DATA FIELDS AND CONVERGENCE REGRESSIONS: RESULTS FOR THE OECD

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En el cuarto trimestre de 1991, la Dirección General de Planificación abrió una línea de estudio sobre el crecimiento comparado de la economía española y convergencia con las economías más desarrolladas. Hasta la fecha se han publicado otros ocho documentos de trabajo dentro de este programa:

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ABSTRACT

Structural differences among countries have long been recognized in the literature of growth. However, these differences are often neglected in the empirical analysis, in which the use of multi-country data sets has become a popular alternative to the more conventional time series analysis of macroeconomic relationships. In this paper we estimate the conventional convergence regressions for the OECD sample using the Mean Group Estimator, as proposed by Pesaran and Smith. Although the conditions under which the MGE is consistent are satisfied in our sample, the estimated parameter values differ substantially from those obtained with more conventional methods. These results suggest that the constant returns growth model might not be a good representation of the long run behaviour of the OECD economies from 1960 to 1990. Our results also indicate that more attention should be paid to country specific charateristics when multi-country data sets are used to test empirical propositions derived from theoretical models of the "representative economy".

SUMMARY

Página

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I. Introduction and basic facts.

The literature of economic growth has proceed along two seemingly unrelated avenues. Whilst the available empirical evidence seems to support the view of a worldwide constant returns technology, there is a flow of new theoretical models designed to explain that the growth rate is endogenous and that it depends on the deep technological and behavioural parameters of each economy. The evidence in favour of the exogenous growth model comes mainly from the estimation of convergence equations, in which the assumption of constant returns to scale is rarely tested but imposed. Convergence to the steady state is a property of the adjustment process of the growth model. Although this property (and the convergence rate itself) is country specific, it is difficult to test on the basis of time series observations of a single country. The standard procedure to disentangle long run from short run movements in the series is to take long run averages, which leaves insufficient data points to estimate the parameters of the model. To avoid this limitation, economists have resorted to multi-country data sets. However, in order to increase the degrees of freedom it is necessary to assume that all these observations are realizations from a unique population whose parameters can be consistently recovered with conventional econometric methods.

The mainstream empirical work in this area has focused in the cross-section estimation of convergence equations on time series averages. Many authors have also exploited the time dimension of the information, pooling data for shorter time periods, or even employing proper panel data methods to control for unobserved country specific effects (see Cohen (1993), Knight et al. (1992), Andrés et al. (1994), etc...). The results in these models differ significantly from those obtained in the cross section estimations, although they broadly confirm the ability of the augmented Solow model to explain the long run evolution of economies. The assumption of parameter homogeneity, across countries, is a crucial one in this literature. Under alternative assumptions about the nature of the relationship among the variables and the distribution of the coefficients, there are different estimation techniques that may yield different results. Cross-section or pooling data methods produce unbiased estimators if the regressors are strictly exogenous and the coefficients differ randomly across countries and independently of the regressors. If the model is dynamic, cross-section estimates yield consistent estimates only when they are based in long time averages, and when other non-trivial assumptions about the relationship between coefficients, disturbances and regressors hold. If this is not the case, and if parameter differences extend beyond the constant term, not even standard panel data methods can help to consistently recover the parameters of interest.

In Andrés and Boscá (1994) we presented evidence of systematic differences in technological parameters within the OECD, and found that, once this is recognized in convergence equations, the constant returns technology no longer shows up. In this paper we extend these results to a more formal econometric setting put forward by Pesaran and Smith (1993), and investigate to what extent the estimated parameter values survive to alternative estimation techniques that impose less a priori assumptions about the distribution of the parameters across countries.

The convergence equation for the OECD sample is estimated in section II. We compare the results of different econometric approaches: cross-section, pooling and individual effects methods. In order to exploit the time dimension in full we consider annual observations from 1960 all through 1990. We also present results for two alternative data sets, in which short run fluctuations have been removed applying standard smoothing techniques. With some exceptions, all these methods produce similar estimates of the relevant parameters. In section III, we obtain consistent estimates of the mean coefficients across the OECD sample, applying the mean group estimator (MGE) proposed by Pesaran and Smith (1993). We find that when the assumption of parameter homogeneity is removed the exogenous growth model does less well in most specifications. The MGE coefficients differ quite substantially from the ones obtained by any other method; only few parameters are significant and the convergence rate becomes unappealingly high. When the restrictions of constant returns to scale are imposed all parameters, in particular the convergence rate, present more conventional values. However, this is not very encouraging as far as the exogenous growth model is concerned, since these restrictions are not accepted by the data in most countries. In section IV we find that the conditions under which the MGE yields consistent estimates of the average coefficients are satisfied in our sample. However, the distribution of the estimated coefficients around their mean is not normal, so that we cannot carry out standard inference in the MGE coefficients. Section V concludes with some additional remarks. Our results indicate that some of the coefficients estimated on the basis of multi-country data sets might be inconsistent, and that more attention should be paid to the specific characteristics of countries in the sample. In particular, many of the most promising results in the convergence literature cannot be recovered once this generalized parameter heterogeneity is fully addressed.

II. Alternative econometric approaches to the convergence equation.

The saddle point property built-in the constant returns growth model, has been incorporated in the recent empirical growth literature as the convergence proposition. The convergence model has been estimated for a wide range of countries and regions using different econometric methods. There is a set of well established results in this field. Although most restrictions have not been usually tested, the data seem to support the existence of a well behaved constant returns technology in capital (both human and physical) and efficient labour. On the other hand, differences in accumulation rates seem to account for the bulk of permanent differences among countries. Finally, economies do return to their steady state growth path at an average rate of 2 per cent.

