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# Growth Convergence: Some Panel Data Evidence


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**Abstract:** This paper implements a panel data approach of the Solow model to study the phenomenon of growth convergence for 22 OECD countries. It shows that although the derived estimable Solow model is probably underspecified from an econometric point of view, it is still possible to conclude that there is a likely convergence to a steady state of a rate about 2–4%.



**Key words:** Solow model, Dynamic models, Error components models, Growth convergence, Panel data.


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## 1. Introduction

Amidst a recent upsurge of empirical work focusing on the convergence hypothesis (see, for example amongst others, *Bernard and Jones* [1996], *Galor* [1996], *Nonneman and Vanhoudt* [1996], *Quah* [1996] and *Sala-i-Martin* [1996]) a robust affirmation of the general validity of the neoclassical growth model emerges. (See the seminal works of *Barro* [1991] and *Mankiw et al.* [1992] for example.) Roughly speaking, controlling for such factors as savings and population growth rates, the convergence hypothesis (more precisely, the $\beta$-conditional convergence in the terminology of *Sala-i-Martin* [1992]) asserts that economies with low initial per capita income tend to grow faster than those with high initial income. The finding of the convergence in these studies is generally taken to be consistent with a prediction of the neoclassical model. Conventionally, the empirical work related to this model has been cast in the cross section regression approach.

The single cross section regression implies, however, a too low growth rate and a too large share of capital. The essential feature inducing such a result is due to non-discriminate incorporation of country specific differences in the production function. To ameliorate the inadequacy of the single cross section method, two strategies are used: one consists of augmenting the structural model by broadening the nature of capital with human capital, in addition to physical capital, and perhaps with technological capital as well (*Noneman and Vanhoudt* [1996]); and, the other is to treat the convergence hypothesis from a dynamic panel data perspective. *Islam* [1995] and *Nerlove* [1996] advocate and implement the latter strategy.

In the usual cross section regression, the country specific technology shift term is assumed to be uncorrelated with savings and population growth – an unavoidable econometric necessity given the framework. The panel data approach, on the other hand, allows control for this country specific technology shift with the explicit introduction of country specific effects.

## 2. The theoretical model

To derive the analytical form of the model used in this analysis, we start from the standard neoclassical formulation with exogenous population growth, fixed savings and labour–augmenting technological progress of rates $n$, $s$ and $g$, respectively, and a Cobb–Douglas production function. We then have $y_t = A_t^{(1-\alpha)} k_t^{\alpha}$, where $y_t$ is the per capita output, $k_t$ the capital intensity and $A_t$ is any Harrod–neutral technology that affects the productivity. In the Solow model, savings equals gross investment. The change in per capita capital stock is the same as the gross investment less the depreciation. This yields the model

$$\frac{y_t}{A_t} = \frac{(1+n)(1+g)}{s}\left(\frac{y_{t+1}}{A_{t+1}}\right)^{1/\alpha} - \frac{1-\delta}{s}\left(\frac{y_t}{A_t}\right)^{1/\alpha}, \tag{1}$$

where $\delta$ denotes the constant depreciation rate of the capital stock. In the steady state, the output per effective labour is constant so that neglecting the product term $ng$ produces the

$$y_t^* = \left(\frac{n+g+\delta}{s}\right)^{-\alpha/(1-\alpha)} A_t$$

model and taking the logarithms results in the

$$\log y_t^* = -\frac{\alpha}{1-\alpha}\log(\frac{n+g+\delta}{s}) + \log A_t \tag{2}$$

model. Though equation (1) proves that the rate of convergence to equilibrium in not strictly constant, this can be approximated by a partial adjustment model, $\log y_t - \log y_{t-1} = (1-\gamma)(\log y_t^* - \log y_{t-1})$, which in turn produces a form manageable with econometric tools, and which has been used in several recent studies:

$$\log y_t = \frac{\alpha(1-\gamma)}{1-\alpha}[\log s - \log(n+g+\delta)] + (1-\gamma)\log A_t + \gamma \log y_{t-1}\,. \tag{3}$$

The rate of convergence to the equilibrium level here is inversely proportional to $\gamma$. If $\gamma$ is smaller than 1 there is such convergence, with convergence speed increasing as $\gamma$ decreases. It is obvious that the convergence depends on $s$, $\delta$, $n$, $g$ and $A_t$. In this analysis we adopt the approach used by *Islam* [1995], *Nerlove* [1996] and others: we allowed $s$ and $n$ to vary over time and across countries.

