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GROWTH EMPIRICS: CONVERGENCE STUDY BY PANEL DATA ANALYSIS

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ABSTRACT

This paper examines recent convergency issues in economic on growth. Taking the recent works by M-R-W and Islam as its starting point this paper analyzes how these results change with the adoption of the panel data approach. The regression equation used in the study of convergence is reformulated into a dynamic panel model with individual country effects and is estimated by the panel data procedures. It hardly seems to say that there exists a reasonable evidence of a rapid convergence considering the time period required for the convergence

I. Introduction

In neoclassical growth models, such as Solow (1957) or Swan (1956), a country's per capita growth rate tends to be inversely related to its starting level of per capita income. In particular, if countries are similar with respect to structural parameters for preferences and technology, then poor countries tend to grow faster than rich countries. Thus, there is a force that promotes convergence in the levels of per capita income across countries.

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The main element behind the convergence result in neoclassical growth models is diminishing returns to capital. Poor countries, with low ratios of capital to labor, have high marginal products of capital and thereby tend to grow at high rates. This tendency for low income countries to grow at high rates is reinforced in the extension of the neoclassical models that allow for international mobility of capital and technology.

The hypothesis that poor countries tend to grow faster than rich countries seems to apply empirically for economies that have similar underlying structures -- such as the regions of the major developed countries or among the OECD countries -- but seems to be inconsistent with the heterogeneous collection of countries that includes the poor countries of Africa, South Asia, and Latin America, which indicates that per capita growth rates have little correlation with the starting level of per capita product.

FIGURE 1. Annual Average Growth Rate of per Capita GDP vs. GDP per Capita 1960, (22 OECD countries)

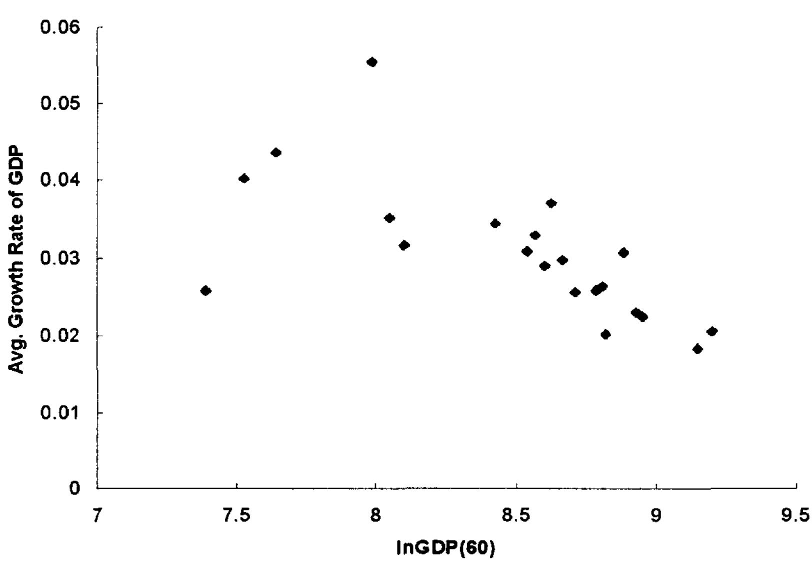
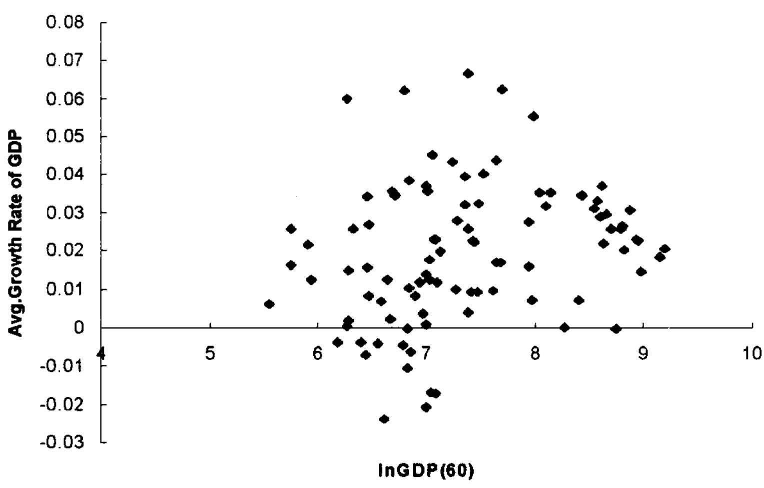