However, the question of whether these values are consistent estimates of the mean convergence rate and other parameters in the multi-country set is crucially dependent on the assumptions made about the distribution of parameters across countries. To fix ideas, consider the basic conditional convergence equation, in standard notation,

$$\Delta y_{it} = \pi_{i0} + \pi_{i1} y_{i,t-\tau} + \pi_{i2} s^{*}_{it} + \pi_{i3} h^{*}_{it} + \pi_{i4} n^{*}_{it} + \pi_{i5} \text{Trend} + \varepsilon_{it} \qquad (1)$$

$$i=1,2,\ldots,N,\ t=1,2,\ldots,T.$$

$$\pi_{is} = \pi_{s} + \eta_{is}\ \forall i,s,$$

where, y is income per capita, s is the investment rate, h is the rate of accumulation of human capital, n is the augmented rate of population growth and the *TREND* variable captures the effect of exogenous technological progress. The π_{is}'s parameters and their mean value (π_s) are the ones we are interested in. If these parameters are homogeneous across countries (i.e. $\eta_{is}=0\ \forall i,s$) or if the η's are distributed with zero mean and constant variances, a consistent estimate of π_s will also be a consistent estimate of each of the π_{is}. If none of these assumptions hold, the mean parameter carries little useful information. Under the assumption of parameter homogeneity, the estimation of the mean parameter is a trivial matter and can be carried out in a number of ways. Otherwise, the way to obtain consistent estimates of the π_s's is more cumbersome and it depends on the size of T. If T is not very large, we simply do not have enough data points and we must either assume parameter homogeneity or abandon the purpose of estimating (1) altogether. If T is large enough we can choose either to impose homogeneity or not to do so. The main advantage of data fields, in which N and T are similarly sized and reasonable large, is that we can relax and test that assumption.

Multi-country averaged data sets behave as any other longitudinal data sets in which T is small[1] in relation to N. This makes difficult to allow for country specific effects other than in the constant term. As Andrés and Boscá (1994) discuss, there are sound theoretical reasons to expect not only the constant term but also the slopes to vary across countries. In fact, when convergence regressions are estimated for different subsamples, the null of parameter homogeneity is overwhelmingly rejected[2]. Furthermore, mean parameters are different from the ones obtained in the full sample estimation too. Pesaran and Smith (1993) discuss under what circumstances we can consistently recover the parameter of interest in data fields, all of which have been extensively used in the growth literature. Three of these methods impose parameter homogeneity across countries, at least up to a time invariant effect. Under this assumption we could either run a cross-section regression on time series averages, or a time series regression on cross-section averages; alternatively, we could exploit both dimensions of the data set and control for individual time invariant effects.

If we had a proper data field we could run separate regressions for each country and calculate the average coefficient ($N^{-1}\Sigma\hat{\pi}_{is}$) as an estimate of

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[1] Usually no more than five or six observations.

[2] As in Durlauf and Johnson (1992).

π_s. The empirics of growth deals with the long run, so that the information contents of 30 annual observations about the steady state can be very tiny, since these observations are contaminated by cyclical fluctuations that ought to be removed. We can do so in a number of ways (e.g. moving averages, or any filtering method such as the Hodrick and Prescott's smoothing method or the Beveridge and Nelson procedure). Although none of them is fully satisfactory, there are no reasons to expect them to perform worse than the conventional five, ten or thirty years averages[3]. Our approach in this paper is to exploit an OECD data base[4] as a proper data field, and hence we shall avoid conventional averaging methods that drastically reduce T. We consider three alternative characterizations of the long run[5]. The first one is simply the annual raw data (RD). Alternatively, we have taken five years moving averages (MA) to cancel out cyclical fluctuations. Finally, we have smoothed out the series using Hodrick and Prescott's filtering method[6], and taken the fitted trend as an approximation of the steady state (HP)[7]. Given

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[3] As Romer (1989) points out, eliminating high-frequency variation in the data may introduce inefficiencies, but it is not clear which methods of doing so are better than the others.

[4] See Dabán, Doménech and Molinas (1994) for the details in the elaboration of the data base.

[5] An alternative method is used in Holtz-Eakin (1992) who obtains annual proxies for the steady state variables in US regions by taking averages from t_0 all through t for all t.

[6] Except for the human capital proxy which was itself constructed from observations obtained every five years. The annual series is itself very much a trend with changing slopes so that there is no point in attempting any sophisticated further smoothing.

[7] See Prescott (1986) for a description of this method. Basically, it consists of selecting the trend path which mimnimizes the sum of the

the widespread use of HP filtered residuals in the analysis of business cycle fluctuations, the latter approach seems a natural one to represent long run fluctuations or the adjustment to the growth path.

In table 1 we present the basic convergence model estimated for each data set (RD, MA and HP). The model is estimated in three different ways. In columns 1 to 3 we present cross-section estimates on time series averages, whereas in columns 4 to 6 we pool the observations for all the OECD economies, exploiting their cross-section and time series dimension at the time. Models in columns 7 to 12 partially relax the assumption of parameter homogeneity allowing for a different constant term across countries. The individual effect is treated as fixed, and removed through the within groups estimator (as in cols. 7 to 9), or as random and hence the model is estimated by GLS (cols. 10 to 12).

The cross-section estimates are remarkably similar all along the three data sets. All the coefficients have the expected sign and, with the exception of the human capital, are significant at the 5 per cent level. The coefficient of the initial income per capita (in 1960) is high and significant too, and yields an implicit convergence rate ranging from 1.8 to 2.0 per cent. The HP data set displays the best fit of all although quite marginally. Turning now to the pooling model (cols. 4 to 6), differences in the goodness of fit are

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squared deviations from a given series, subject to the constraint that the sum of the squared second differences is not too large. Given the yearly dimenssion of our data we have choosen the Lagrange multiplier of the constraint to be 400. In Nicoletti and Reichlin (1993) it can be found a comparison between the Hodrick-Prescott filter and other smoothing methods, like the Beveridge and Nelson procedure.

now substantial. The R^2 in the HP data set is between two and three times larger than in the two other samples, and a similar pattern can be found in the estimated standard error of the regressions. In all three cases the trend variable has a negative sign which is the opposite to what was expected. This will also happen in some of the specifications we present throughout the paper. This might be due to the fact that our human capital variable is a poor proxy of the share of output devoted to accumulate human capital. In fact this variable is very trended (while it should not be) and may be picking up some of the conventional exogenous technological progress effect. As far as the implicit convergence rate is concerned, differences are now bigger but still within the range of values that are common in the literature (from 1.6 to 2.3 annual rate).

