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Productivity convergence in OECD manufacturing industries

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Abstract

The extent of β- and σ-convergence of average labor productivity across manufacturing industries in 18 OECD countries over the period 1972–1992 shows large inter-industry differences. One reason for these differences is knowledge and capital barriers preventing the occurrence of catch-up. We find the level of average labor productivity, as a proxy for these barriers, is correlated with the extent of convergence.   © 2000 Elsevier Science S.A. All rights reserved.

1. Introduction

The extent to which economies converge has received abundant attention by economists and politicians. Research has concentrated on the question of convergence of GDP per capita but much less so on the question of convergence of labor productivity at the disaggregated level of industries. The mechanisms behind catch-up and convergence of GDP per capita can never be established unless the developments of its lower level of aggregation equivalent of labor productivity are well understood. The current analysis aims at estimating the extent of convergence in labor productivity at the industry level and relating it to a simple measure of physical capital and knowledge barriers, viz. the average level of labor productivity. Industries with high barriers may also be expected to be industries with relatively low degrees of convergence.

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Recently, Bernard and Jones have published a series of papers on productivity convergence at the sector level (Bernard and Jones, 1996a–c). They claim that β-convergence at the macro level of GDP per capita has not been caused by productivity convergence in the manufacturing sector but instead by convergence in the service sector (see also Gouyette and Perelman, 1997). Arguments for catch-up resulting from technology transfer in manufacturing between countries and/or globalization of the manufacturing sector therefore seem not to have empirical support. However, the lack of convergence found within the manufacturing *sector* does not reveal the spread of the extent of convergence across manufacturing *industries*. Differences in convergence rates across industries help to understand why productivity gaps between countries exist and (dis)appear. Dollar and Wolff (1993) pay some attention to convergence at the industry level in their Chap. 3. The current paper is a more formal approach to this line of research.

The convergence debate has been increasingly shifting into a debate on econometric techniques with claims that the rates of convergence have been overestimated (Lichtenberg, 1994) or underestimated (Islam, 1995; Lee et al., 1998). A first choice a researcher is confronted with is whether to consider β-convergence or σ-convergence. β-convergence implies that less developed countries or industries perform better (catch up) on average when compared to more developed countries or industries. The effect of GDP per capita or productivity in the first period on its relative change in the consecutive period should therefore be negative. The idea behind σ-convergence is that the variance of (log) GDP per capita or productivity decreases as production techniques become more similar. It can easily be shown that σ-convergence is a sufficient condition for β-convergence, but not the other way around (Lichtenberg, 1994; Quah, 1993). In this paper we consider both β-convergence and σ-convergence and compare the results when either of these two measures is chosen.[1]

The remainder of this paper is organized as follows. In Section 2 we discuss a simple model of endogenous technological progress to explain differences in speed of convergence across industries. In Section 3 the two measures of convergence are introduced. Next, the measurement of average productivity level at the industry level is discussed. In Section 4 the results are presented for the 28 manufacturing industries in the OECD countries. The measures of convergence are compared and related to the initial level of labor productivity. The last section is used for concluding remarks and questions for future research.

2. Convergence of productivity

In this section a model of endogenous technological progress is presented. Technological progress is assumed to be a function of conscious action by agents who may be involved in production work, R&D and learning from other countries' technological lead.

Assume that A_{ijt} is a measure for (labor) productivity in industry i, country j and time period t. The objective function is a weighted combination of productivity in this period and in the next period. Employees in the industry may be engaged either in producing or in improvement of technology. Technology can be improved by transferring technologies from the country with the technological lead, or by independently undertaking R&D. The extent to which imitation improves technology is

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[1]Le Pen (1997) provides an overview of the theoretical and empirical literature on the international convergence of per capita income distribution. See also Baumol et al. (1989); Dollar and Wolff (1993); Baumol et al. (1994).

assumed proportional to $\ln(A_{ijt}/A_{it}^{\max})$ where $A_{it}^{\max}$ is the maximum of the productivities across the countries in industry i. The larger the distance to the most productive country the more opportunities to learn in case capital and knowledge barriers are not too high. The extent to which undertaking R&D improves technology is assumed to be proportional to $\ln(A_{ijt})$. Countries lagging in their technology performance are less likely to produce innovations than highly productive industries using modern technologies. This idea is related to the concept of 'absorptive capacity' (Cohen and Levinthal, 1989).