## 3. The econometric model, estimation methods and the data set

Model (3) yields the following econometric formulation:

$$y_{it} = \gamma y_{it-1} + x_{it}'\beta + \mu_i + u_{it}, \qquad t = 1,\ldots,T, \quad i = 1,\ldots,N\,, \tag{4}$$

where $y_{it}$ stands for the GDP per capita for country $i$ in year $t$, $x_{it}$ = [log(savings), log(population growth rate + rate of technical progress + depreciation rate)], $\mu_i$ represents the individual, country specific effects, $u_{it}$ is a white noise and therefore the composite disturbance terms $v_{it} = \mu_i + u_{it}$ have a nonscalar covariance matrix $\Omega_v$ (see more about this model in *Sevestre and Trognon* [1995], for example).

The "usual" assumptions about this model are that: the $u_{it}$'s are serially uncorrelated, have zero mean, scalar variance $\sigma_u^2$, and are uncorrealted with individual effects $\mu_i$ and the starting values $y_{i0}$; the $\mu_i$'s have zero mean and $\sigma_\mu^2$ variance, and the exogenous variables are non-stochastic and uncorrelated with either the $u_{it}$'s or the $\mu_i$'s. The two main approaches to get $N$ consistent estimators for the unknown parameters $\gamma$ and $\beta$ of this model are to use either IV or GMM estimation techniques. Once an instrument set $Z$ has been defined, one has three choices of consistent Generalised IV (GIV) estimators (*Bowden and Turkington* [1984]) $\widehat{\beta} = (X'P^i_{\Omega Z}X)^{-1}X'P^i_{\Omega Z}y$: (i) $P^a_{\Omega Z} = Z(Z'\Omega_v Z)^{-1}Z$, (ii) $P^b_{\Omega Z} = \Omega_v^{-1}Z(Z'\Omega_v Z)^{-1}Z\Omega_v^{-1}$, and (iii) $P^c_{\Omega Z} = \Omega_v^{-1/2}Z(Z'Z)^{-1}Z\Omega_v^{-1/2}$ of which only (i) is appropriate if lagged values of the endogenous variable as are used as instruments.

Many authors choose to work with equation (4) in first differences, as this removes the troublesome individual effects. However, the model still cannot be consistently estimated by OLS because of the short time series assumed. Also, if the original disturbances are "well-behaved", the transformed ones will follow a classical MA(4) process.

The *Balestra-Nerlove* [1966] ($\text{BN}^{(\Delta)}$) type estimator for the differenced model has $\Delta X_{-1}$ as instruments for $\gamma y_{it-1}$. *Sevestre and Trognon* [1992] (ST) suggest the same instrument, but using it with methods (ii) and (iii) above. *Anderson and Hsiao* [1982] (AH) suggest $\Delta y_{it-2}$ and *Arellano* [1988] (AR) $y_{it-2}$ as appropriate instruments. Once the number of instruments exceeds the number of explanatory variables, a GIV becomes appropriate. Therefore one can consider augmented AH and AR IV estimators ($\text{AH}^+$ and $\text{AR}^+$) which additionally include $\Delta X_{-1}$ as instruments. Finally, assuming that the time series run from $t = 0$ to $T$, *Arellano and Bond* [1991] (AB) point out that in the case of $t = 2$, $y_{i0}$ is an appropriate instrument for $\Delta y_{it-1}$. Moreover, in the following period $y_{i0}$ remains a valid instrument, but so is $y_{i1}$, and the triangular expansion continues in subsequent time periods. If the $x$ variables are strictly exogenous, the augmented AB IV set also includes the full time series of these ($\text{AB}^+$).