The within groups estimator enhances the differences among the three data sets. The rate of secondary schooling is now non significant in the RD and MA models and is negative in the HP one, in the latest case the coefficient of the trend becomes positive. These results confirm the poor quality of our human capital proxy, and are consistent with the results reported by Cohen (1993) who finds that the significance of human capital variables in convergence regressions might be picking up country specific differences. The differences in the parameter of investment and population growth are also quite big, and so are those in the R^2 and $\hat{\sigma}$ statistics. The differences in the implicit convergence rate are also striking. The implicit λ increases sharply in the two first models (to 7.8 and 7.2 respectively). These values are far above those obtained in the literature, but are consistent with the ones obtained by Knight et al (1993), as well as in Andrés and Boscá (1994), who find that once structural differences among economies are removed, the convergence rate turns out to be much faster. Surprisingly, though, the convergence rate in the HP model is much smaller (around 2.8 per cent) and close to the universal 2 per cent rate. Apart from the coefficient on human capital and on the trend, things turn to be fairly similar in the GLS random effects models (cols. 10 to 12). Again the results in the RD and MA data sets are very similar each other, and both differ from the estimated coefficients in the HP case, which again presents the best fit of all three. The convergence rate returns to its most common value (between 2.2 and 2.5 per cent).

The overall picture we get from the results in this table is that they are sensitive both to the estimation method and to the method of smoothing the data. As far as the comparison between alternative smoothing procedures is concerned, the HP procedure seems to perform better than the others in several grounds. First, the better fit indicates that it is more suitable to test propositions about the long run than the alternative methods. Second, the implicit convergence rate is rather more stable than in the two other data sets. The coefficients have, in general, the correct sign and are significant, including that of the trend in some specifications[8]. In

[8] The time series regression over cross-section averages gives rather awkward results for all three data sets. In addition, the HP data set is the only one for which the Anderson-Hsiao method yields reasonable parameter values, similar to those presented in table 1 (the convergence rate, for instance is 2.5 per cent, whereas it reaches a value of over 30.0 per cent in the other two cases).

general, most models confirm the importance of investment in growth and a significant autorregressive pattern with a moderately stable convergence rate. On the other hand, the coefficient of human capital is much less stable and bounces around from one model to the next. In particular, it becomes negative or non significant as we move to less restricted models (the ones with country specific effects). This suggests that the possibility of parameter heterogeneity should be extended to the slopes as well.

III. The MGE and the convergence regression.

Zellner (1969) has shown that all the econometric methods discussed in the previous section produce consistent estimates of the coefficient means, if the regression is static and the regressors are strictly exogenous. However, the convergence model does not meet this requirements. The saddle point property generates a sort of error correction mechanism, which implies some degree of autocorrelation in (at least one of) the regressors. Furthermore, the right hand side variables are endogenously determined with the growth rate. In this case, Pesaran and Smith (1993) have shown that pooling, time series and (to a lesser extent) cross section regressions generate a substantial bias, even if the assumptions about the stochastic behaviour of the coefficients are satisfied[9]. These authors propose to compute the mean

[9] It has to be noticed, however, that cross section estimates have a relative advantage to the other techniques; if the regressors are really exogenous and T is large enough, the cross section regression yields consistent estimates of the mean or average coefficients $\{\pi_s\}$.

group estimator (MGE), i.e. to run separate regressions and take the average of the estimated coefficient for each country. They show that under some assumptions both the unweighted average and the GLS weighted average (Swamy (1971)) yield consistent estimators of the mean coefficients $\{\pi_s\}$.

Let us consider again the system of equations in (1), in which the regressors and the ε's are independently distributed, and both are independently distributed of the η's. All the other assumptions in Pesaran and Smith (1993) are assumed to hold, and will not be tested. We have run separate convergence regressions for each of the 24 countries in the OECD sample, using the three alternative data sets we discussed in the previous section. To save space we do not present here the results for each country[10], although we shall mention them when necessary.

In table 2, column 1 the mean coefficients have the correct sign but only the lagged dependent variable and the investment rate turn out to be significant. The rate of growth of population and the trend have t statistics above 1, while human capital is not significantly different from zero[11]. The picture on a country by country basis is quite promising as far as the individual coefficients is concerned; with the exception of Ireland (in which $\hat{\pi}_2$ is negative) these two coefficients have always the expected sign (i.e. $\hat{\pi}_1$ negative and $\hat{\pi}_2$ positive) and are very often significant. The

[10] They are available from the authors on request.

[11] Correcting for heteroskedasticity the t statistics of the population growth and the trend coefficients get close to 1.5.

other coefficients have in general the expected sign although they are seldom significant. Overall, the convergence model performs rather well for a significant number of countries. Less promising, though, is the extraordinarily high mean rate of convergence, its implicit value (39 per cent) is far above the values obtained in the previous section. The models for the MA and HP filtered data (cols. 2 and 3) give a rather gloomier picture. Although having the expected sign, none of the mean coefficients is significant; on the other hand, signs do vary substantially across countries and the convergence model seems quite inadequate for most countries in the sample.