The objective function is equal to:

$$\max_{\alpha\beta} \{A_{ijt}(1 - \alpha)(1 - \beta)\}^{\nu} A_{ij,t+1}^{1-\nu} \quad \text{with } 0 < \nu < 1 \tag{1}$$

$$\text{subject to } A_{ij,t+1} = A_{ijt}(1 + \alpha\theta_1 \ln(A_{ijt}))(1 - \beta\theta_2 \ln(A_{ijt}/A_{it}^{\max})) \tag{2}$$

where α is the share of time spent on undertaking R&D and β is the share of time (R&D effort excluded) spent on imitation efforts. The growth of labor productivity may be increased by increasing the parameters α and β. However, this goes at the expense of productivity in the current period. The optimal values for these two parameters are:

$$\alpha = 1 - \nu - \frac{\nu}{\theta_1 \ln(A_{ijt})} \quad \text{and} \quad \beta = 1 - \nu + \frac{\nu}{\theta_2 \ln(A_{ijt}/A_{it}^{\max})} \tag{3}$$

The optimal growth rate of labor productivity, $\ln A_{ij,t+1} - \ln A_{ijt}$, can be derived from Eq. (2) and equals $2 \ln(1 - \nu) + \ln(1 + \theta_1 \ln(A_{ijt})) + \ln(1 - \theta_2 \ln(A_{ijt}/A_{it}^{\max}))$. Using the fact that $\ln(1 + x) \approx x$ when x is close to zero, the optimal growth rate can be approximated by $-2\nu + \theta_2 \ln A_{it}^{\max} + (\theta_1 - \theta_2) \ln A_{ijt}$. As in Romer (1990) the optimal growth rate is positively affected by the research success coefficient and negatively by the discount rate. The model predicts convergence in case the technology transfer success coefficient θ_2 is larger than the research success coefficient θ_1. That is, industries faced with high knowledge barriers and/or with absorptive capacity being an important determinant of successful R&D efforts will tend not to have a high catch-up rate.

The empirical question is whether opportunities for technology diffusion for a specific industry are large enough to have productivities across countries converging over time. An important source of lack of technology diffusion is the prevalence of knowledge barriers, which is related to the complexity of the production technology. High complexity of the technology is bound to lead to high knowledge barriers and to the importance of being able to assimilate and exploit information, i.e. having a high absorptive capacity. Hence, the difference between θ_1 and θ_2 is a rising function in the complexity of the technology.

3. Testing for convergence at the industry level

There are two main approaches to test for convergence. The first is to measure β-convergence and the second is to measure σ-convergence. In this section we discuss these two measures. This is followed by a short discussion of the measurement of productivity levels. We end the section with a brief review of the data set of 28 manufacturing industries.

We denote the logarithm of the productivity in industry i, country j and period t, by y_{ijt}. Denote by

$\hat{\sigma}_{it}$ the standard deviation of y_{ijt} across the countries in year t. The measure of β-convergence is then derived from the least-squares regression of y_{ijT} on a constant and y_{ij1} where 1 is the first period of investigation and T the last period. For each industry i we have the following regression equation:

$$y_{ijT} = \alpha_i + (1 - \beta_i)y_{ij1} + \varepsilon_{ij} \tag{4}$$

The estimate of β_i indicates the rate of β-convergence, with 0 implying no convergence and 1 implying complete convergence. Whether the rate of convergence is significantly different from zero is derived from the t-value of the estimated β_i. It is clear that in the current study β_i is equal to $\theta_2 - \theta_1$ for industry i. A larger value of $\theta_2 - \theta_1$ corresponds to a less complex production technology and, hence, more possibilities for catch-up.

Some authors have criticized the use of the β-convergence criterion as it may indicate convergence when in fact there is regression to the mean (Friedman, 1992). A solution to this problem is to consider the development of the standard deviation of y_{ijt} over time. The rate of σ-convergence can be measured by the change in the value of the standard deviation from period 1 to period T, i.e. $\hat{\sigma}_{iT} - \hat{\sigma}_{i1}$. The extent to which this convergence measure is significantly different from zero is measured by a test statistic recently introduced by Carree and Klomp (1997). Their T_3-statistic has a standard normal distribution under the null hypothesis of no σ-convergence and is computed as follows:

$$S_{1T} = \sqrt{N} \, \frac{\hat{\sigma}_{i1}^2 / \hat{\sigma}_{iT}^2 - 1}{2\sqrt{1 - (1 - \hat{\beta}_i)^2}} \tag{5}$$

where N is the number of countries.