Figure 1 and 2, which use the data from the Penn World Table 5.6 (PWT5.6), show these types of relationship. They plot the average growth rate of per capita real gross domestic product (GDP) from 1960 to 1985 against the logarithm of real per capita GDP in 1960. Figure 1 shows a striking inverse relationship, that is, the places that were poorer in 1960 grew significantly faster in per capita terms over the subsequent 25 years. Thus, the behavior of growth rate across 22 OECD countries is consistent with convergence, in the sense of the poor places growing faster than the rich one.

FIGURE 2. Annual Average Growth Rate of per Capita GDP vs. GDP per Capita 1960, (94 countries)



In contrast to the clear inverse relationships in Figure 1, the growth rate and initial level are not significantly related to the 1960 value of per capita real GDP in Figure 2. The heterogeneous cross-country data therefore do not reveal convergence; the poor countries did not tend to grow faster than the rich, and hence, the typical poor country did not tend to catch up to the typical rich country.

This finding accords with recent models, such as Romer

(1986) and Lucas (1988), that assume constant returns to a broad concept of capital, which includes human capital. In this model the growth rate of per capita product is independent of the starting level of per capita product. Another response to this finding was the proposition of the concept of "*conditional convergence.*" Barro (1989) showed that if differences in the starting level of human capital are controlled for, then the correlation between the starting level of income and subsequent growth rate turns out to be negative even in the wider sample of countries. Barro and Sala-i-Martin (1992) (hereinafter B-S) and Mankiw, Romer, and Weil (1992) (hereinafter M-R-W) developed this concept of conditional convergence and emphasized the fact that the neoclassical growth model did not imply that all countries would reach the same level of per capita GDP but that countries would reach their respective steady states.

A common feature of existing empirical studies on this problem of convergence was preceded under the assumption of identical aggregate production functions for all countries. Since most of these studies have been conducted in the framework of single cross-country regression, it was econometrically difficult to allow for some differences in the production function in such framework. However, the country-specific aspect of the aggregate production function, which is ignored in the single cross-section regression, is generally correlated with the included explanatory variables, and hence this creates omitted variables problems.

Unlike single cross-section analysis, the panel date framework makes it possible to allow for such differences in the form of unobservable individual "country effect." Recent several scholars, including Islam(1995), Knight-Loayza-Villanueva (1993), implemented a panel date approach to deal with this issue. They argued that persistent differences in technology level and institutions are significant factor in understanding cross-country economic growth. There are, however, some drawbacks in their estimation methods, and so in hypothesis tests, because such tests rely generally on the estimated coefficient of the initial value of the lagged dependent variable in dynamic panel models.

As Nerlove (1996) notes, there exist some bias in this test. One source of such bias is omitted variables, especially infrastructure and investments in infrastructure over time, and the natural resource available to each country in cross-sectional or panel studies. Because such variables are likely to be correlated with savings of investment rates in conventional or human capital and with population growth rates, it is not altogether clear what the net effect of omitting them on the coefficient of the initial value will be in a single cross-section regression model. Thus, these differences across countries of regions will systematically lead to biased conclusions. This typed source of bias has been well-known since the early paper by Balestra and Nerlove (1966) and is well-supported by the Monte Carlo Studies reported in Nerlove (1971).

Second, since there are likely to be many sources of cross country or cross region differences, many of which cannot be observed of directly accounted for, it is natural to try to represent these by fixed effects in a panel context as Islam did. But, as is well-known from the Monte Carlo investigations reported in Nerlove (1971) and demonstrated analytically by Nickell (1981), the dynamic model with fixed effects biases the coefficient of the initial value of dependent variable, which is included as an explanatory variable in the regression equation, downwards, towards zero and thereby towards support for the convergence hypothesis.