Upon the imposition of the constant returns to scale constraints, things look different. The model with raw data (col. 4) improves slightly, whereas the MA (col. 5) one does not change in a significant manner. As far as the HP model is concerned (col. 6), the improvement is dramatic. Unlike the unrestricted model, all mean coefficients but π_3 are now strongly significant[12] and with the correct sign, this is true also for the positive coefficient in the trend. This improvement carries over most individual countries too. The initial income, the investment rate and the rate of growth of population are significant in twenty two out of the twenty four countries. Among these, π_1 is negative in eighteen cases whereas π_2 is positive (π_4 is negative) in nineteen. Similarly the trend is significant for eighteen countries, in most of them with the expected positive sign. Even the coefficient of human capital is significant in fifteen out of the

[12] In particular when corrected for heteroskedasticity.

twenty four OECD countries, in most of them also positive[13].

The convergence model seems to meet the challenge of the mean group estimator only if we choose the HP filtering procedure, and when the assumptions of constant returns to scale have been imposed. Under this conditions, the most relevant results we got in the pooling method, carry on into the mean coefficients. All coefficients retain the same sign as in the conventional estimation methods, although they are much less precisely estimated now. The most dramatic changes are those referring to the coefficient of human capital as well as the trend variable. The mean group estimator of the contribution of human capital to the steady state of each economy is non significant whereas the trend is positive and significant. This confirms that although the cross section variation of schooling rates accounts for part of the observed income differentials, in fact they may be picking up the effect of structural differences across countries, since their contribution on a country by country basis is far more modest, and is overcome by that of the trend. However we must bear in mind the precise conditions under which these results hold. Formal *F* test indicate that the restrictions imposed to the parameters by the constant returns to scale technology are not supported by the data in most of the countries.

The results obtained for the convergence rate deserve a careful scrutiny. When the cyclical effects have been netted out (i.e. in the HP data set) the

[13] Although a few strong negative signs drive the mean coefficient towards zero.

convergence rate settles at 17 per cent which is still pretty high as compared with the widely accepted 2 per cent but half of the value obtained in the RD model of column 4. This is what one should expect, since short run cyclical fluctuations die away more quickly than fluctuations in the trend itself from its steady state value. This point estimate implies that deviations from the steady state take 4.5 years to return to it. A more accurate convergence rate can be obtained if we remove Switzerland and Austria from the sample, with abnormally high convergence rates (123 and 92 per cent respectively). In this case the average convergence speed of the remaining 22 countries drops to 7 per cent annual rate[14], which implies a the average OECD country would return to its steady state in 10 years following a shock to its growth rate.

These values are still above the 2 per cent convergence rate[15]. If the higher mean coefficient estimate is taken as the true one, it would imply that the definition of the steady state that one can obtain from the pooling or cross section models carries little information about the true potential per capita income of each country. The argument can be given a simple and intuitive explanation in terms of the presence of generalized country specific effects. When the model (1) is estimated imposing parameter homogeneity, we are in fact leaving all structural differences among

[14] A similar value can be obtained if we also remove those countries with a negative implicit convergence rate.

[15] Notice that an average 2 per cent rate of convergence should indicate that many countries would in fact diverge from their steady state or at least they would converge to it at an extraordinary low speed.

countries to be explained by differences in their accumulation rates. The 'average steady state' bears then little relationship with the truly long run prospects of each economy. In other words, although the residuals from the OECD regression add up to zero, it might well be the case that most countries observations never cross their alleged steady state[16]. In this case, the rate of convergence is biased towards zero. However, as we allow for parameter heterogeneity the steady state of each country is better specified, and it becomes a truly long run relationship with stationary deviations from it.

The convergence rate obtained in this way is also more reliable than the one obtained under the alternative econometric procedures. As Quah (1993) has rightly argued, a positive convergence rate in a cross section or pooling regression, might not deliver any information about how the cross country distribution of income evolves. A positive convergence rate may in fact be consistent with a stationary or widening dispersion of incomes across countries. Estimating the model for every individual country does simply tell us what is the speed at which each of them closes the gap with its own long run trend if, for any reason, it happens to be away from it. There is no implication whatsoever to be drawn about the dynamics of the cross section distribution. Hence, our estimated mean convergence rate is free from the Galton's fallacy type of critique. This rate must better be interpreted as an error correction parameter, indicating for how long deviations from the attainable long run level of per capita income may last.

[16] And indeed it is so, as discussed in Andres and Lamo (1994).

IV. Consistency and inference with mean group estimates.

The differences among MGE and the other popular econometric methods in the growth literature cast some doubts on the widely accepted result of convergence and constant returns to scale as a good representation for the long run behaviour of the OECD sample. In this section, we move an step forward and discuss to what extent mean group estimates are themselves reliable. In particular we investigate in some detail whether the stochastic hypothesis behind the MGE are likely to hold in our sample. The analysis above, assumes a particular structure for the parameters in the data field. Under those assumptions, the MGE is the appropriate benchmark for the alternative estimation methods to be compared with. However, these assumptions are quite restrictive and should not be taken for granted. We analyze the distribution of the estimated coefficients, as well as the correlation among coefficients and regressors.

Pesaran and Smith (1993) assume just a constant mean and variance parameter distribution as a necessary condition for MGE consistency. However, in order to make further inference we need a closer characterization of this distribution. In figures 1 to 4 we display the distribution of some individual country parameters[17], and in table 3 we report the tests of

[17] In figures 1 and 3 we report the distribution of $\hat{\pi}_1$ and $\hat{\pi}_2$ in the RD model. In figures 2 and 4 we report the distribution of $\hat{\pi}_1$ and $\hat{\pi}_2$ in the HP model.

skewness and kurtosis of all parameter distributions. In general, the shape of the histograms do not suggest, except in a few cases, a normal distribution centered around the mean. In fact, in most cases skewness and kurtosis are significantly different from zero at the 5 per cent level. High order moments are significantly different from zero in all parameters in the HP model[18] as well as in the two other ones (RD and MA), although in this case with lower point estimates. If the distributions are not normal the possibility of making inference are quite limited. In particular we cannot test the restrictions of constant returns to scale in the mean group estimates. Furthermore, we cannot test for significant differences among countries nor for homogeneous groups of countries on the basis of the estimated π_{is}.