Our measure for labor productivity is value added per employee. We deflate industry value added by the purchasing power parity (US$=$1) and divide it by the number of employees in the industry. The use of a general price index instead of an industry-specific price index is largely a consequence of lack of price data for value added across the countries in our data set. Additionally, the quality and composition of the industry product package changes quite significantly over a two-decade period, which complicates the use of price data.[2] Our data set is the OECD STAN Database 1970–1995 (OECD, 1997). It provides us with data on 28 manufacturing industries over the 1972–1992 period at the three-digit ISIC level. The countries for which data are available are Australia, Austria, Belgium, Canada, Denmark, Finland, France, (West) Germany, Greece, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Sweden, the United Kingdom and the United States. It should be stressed that some of the data points in the OECD STAN Database are estimated by the OECD Secretariat to achieve international comparability at a detailed industry level.

Table 1 shows some key figures on the data set of 28 manufacturing industries retrieved from the OECD STAN Database. Data are available for 18 countries with the exception of 'petroleum and coal products' (ISIC 354) for which data are available for 16 countries and 'other manufacturing' (ISIC

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[2]See OECD (1996) for a collection of papers on the measurement of price indices. For example, it has been reported by several authors (e.g. Hooper, 1996) that prices in the Japanese food industry are much higher than the international average. Gersbach and Baily (1996) find that, when using an industry PPP, the real value added per hour is much lower in this industry in Japan. Conversions of industry-level indicators to a common currency based on PPP's should therefore be interpreted with caution (OECD, 1997). We note here that leaving out Japan from the analysis for the 'food' industry barely affected the results for that specific industry. Clearly, this is an incomplete test.

Table 1
Summary statistics of manufacturing industries[a]

ISIC	Industry	Employment	Productivity (1992)	μ_1
3	Total manufacturing	3670	41.2	2.182
311/2	Food	341	42.5	2.220
313	Beverages	38	88.2	2.789
314	Tobacco	9	258.9	3.138
321	Textiles	203	29.2	1.870
322	Wearing apparel	166	21.0	1.571
323	Leather and products	16	26.2	1.808
324	Footwear	29	22.2	1.568
331	Wood products	113	29.4	1.931
332	Furniture and fixtures	95	28.5	1.911
341	Paper and products	111	49.4	2.266
342	Printing and publishing	214	39.6	2.117
351	Industrial chemicals	94	66.1	2.720
352	Other chemicals	106	64.1	2.578
353	Petroleum refineries	13	208.3	3.512
354	Petroleum and coal products	6	117.9	2.822
355	Rubber products	45	42.0	2.170
356	Plastic products, n.e.c.	134	41.1	2.156
361	Pottery, china, etc.	23	29.0	1.851
362	Glass and products	31	42.8	2.217
369	Non-metallic products, n.e.c.	85	44.5	2.283
371	Iron and steel	112	43.7	2.361
372	Non-ferrous metals	50	52.4	2.427
381	Metal products	310	33.7	2.000
382	Non-electrical machinery	406	37.9	2.158
383	Electrical machinery	395	40.8	2.123
384	Transport equipment	352	40.6	2.219
385	Professional goods	107	37.6	2.071
39	Other manufacturing	69	37.4	1.965

[a] 'Employment' is the average employment (in 1000 number engaged) in the industries across the countries. 'Productivity (1992)' is the value added (in $1000) per employee in 1992. μ_1 is the logarithm of the value added (in $1000) per employee in 1972 (Year 1).

39) for which they are available for 17 countries. The first row of the table shows the data for the 'total manufacturing' sector. The third column of Table 1 shows the average employment in 1992 (in 1000 persons) per industry across the countries. The average employment in the manufacturing sector per country is about 3.7 million persons. Industries with many employees on average include 'non-electrical machinery' (ISIC 382), 'electrical machinery' (ISIC 383), 'transport equipment' (ISIC 384), 'food' (ISIC 311/2) and 'metal products' (ISIC 381). These five industries provide on average about half of total manufacturing employment. The fourth column shows the average value added per employee (in $1000), i.e. our measure of labor productivity, also in 1992. The last column of Table 1 shows the logarithm of the labor productivity in 1972. This is highly correlated (correlation coefficient of 0.98) with the same variable in 1992.

The average labor productivity in manufacturing in 1992 was $41 200 per employee across the countries. The average labor productivity of many individual industries is quite close to this average, such as of the five 'large' industries discussed above. Two industries have an average productivity that

is far higher than the other industries. These are 'tobacco' (ISIC 314) and 'petroleum refineries' (ISIC 353). These two industries are capital-intensive and provide only a fraction of total manufacturing employment. The 'tobacco' industry is a somewhat special case as it is confronted with relatively high taxes resulting in higher value of sales. The correlations computed in Section 4 are based upon each of the industries in Table 1 with the exception of 'total manufacturing' (ISIC 3) and 'other manufacturing' (ISIC 39). However, we will also discuss results when leaving out the two industries with the lowest average employment, viz. 'tobacco' (ISIC 314) and 'petroleum and coal products' (ISIC 354). The first industry is affected by high sales taxes while the second industry is not observed in two of the 18 countries.

