK	67	61	58	44
FIN	82	69	52	31
FRA	67	57	47	29
GER	89	87	81	69
ITA	42	34	21	12
JPN*				
NOR	88	83	75	61
SWE	85	78	63	46
UK	81	71	62	51
USA	86	88	83	73

Note : Source OECD, 1996, *Lifelong learning for all*,  
Table A.12. (\*) No data available.

Figure 1: Log of TFP and its standard deviation