Even if the parameter distributions are not normal, the point mean group estimate and its *t* value of significance at the 5 per cent level, are still consistent estimators of the mean coefficients if some additional assumptions are satisfied. In particular, as Pesaran and Smith (1993) point out the coefficients in the system (1) must be independently distributed of the regressors. However, if Pesaran and Smith's hypotheses do not hold we cannot make use of the mean group estimator. The bad news is that in this case the other proposed estimation techniques (cross-section, averaging over groups, pooling or panel) would be inappropriate too, and the estimation of mean coefficients would be helpless. If this turns out to be the case we could not use the MGE approach to test other growth related aspects, such as

[18] The only parameter whose distribution is close to normality is $\hat{\pi}_1$.

the impact of macroeconomic performance, etc., and we should resort to a purely country by country analysis. This would be of major concern for empirical research in macroeconomics using multi-country data sets.

Alongside with the regressors exogeneity, the independence among coefficients and regressors is crucial to obtain consistent mean group estimates. The correlation among the estimated coefficients and the different regressors is analyzed in tables 4 and 5. The correlation coefficient in table 4 is quite low in most cases. In the RD model, the parameters π_2 and π_3 are the more troublesome with coefficients up to 0.4 with some right hand side variables. The same is true for π_3 and π_4 in the MA case and, to a lesser extent, for π_1 in the HP model[19]. The partial correlation in table 5 is more informative though. In most cases no single regressor is individually significant in regressions with the estimated coefficients as the dependent variable. In particular this is true for the HP data set, for which only the human capital proxy seems to be correlated with π_1 and π_5. Similarly, the F test of the joint significance of all regressors to explain the variation of the $\hat{\pi}_{is}$'s can be safely accepted at the 5 per cent level in all cases but one.

According with the results in tables 4 and 5, the conditions for consistency of MGE are satisfied (mildly at the very least). There are several possible explanations for the observed differences among the MGE and alternative

[19] Although this is worrying since it contains the estimate of the adjustment or convergence parameter.

estimation methods. We could simply argue that MGE is consistent whereas the others are not. This is the most straightforward conclusion, but it is somewhat unsatisfactory since all the other econometric approaches come up with surprisingly similar results. The fact that all the other methods, inconsistent as they are, lead to the acceptance of the Solow model whereas the MGE does not so, except in some specifications, is a bit unappealing. There is, though, an alternative and rather more tentative explanation. In the exogenous growth model, convergence is an error correction process and the steady state variables should be cointegrated with income whenever the CRS assumption is satisfied. If we pool all countries together, the parameters we get resemble those in the countries in which CRS holds since these are the ones which minimize the variance of the residuals in the existing cointegration relationships. Some related results by some of us (Andrés and Boscá (1994)) indicate that this might well be the case: although the pattern of growth differs substantially across countries, the parameters of the convergence model in the pooled sample are very close to the ones obtained for the countries for which the constant returns to scale assumption seems to hold[20]. In order to asses to what extent this hypothesis is a plausible one a more detailed investigation is needed, testing for cointegration relationships among income and the accumulation rates on a

[20] This issue could also be reformulated along the following lines: assuming that in a N,T data field there are N_1 ($N_1 < N$) cointegration relationships $\{Y=\alpha+\beta X\}$; how likely is that we find such a cointegration relationship in a pooling (N,T) model? how big needs N_1 to be to get such result?. This can be approached either theoretically or by means of Monte Carlo experiments.

country by country basis.

V. Concluding Remarks.

Most propositions in growth theory refer to the dynamics of the representative economy. Nevertheless multi-country data sets have become increasingly popular in the empirics of growth more than in any other field in macroeconomics. Given the long run nature of the issues involved, considering many economies in short periods of time has become a natural alternative to the analysis of single economies over very long periods of time. The payoff of doing so has been high, and the contribution of this empirical approach to the development of our understanding of long run trends is widely acknowledged. However, pooling data for many countries has its limitations too. First of all, the estimates we get from this approach are at best consistent estimates of the average parameters across the sample. When we are interested in the catching up process among economies, the average speed of return to the growth path after a shock can be of little interest. Second, and more worrying, is the fact that the currently widely used econometric methods do not even guarantee that the estimates of the 'average economy' are consistent.

The assumption of parameter homogeneity across countries, which is crucial to make multi-country data operational, is quite unlikely to hold even if we deal with a well defined economic region as the OECD. This heterogeneity goes beyond the presence of country specific time invariant effects and might affect other technological parameters as well. In this event, as Pesaran and Smith (1993) have shown, any econometric method that fails to recognize such heterogeneity is bound to yield inconsistent estimates of the average coefficients. It can be argued that this is a problem one must learn to live with, since the short time dimension left after averaging to eliminate short run fluctuations, leaves too few data points. Hence if we are willing to say something about the long run, we must be prepared to accept this limitation. There are, however, smoothing methods that do not impose such costs and whose information contents needs not be worse than that of five or thirty years averages.

Once we have reasonable large T and N dimensions we can evaluate to what extent some of the most popular results in the empirical growth literature are based on inconsistent estimates of the technological and behavioural parameters. In particular, we have focused on the augmented Solow model and its implicit convergence rate. The results suggest that all three conventional approaches yield broadly similar results. As we move from more to less restricted models (i.e. as we allow for time invariant specific effects) some things change (e.g. the human capital becomes non significant and the convergence rate gets bigger) although the general picture remains very much the same. However, as we allow for specific effects in both the constant and the slopes, the landscape changes dramatically.