4. Results for 28 OECD manufacturing industries

The convergence estimates for labor productivity are presented in Table 2. In the second column of the table the estimate of β_i is presented followed in the third column by the corresponding t-value. For 'total manufacturing' (ISIC 3) the estimated rate of β-convergence is about 0.2. It is significantly different from zero (i.e. no convergence) only at the 10% significance level. Ten out of 28 industries have a rate of β-convergence of labor productivity that is significantly in excess of zero at the 1% significance level. This number increases by six when considering a 10% significance level. The fourth and fifth column of Table 2 show the value of the standard deviation of the logarithm of labor productivity in the years 1972 and 1992. A decrease of this value indicates that productivity differences across countries have declined over this 20-year period. In the sixth column the S_{1T}-statistic, introduced in Eq. (5), is presented. According to this statistic only seven industries show a significant F-convergence at the 10% significance level.

The results for labor productivity show that σ-convergence is indeed a sufficient but not necessary condition for β-convergence. Each industry showing a significant positive value of the S_{1T}-statistic also has a significant positive value of β_i. However, there are also industries ['industrial chemicals' (ISIC 351) and 'rubber products' (ISIC 355)] which show significant β-convergence but have an *increase* in the value of $\hat{\sigma}_{it}$. This may be interpreted as evidence for regression to the mean. The correlation between the estimated values of β_i and $\hat{\sigma}_{iT} - \hat{\sigma}_{i1}$ is quite strong: -0.78. When leaving out the 'tobacco' (ISIC 314) and 'petroleum and coal products' (ISIC 354) industries, this correlation is -0.76.

The results confirm the finding by Bernard and Jones (1996a,b) and Gouyette and Perelman (1997) that labor productivity in the manufacturing *sector* is only slowly or even not at all converging. However, they also show that the spread of the speed of convergence across *industries* is large.[3] We

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[3]The standard likelihood ratio test of the equality of the β_i's across industries has a value of 49.3 (larger than the critical value of the $\chi^2(27)$-distribution corresponding to the 1% significance level). This not only shows that the speed of convergence is not identical across industries, but it also indicates the presence of a possible 'aggregation bias' (see Theil, 1954, for the pioneering work on the problems of aggregation over micro units). The (unweighted) average of the estimates of β_i across industries is 0.326. When weighted with employment this average decreases somewhat to 0.282. Both exceed the estimated β-convergence for the entire manufacturing industry (ISIC 3). Hence, the slow rate of convergence found for the manufacturing *sector* appears to be partly due to an 'aggregation bias'.

Table 2
The rate of convergence of productivity in manufacturing industries[a]

ISIC	β	t_β	σ_1	σ_T	S_{1T}
3	0.195	1.79[a]	0.232	0.212	0.71
311/2	0.416	4.37[c]	0.326	0.227	2.78[c]
313	0.230	1.65	0.335	0.318	0.36
314	0.006	0.05	0.853	0.948	−3.69
321	0.307	1.76[a]	0.256	0.252	0.09
322	0.519	3.50[c]	0.403	0.307	1.75[a]
323	0.751	4.25[c]	0.363	0.272	1.71[a]
324	0.448	3.55[c]	0.491	0.367	2.01[b]
331	0.477	5.77[c]	0.442	0.273	4.04[c]
332	0.043	0.29	0.424	0.478	−1.56
341	0.437	3.12[c]	0.200	0.159	1.49
342	0.207	1.81[a]	0.283	0.259	0.68
351	0.473	1.85[a]	0.282	0.325	−0.62
352	0.121	0.62	0.279	0.327	−1.21
353	0.215	1.04	0.717	0.818	−0.79
354	0.378	1.85[a]	0.796	0.785	0.07
355	0.594	2.57[c]	0.282	0.286	−0.06
356	−0.069	−0.19	0.217	0.390	N.A.
361	0.176	1.08	0.314	0.331	−0.37
362	0.513	3.72[c]	0.311	0.229	2.05[b]
369	0.345	2.58[c]	0.337	0.285	1.12
371	0.753	5.11[c]	0.480	0.307	3.16[c]
372	0.225	1.09	0.488	0.551	−0.72
381	0.327	2.00[a]	0.321	0.301	0.39
382	0.061	0.46	0.331	0.357	−0.87
383	0.168	1.13	0.225	0.230	−0.16
384	0.495	3.12[c]	0.301	0.244	1.28
385	0.396	2.18[b]	0.307	0.290	0.32
39	0.106	0.63	0.582	0.642	−0.82

[a] For the industries corresponding to the ISIC codes, see Table 1. The superscripts a, b and c mean significant convergence at the 10%, 5% and 1% significance levels. N.A. means 'not available'.

claim that one of the reasons for this spread is the variety in the complexity of production technologies, or the existence of knowledge and capital barriers. A possible proxy for the complexity of production technologies is the level of labor productivity. Industries with high levels of labor productivity use, on average, technologies of a higher complexity and capital intensity than industries with a low level of labor productivity.