The model can also be consistently estimated in levels, for example the *Balestra and Nerlove* [1966] ($\text{BN}^{(L)}$) estimator uses lagged values of the exogenous variables as instruments. This approach is expanded by *Hausman and Taylor* [1981] (HT) to include time means and deviations from such of lagged values of the exogenous variables. Along similar lines to the AB$^+$ estimator, the *Amemiya and MaCurdy* [1986] (AM) estimator considers both the full time series of the exogenous variables and deviations from time means of the lagged values of the exogenous variables as instruments. *Arellano and Bover* [1993] (ABov) propose a unifying framework for many of the preceding estimators. The particular estimator we consider has an instrument set akin to that of AB$^+$, although ABov only transforms the first $T-1$ equations (by any $(T-1) \times T$ matrix of rank $T-1$, for example the first $T-1$ rows of the first difference operator). Therefore for the final time equation, only the strictly exogenous variables are valid instruments.

*Harris and Mátyás* [1996a] proposed another estimator based upon the ideas of *Wansbeek and Bekker* [1996] (WB). Now the full string of observations on $y$ and transformations of this are valid instruments, given that the transformation matrix $A_i$ conforms to certain restrictions to ensure consistency and to remove the individual effects. Such restrictions impose a particular structure on $A_i$ such that its rows sum to zero, as do each of its lowest quasi-diagonal elements. Applying GLS to this transformed model yields an estimator which has a variance dependent upon $A_i$ (which is unspecified apart from the restrictions). An "efficient" WB estimator is finally obtained by numerically minimising the trace of the estimator's variance–covariance matrix with respect to $A_i$ subject to the appropriate restrictions (the trace is minimised as one is primarly concerned with the parameter vector's variance).

Utilising more orthogonality conditions, *Ahn and Schmidt* [1995] suggest a GMM estimator based upon certain nonlinear conditions implied by the "usual assumptions". Moreover, *Crépon et al.* [1996] identify even more such conditions. Although efficient GMM estimation involves using all such conditions, as noted by *Harris and Mátyás* [1996a], to invert the covariance matrix of the empirical moment conditions (the weighting matrix required for GMM estimation) some conditions may have to be dropped. Thus, two GMM-type estimators are considered, one which uses all of the possible moment conditions and the identity matrix as weighting matrix (GMM(I)), and one which uses numerically the maximum number of such conditions, with the empirical covariance matrix as a weighting matrix (GMM(W)).

Following *White* [1980], for those estimators that require the use of the term $Z'\Omega Z$, where $\Omega$ is the unspecified covariance matrix of the residuals, it is possible to get a consistent estimator for this as

$$\widehat{\Omega}_{\Delta Z} = \left(\frac{1}{N}\sum_{i=1}^{N} Z_i' \Delta\widehat{u}_i \Delta\widehat{u}_i' Z_i\right).$$

The resulting estimators are called "hat" estimators in the Tables summing up the empirical results. We also calculated the Within estimator which is consistent only when $N$ and $T$ go to infinity, but despite this is very popular amongst practitioners and also has a finite sample bias known to the order $N^{-1}T^{-3/2}$. (For the data set we are using made up of 22 OECD countries and $T = 41$, when working with yearly data, and $T = 9$ when using five–yearly data, this means a relatively small bias in practical terms, see *Kiviet* [1995].)

Some estimators, such as the Arrelano–Bond and the Arellano–Bover estimators are numerically difficult to estimate as $T$ increases since the number of columns in the matrix of instruments increases substantially, causing a serious multicollinearity problem. Similarly, the different variants of the WB estimator could not be calculated for the yearly data set since the objective function would have to be minimised over more than 1000 parameters.

The data set for this study was downloaded from the Penn World Tables 5.6. It contains data for 22 OECD countries for the period 1950–1990. We use yearly data to estimate our model ($T = 41$) then transform it to quinquennium data using levels at the end of each five year period ($T = 9$) to get similar data to that which *Islam* [1995] (same countries for the period 1960–1985) and *Nerlove* [1996] (same countries same period as Islam) used. (The main reason in these two studies for not using the yearly data was the difficulty in coding the above estimators for large $T$.) Summary results of these two previous panel data studies are presented in Table 1. It is interesting to note that using the same estimation methods (OLS, Within) the two studies get slightly different results, although in both cases the Within produces the smallest parameter estimate while the OLS the largest.