Our results suggest that the conditions under which the mean group estimator is consistent are accepted in the OECD sample, since the correlation among the coefficients and the regressors is fairly low. However these mean group estimates differ quite substantially from the ones obtained by any other method. In particular, the lagged income coefficient is much higher and the other parameters have low t statistics. Once we get rid of the representative economy assumption, the convergence rate is much larger than the usual one. This rate has no implication whatsoever about the way the cross country distribution of income evolves, nor about poor countries approaching the richer ones in any finite period of time. It is also true that when the restrictions of constant returns to scale are imposed in the HP model, all parameters and in particular the convergence rate, present more conventional values. This gives some hope for the conventional procedure in the empirical growth literature. However a closer look at the results gives a more disappointing picture. First, the constant returns to scale constraints are not accepted by the data in most countries. Second, the distribution of the estimated coefficients around the MGE is not normal, so that we cannot carry out standard inference on the basis of the MGE coefficients.

These results cast legitimate doubts on the explanatory power of the exogenous growth model, and also on the way in which the empirical analysis of the long run has been conducted in recent times. The notion of steady state as it is usually portrayed in the conventional pooling models is very simplistic since the differences across countries are not fully captured by the differences in their accumulation rates. This suggests that endogenous growth models that take more account of individual country characteristics could be more suitable to analyze the long run behaviour of the economies in our sample. However, regardless of the theoretical framework we think is more suitable, the general message remains the same: the *inconsistency* problem of pooling methods might also affect much other work based in multi-country data (such as the influence of macroeconomic variables on growth, the role of expenditure in research and development, openness and growth, etc.), and more attention should be paid to the specific characteristics of the countries in the sample.

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Table 1

	1*	2**	3***	4*	5**	6***	7*	8**	9***	10*	11**	12***
Const.	-0.12	-0.09	-0.10	-0.13	-0.12	-0.09				-0.15	-0.06	0.02
	(2.58)†	(2.34)†	(2.68)†	(3.75)	(4.23)	(10.7)				(4.59)	(2.42)	(1.65)
$\log(y^i_{t-1})$	-0.020	-0.018	-0.018	-0.023	-0.016	-0.016	-0.075	-0.070	-0.027	-0.024	-0.024	-0.021
	(5.17)†	(5.14)†	(5.45)†	(6.86)	(6.91)	(21.5)	(7.40)	(11.5)	(16.7)	(6.79)	(8.64)	(15.6)
$\log(I/Y)^i_t$	0.019	0.019	0.020	0.014	0.016	0.020	0.038	0.033	0.005	0.025	0.023	0.007
	(2.65)†	(3.34)†	(3.63)†	(3.17)	(5.20)	(18.7)	(4.99)	(6.45)	(3.17)	(5.30)	(6.24)	(4.56)
$\log(n+g+\delta)^i_t$	-0.030	-0.019	-0.023	-0.045	-0.046	-0.026	-0.041	-0.006	-0.006	-0.046	-0.017	-0.014
	(2.36)†	(1.50)†	(1.84)†	(3.98)	(4.57)	(9.13)	(3.27)	(0.70)	(1.54)	(4.70)	(2.20)	(3.92)
$\log(Her2)^i_t$	0.011	0.012	0.011	0.012	0.003	0.006	0.005	0.003	-0.002	0.008	0.008	-0.001
	(1.48)†	(1.68)†	(1.68)†	(2.22)	(0.81)	(4.78)	(0.74)	(0.70)	(2.02)	(1.62)	(2.33)	(1.59)
Trend				-0.07	-0.05	-0.02	-0.11	-0.12	0.02	-0.05	-0.04	0.005
				(4.69)	(4.43)	(6.99)	(3.41)	(5.77)	(4.41)	(3.58)	(3.71)	(1.03)
R^2 Adj.	0.551	0.556	0.601	0.188	0.243	0.659	0.205	0.434	0.771	0.196	0.376	0.750
σ	0.006	0.005	0.005	0.024	0.012	0.005	0.023	0.011	0.003	0.024	0.011	0.003
N.O.	24	24	24	672	456	672	744	624	744	744	624	744
λ_{imp}	0.020	0.018	0.019	0.023	0.016	0.016	0.078	0.072	0.028	0.024	0.025	0.022

Notes: *Dependent Variable:* $\log(y^i_t/y^i_{t-1})$.

Estimation method: Cols. 1, 2, 3: Cross Section; Cols. 4, 5, 6: Pooling with I.V.; Cols. 7, 8, 9: fixed effects, within-groups estimators; Cols. 10, 11, 12: random effects, GLS estimators.

Instruments in Cols. 4 and 6: $\Delta\log(y^i_{t-1})$, $\Delta\log(y^i_{t-2})$, $\Delta\log(y^i_{t-3})$, $\log(y^i_{t-1})$, $\log(I/Y)^i_{t-1}$, $\log(I/Y)^i_{t-2}$, $\log(I/Y)^i_{t-3}$, $\log(n+g+\delta)^i_{t-1}$, $\log(n+g+\delta)^i_{t-2}$, $\log(n+g+\delta)^i_{t-3}$, $\log(Her2)^i_{t-1}$, $\log(Her2)^i_{t-2}$, $\log(Her2)^i_{t-3}$, constant and trend.

Instruments in Col. 5: $\Delta\log(y^i_{t-5})$, $\Delta\log(y^i_{t-6})$, $\Delta\log(y^i_{t-7})$, $\log(y^i_{t-1})$, $\log(I/Y)^i_{t-5}$, $\log(I/Y)^i_{t-6}$, $\log(I/Y)^i_{t-7}$, $\log(n+g+\delta)^i_{t-5}$, $\log(n+g+\delta)^i_{t-6}$, $\log(n+g+\delta)^i_{t-7}$, $\log(Her2)^i_{t-5}$, $\log(Her2)^i_{t-6}$, $\log(Her2)^i_{t-7}$, constant and trend.