The relationship between the rates of β-convergence and σ-convergence on the one side and the logarithm of labor productivity in 1972, μ_{1i}, on the other side is computed by the correlation coefficients of $\hat{\beta}_i$ with μ_{1i} and of $\hat{\sigma}_{iT} - \hat{\sigma}_{i1}$ with μ_{1i}. We also employ $\hat{\beta}_i$ weighted with the reciprocal of its standard error, i.e. the t-value t_{β_i}. The correlation between the estimated values of β_i for the 27 industries and their μ_{1i} is −0.27. The correlation between the t-values of β_i and μ_{1i} is somewhat stronger: −0.36. For the variable $\hat{\sigma}_{iT} - \hat{\sigma}_{i1}$ we find a correlation coefficient of +0.47. These three correlation coefficients change somewhat to −0.18, −0.28 and +0.42, respectively, when the

'tobacco' (ISIC 314) and 'petroleum and coal products' (ISIC 354) industries are excluded.[4] That is, we find evidence for industries with a relatively high labor productivity having a low rate of (especially σ-)convergence of productivity.[5] This is in line with high knowledge or capital barriers preventing quick catch-up.

5. Conclusion

We investigate convergence of average labor productivity across manufacturing industries in 18 OECD-countries over the period 1972–1992. For each industry we determine the extent of β-convergence and σ-convergence and their statistical significance. The results show large inter-industry differences in the extent of convergence, part of which can be explained from differences in the level of average labor productivity. This level may function as a proxy for knowledge or capital barriers preventing catch-up occurring.

Low knowledge barriers which allow for imitation of new technologies and which limit the degree of absorptive capacity necessary for technological progress may facilitate convergence. High knowledge barriers which make imitation difficult and which can generate technological gaps into lasting ones may hamper convergence. This may be a reason for the lack of convergence of GDP per capita found in many large data sets including developing countries while there is ample evidence of convergence having taken place for developed countries (Carree and Klomp, 1997).

The current analysis leaves some questions unresolved. First, the use of the level of labor productivity as a measure for capital and knowledge barriers is an indirect approach. Do more direct measures give the same conclusion as our indirect measure? Second, what is the effect of industries being more or less internationally oriented? Gersbach and Baily (1996), for example, claim that an industry in which there is only local competition (such as the Japanese food industry) rank quite low on the productivity scale. Resolving these and other questions will allow us to better understand when convergence takes place and when it does not.

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[4]We tested whether these correlation coefficients are sensitive to outliers. For the sample of 25 industries ('tobacco' and 'petroleum and coal products' industries excluded) we find two outliers. Both are capital-intensive industries in Belgium that have increases of labor productivity which are much larger than for any other observation. These two industries are the 'petroleum refineries' (ISIC 353) and the 'iron and steel' (ISIC 371) industries. The rate of convergence for those two industries decreases substantially when Belgium is excluded from the sample. The estimates of β, t_β, σ_1 and σ_T for the 'petroleum refineries' (ISIC 353) industry change to -0.079, 0.38, 0.628 and 0.843, respectively, when excluding the Belgian refineries from the sample. Similarly, the estimates of β, t_β, σ_1 and σ_T for the 'iron and steel' (ISIC 371) industry change to 0.392, 2.14, 0.337 and 0.315, respectively. The correlation between convergence and productivity becomes stronger as a result of excluding the two Belgian industries. The correlation coefficients between the estimates of β, t_β and $\Delta\sigma$ and the logarithm of labor productivity in 1972 change to -0.40, -0.39 and $+0.62$, respectively. That is, the correlation coefficients are somewhat sensitive to outliers but when removing these outliers the results are reinforced.

[5]The relation between convergence and level of productivity can also be seen from the five industries with the highest (excluding 'tobacco' and 'petroleum and coal products') and the lowest μ_{1i}. Of the five industries with highest labor productivity in 1972 only one shows β-convergence at the 10% significance level while none shows σ-convergence. Out of five industries with the lowest labor productivity four show β-convergence and three show σ-convergence.

Acknowledgements

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