**Table 1:**
**Estimates for $\gamma$ in previous panel data studies**

| | *Islam* [1995] | *Nerlove* [1996] |
|---|---|---|
| Data span: | 1960–1985 | 1960–1985 |
| Est. methods: | | |
| | OLS: 0.92 | OLS: 0.88 |
| | Min. distance: 0.71 | Cond. ML: 0.82 |
| | Within: 0.62 | Within: 0.76 |

## 4. Estimation results

We know from the theory that if $\widehat{\gamma}$ is less than one, the countries with low initial GDP per capita values are growing faster than those with high values which supports the theory of growth convergence. It can be seen from the results that all estimated coefficients for the parameter of interest $\gamma$ are smaller than one. This suggests that there is growth convergence between the OECD countries. We know from econometric theory (*Sevestre and Trognon* [1985] and *Kiviet* [1995]) that in large samples the OLS overestimates the true $\gamma$ while the Within estimator underestimates it. Given that the Within estimator is consistent (and $T = 9$ and especially $T = 41$ can be considered quite large in panel data) and that we can approximate the bias of the OLS estimator for known values of the parameters, we can be quite confident that the true parameter value lies close to the (0.904 – 0.869) intervallum for the 5–yearly data and close to the narrower (0.976 – 0.964) intervallum for the yearly data. If we take into account the estimated standard errors of $\widehat{\gamma}$, many parameter estimates provided by the other estimators fall into this range. The bad news is, however, that several estimators, which theoretically are supposed to have quite good properties, produce parameter estimates completely out of range, with highly unrealistic implied convergence rates.

To understand this we have to be reminded that all estimators rely on several assumptions. The most important ones here are that the $x$'s are supposed to be exogenous (no correlation between the $x$'s and the individual and/or white noise terms in (4)), the individual effects and the white noise terms in (4) are also assumed to be uncorrelated and the white noise disturbance terms should not be autocorrelated. When the model is misspecified some of these assumptions are violated which has serious consequences on all the calculated estimators. There are, however, estimators which are less affected by some types of misspecification (they are more robust), while others are more fragile in this respect (see *Harris and Mátyás* [1996b]). The estimators producing the unrealistic parameter estimates are exactly those which are the most affected by the lack of exogeneity of the $x$'s. This is likely to happen when the model is underspecified, that is one or several important explanatory variables are missing from the model which results in this type of endogeneity of the $x$'s. One obvious candidate to include into the model as an additional explanatory variable is the human capital. But, as it can be seen in *Islam* [1995], this does not give a complete answer to the problem and rises additional questions.

The bottom line here is that we can be quite confident that there is a likely growth convergence between the OECD contries of a rate about 2% – 4%, but we also have to realise that the derived econometric model should be refined if we want to conduct further analysis in this area. This is another typical example of the case when although economic theory does not provide a completely specified and satisfactory econometric model, this model can still be used—with caution—for economic analysis.

## 5. Conclusion

Using the neoclassical Solow model, in this paper we derived and estimated a dynamic panel data model to analyse the eventual convergence of the growth rate of 22 OECD countries. By using over thirty different methods to estimate the model and comparing the results we could conclude that, although the Solow model is likely to be underspecified from an econometric viewpoint, there is strong evidence to suggest that the GDP per capita difference between the less developed and the more developed OECD countries is probably going to be halved in about 20 to 30 years.