Sample: i: 1,..,24; t* and t***: 1961,62,...,91 or t**: 1963,64,...,88.

*Raw data; **Five years moving averages; ***Hodrick-Prescott filtered data (except for Her2); †White's heteroskedasticity corrected.

Table 2

	1*	2**	3***	4*	5**	6***
Cte.	-0.61 (0.72)	-0.11 (0.19)	-0.13 (0.19)	-0.27 (0.57)	0.06 (0.14)	-0.49 (2.66)
y_{t-1}	-0.32 (2.49)	-0.07 (0.62)	-0.14 (0.60)	-0.29 (2.55)	-0.13 (1.57)	-0.16 (3.54)
I/Y	0.12 (1.82)	0.04 (0.71)	0.09 (0.85)	0.11 (1.81)	0.05 (0.87)	0.13 (3.74)
n	-0.14 (1.23)	-0.01 (0.10)	-0.05 (0.18)	-0.15 (1.88)	-0.04 (0.53)	-0.13 (3.86)
Her2	0.13 (0.67)	0.04 (0.32)	0.00 (0.23)	0.03 (0.52)	-0.01 (0.23)	0.00 (0.34)
Trend	0.50 (1.27)	0.06 (0.17)	0.33 (0.54)	0.55 (1.66)	0.32 (1.34)	0.38 (3.08)
λ_{imp}	0.39	0.08	0.15	0.34	0.14	0.17
N.O.	744	624	744	744	624	744

Notes: *Dependent Variable:* $\Delta\log(y_t)$
Cols. 1, 2, 3: Mean Group Estimates.
Cols. 4, 5, 6: Mean Group Estimates imposing constant returns to scale.
* Raw data; ** Five years moving averages; *** Hodrick-Prescott filtered data (except for Her2).

Table 3: SKEWNESS AND KURTOSIS OF THE M.G.E. COEFFICIENTS

	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
MOVING AVERAGES DATA						
Skewness	-0.05	2.27	-0.51	-0.45	-1.01	-2.02
	0.92	0.00	0.34	0.40	0.06	0.00
Kurtosis	0.92	7.64	0.40	-0.14	5.16	8.24
	0.43	0.00	0.73	0.91	0.00	0.00
RAW DATA						
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
Skewness	0.44	-0.98	0.35	-0.19	-0.44	0.66
	0.41	0.07	0.51	0.72	0.41	0.22
Kurtosis	0.93	1.29	-0.79	-1.11	3.16	0.38
	0.43	0.27	0.50	0.34	0.01	0.75
HODRICK-PRESCOTT FILTERED DATA:						
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
Skewness	-1.74	0.08	-3.09	-2.15	-0.71	-2.30
	0.00	0.87	0.00	0.00	0.18	0.00
Kurtosis	8.56	2.14	12.00	9.59	4.03	9.73
	0.00	0.07	0.00	0.00	0.00	0.00

Note: Below the Skewness and Kurtosis Coefficients appears the P-Value of the Null that Sk=0 and Ku=0.

Table 4: CORRELATION COEF. BETWEEN M.G.E. COEFFICIENTS AND REGRESSORS						
	COEFFICIENTS:					
REGRESSORS:	RAW DATA:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	0.11	-0.11	0.44	0.15	0.01	0.09
IY	-0.03	0.30	-0.16	-0.26	-0.30	0.05
TL	-0.16	-0.18	0.20	-0.41	-0.07	0.04
HER2W	0.10	0.01	0.31	0.25	0.03	0.06
	MOVING AVERAGES:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	0.33	-0.06	-0.08	0.53	0.00	0.16
IY	0.34	-0.02	-0.06	-0.17	-0.49	0.16
TL	0.17	-0.24	-0.22	-0.31	-0.25	0.22
HER2W	0.29	0.15	0.01	0.45	-0.07	-0.08
	HODRICK-PRESCOTT:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	0.05	0.21	-0.25	-0.04	-0.03	-0.16
IY	-0.31	0.19	0.03	-0.34	-0.17	-0.24
TL	0.02	-0.19	-0.06	0.02	-0.29	0.14
HER2W	-0.20	0.43	-0.14	-0.27	-0.04	0.37

Table 5: META-REGRESSIONS RESULTS: SIGNIFICANCE AT THE 5% LEVEL.

REGRESSORS:	DEPENDENT VARIABLE: COEFFICIENT SERIES					
	RAW DATA:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	N.S.	N.S.	S.	N.S.	N.S.	N.S.
IY	N.S.	S.	N.S.	N.S.	N.S.	N.S.
TL	N.S.	N.S.	N.S.	S.	N.S.	N.S.
HER2W	N.S.	N.S.	S.	N.S.	N.S.	N.S.
	F-TEST:					
	N.S.	N.S.	S.	N.S.	N.S.	N.S.
	MOVING AVERAGES:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	S.	N.S.	N.S.	S.	N.S.	N.S.
IY	N.S.	N.S.	N.S.	N.S.	S.	N.S.
TL	N.S.	S.	N.S.	N.S.	N.S.	N.S.
HER2W	S.	N.S.	N.S.	S.	N.S.	N.S.
	F-TEST:					
	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
	HODRICK-PRESCOTT:					
	CTE.	PIBPOB_1	IY	TL	HER2W	TREND
PIBPOB_1	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
IY	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
TL	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
HER2W	N.S.	S.	N.S.	N.S.	N.S.	S.
	F-TEST:					
	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.

Note: It has been estimated an OLS regression using as dependent variable the M.G.E. coefficient series, and as regressors a constant and the explanation variables itself.

Figure 1: Frequency Distribution
Initial Income Coefficient (Raw Data)

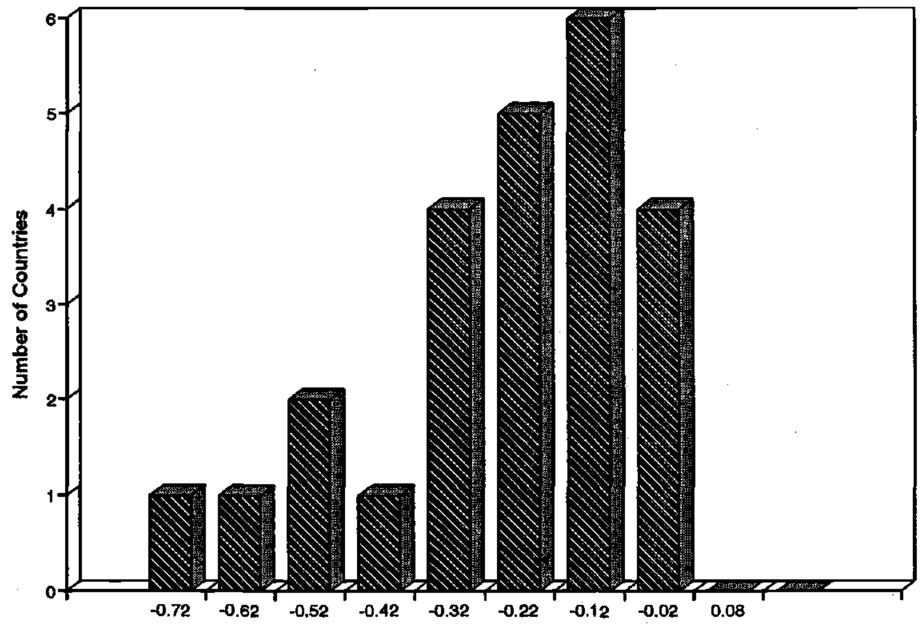

Figure 2: Frequency Distribution
Initial Income Coefficient (HP Data)

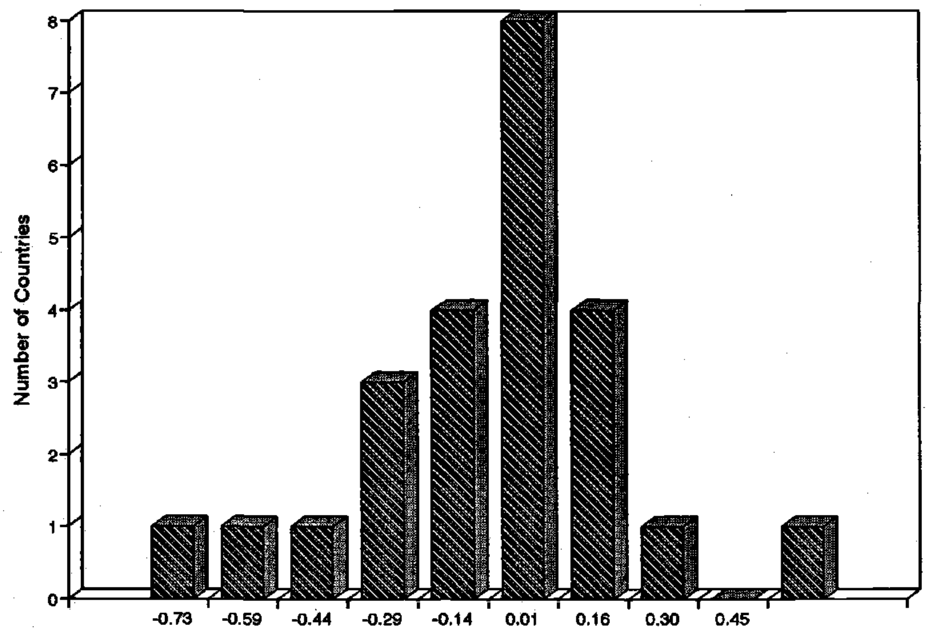

Figure 3: Frequency Distribution
Investment/GDP Coefficient (Raw Data)

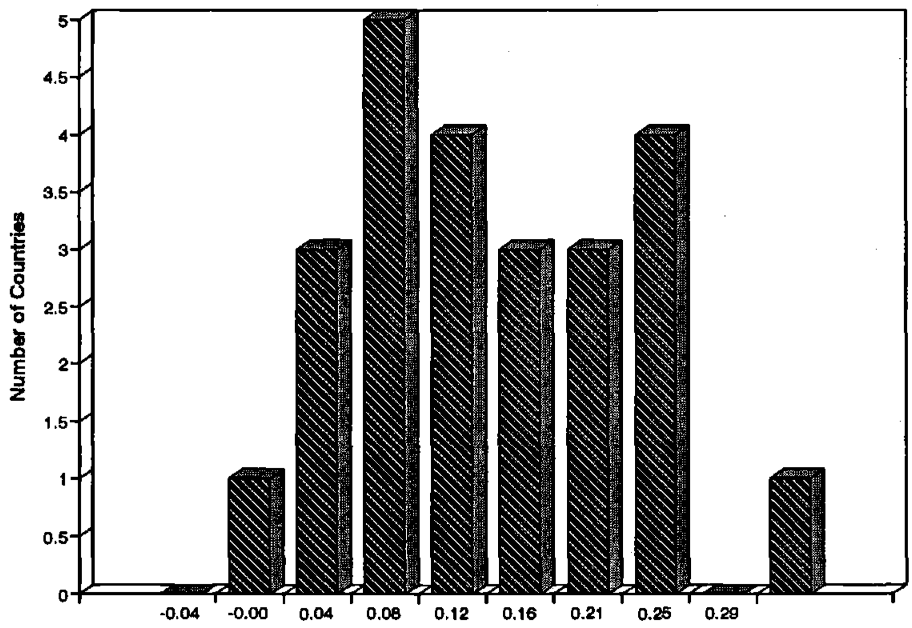

Figure 4: Frequency Distribution
Investment/GDP Coefficient (HP Data)