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**Table 2:**
**Estimation results for the differenced model**

| | 5-yearly data | | | yearly data | | |
|---|---|---|---|---|---|---|
| Est. meth. | $\widehat{\gamma}$ | SE($\widehat{\gamma}$) | S.C% | $\widehat{\gamma}$ | SE($\widehat{\gamma}$) | S.C. % |
| OLS | 0.773 | 0.034 | 5.16 | 0.544 | 0.024 | 60.91 |
| GLS | 0.869 | 0.014 | 2.81 | 0.967 | 0.003 | 3.40 |
| AR | 0.909 | 0.017 | 1.91 | 0.964 | 0.007 | 3.67 |
| $AR^+$ | 0.843 | 0.016 | 3.42 | 0.945 | 0.007 | 5.71 |
| $AR^+$ hat | 0.831 | 0.001 | 3.70 | 0.909 | 0.003 | 9.53 |
| STa | 0.769 | 0.025 | 5.24 | 0.865 | 0.009 | 14.52 |
| STb | 0.747 | 0.025 | 5.83 | 0.705 | 0.012 | 34.96 |
| STa hat | 0.669 | 0.004 | 8.05 | N/A | N/A | N/A |
| STb hat | 0.628 | 0.004 | 9.30 | N/A | N/A | N/A |
| AB | 0.864 | 0.014 | 2.93 | N/A | N/A | N/A |
| AB hat | 0.873 | 0.001 | 2.71 | N/A | N/A | N/A |
| $AB^+$ | 0.827 | 0.012 | 3.80 | N/A | N/A | N/A |
| $BN^{(\Delta)}$ | 0.506 | 0.101 | 13.63 | 0.205 | 0.056 | 158.26 |
| $BN^{(\Delta)}$ hat | 0.473 | 0.008 | 14.97 | 0.206 | 0.002 | 157.93 |
| AH | 0.905 | 0.024 | 2.00 | 0.841 | 0.028 | 17.37 |
| $AH^+$ | 0.881 | 0.056 | 2.53 | 0.688 | 0.139 | 37.37 |
| $AH^+$ hat | 0.869 | 0.005 | 2.81 | 0.575 | 0.008 | 55.37 |

The technical change was set to 0.05 and the depreciation to 0.2 per five years;
S.C. %: Speed of Convergence, % per year

**Table 3:**
**Estimation results for the model in levels**

| | 5-yearly data | | | yearly data | | |
|---|---|---|---|---|---|---|
| Est. meth. | $\widehat{\gamma}$ | SE($\widehat{\gamma}$) | S.C% | $\widehat{\gamma}$ | SE($\widehat{\gamma}$) | S.C. % |
| OLS | 0.904 | 0.009 | 2.01 | 0.976 | 0.002 | 2.47 |
| FGLS | 0.896 | 0.010 | 2.20 | 0.973 | 0.002 | 2.77 |
| Within | 0.869 | 0.012 | 2.81 | 0.964 | 0.003 | 3.64 |
| $BN^{(L)}a$ | 0.812 | 0.027 | 4.18 | 0.897 | 0.010 | 10.90 |
| $BN^{(L)}b$ | 0.799 | 0.026 | 4.50 | 0.902 | 0.010 | 10.30 |
| $BN^{(L)}c$ | 0.765 | 0.032 | 5.37 | 0.899 | 0.011 | 10.64 |
| HTa | 0.828 | 0.023 | 3.77 | 0.918 | 0.009 | 8.50 |
| HTb | 0.827 | 0.022 | 3.80 | 0.908 | 0.009 | 9.60 |
| HTc | 0.815 | 0.026 | 4.08 | 0.909 | 0.011 | 9.57 |
| AMa | 0.892 | 0.012 | 2.29 | 0.968 | 0.003 | 3.21 |
| AMb | 0.892 | 0.012 | 2.29 | 0.969 | 0.003 | 3.13 |
| AMc | 0.895 | 0.012 | 2.21 | 0.970 | 0.003 | 3.06 |
| WB | 0.869 | 0.019 | 2.34 | N/A | N/A | N/A |
| $WB^{+}$ | 0.867 | 0.015 | 2.64 | N/A | N/A | N/A |
| WB hat | 0.872 | 0.017 | 2.73 | N/A | N/A | N/A |
| $WB^{+}$ hat | 0.881 | 0.014 | 2.54 | N/A | N/A | N/A |
| GMM(I) | 0.105 | 0.012 | 45.08 | N/A | N/A | N/A |
| GMM(W) | 0.274 | 0.044 | 25.89 | N/A | N/A | N/A |

The technical change was set to 0.05 and the depreciation to 0.2 per five years;
S.C. %: Speed of Convergence, % per year