Alternative estimates based on more appropriate random -effects model, such as two-stage feasible Generalized Least Squares (FGLS) or Maximum Likelihood Estimation conditional on the initial observations is also biased in small samples and inconsistent in large samples. In the case of Instrumental Variable estimates also have poor sampling properties or are difficult to implement. Recently, Nerlove and Balestra (1996) suggested the alternative of unconditional maximum likelihood.

This paper takes the recent work by M-R-W and Islam as its starting point and examines how the results change with the adoption of the panel data approach. The regression equation used in the study of convergence is reformulated into a dynamic panel model with individual country effects and the panel data procedures is used to estimate it.

The paper is organized as follows. In Section Ⅱ, the growth equation is reformulated as a dynamic panel data model. In Section Ⅲ, the relevant issues of panel data estimation for growth equations and the data and samples are discussed. Data, sample, and estimation results are presented in Section Ⅳ, and Section Ⅴ contains their interpretation. Section Ⅵ involves conclusions.

Ⅱ. Growth Regression As A Dynamic Panel Data Model

The usefulness of a panel data approach can be illustrated on the basis of the work by M-R-W and Islam. They started with the following "textbook Solow model" featuring the Cobb-Douglas production function with labor-augmenting technological progress;

$$(2.1) \quad Y_1 = K_t^{\alpha}\,[A_t L_t]^{1-\alpha} \qquad 0<\alpha<1,$$

where Y is output, K is capital, and L is labor. Population and technology are assumed to grow exogenously at rate n and g so that

$$(2.2) \quad L_t = L_0\, e^{nt}, \qquad\qquad A_t = A_0\, e^{gt},$$

The number of effective units of labor, $A_t L_t$, grows at rate $(n+g)$. The model assumes that a constant fraction of outputs, s, is invested and capital stock depreciates at the constant rate, δ (>0). In terms of effective units, the production function can be written as[1]

$$(2.3) \quad \hat{y}_t = Y_t/(A_t L_t) = (\hat{k}_t)^{\alpha}$$

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[1] I shall use low case letters to denote per capita variables, e.g. $y_t = Y_t/L_t$ and ^ over lower case letters to denote effective measures (unit per effective worker).

The evolution over time of the effective capital stock, $\hat{k}_t$ is given by[2]

(2.4) $\quad \dot{\hat{k}}_t = s.\hat{y}_t - (n+g+\delta)\hat{k}_t = s.(\hat{k}_t)^{\alpha} - (n+g+\delta)\hat{k}_t,$

where a dot over a variable denotes differentiation with respect to time and δ is the constant rate of depreciation. In steady state, the effective capital stock is constant and its steady-state value, $\hat{k}^*$, is given by[3]

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[2] The net increase in the stock of capital at a point in time equals gross investment less depreciation : $\dot{K} = I - \delta K = sY - \delta K$.
If we divide both side of this equation by AL, then we get $\frac{\dot{K}}{AL} = s.\frac{Y}{AL} - \delta.\frac{K}{AL} = s\hat{y} - \delta \hat{k}$. Rewrite $\dot{K}/AL$, as a function of $\hat{k}$ by using the following condition $\dot{\hat{k}} \equiv \frac{d(K/AL)}{dt} = \frac{\dot{K}}{AL} - \hat{k}(\frac{\dot{L}}{L} + \frac{\dot{A}}{A}) = \frac{\dot{K}}{AL} - \hat{k}(n+g)$, where $n = \dot{L}/L$, $g = \dot{A}/A$.
Substituting this result into the expression for $\dot{K}/AL$ and rearranging terms yield the Eq. (2.4).

[3] A steady state can be defined as a situation in which the various quantities grow at constant rates. In this model, the steady state corresponds to $\dot{\hat{k}} = 0$ in Eq. (2.4), that is, to an intersection of the $s.\hat{y}$ curve with the $(n+g+\delta)\hat{k}$ line in Figure 3. To see why, divide both sides of Eq. (2.4) by $\hat{k}$ to get $\dot{\hat{k}}/\hat{k} = s.\frac{\hat{y}}{\hat{k}} - (n+g+\delta)$.
The left-hand is constant, by the definition, in the steady state. Since s, n, g, and δ are all constant, it follows that $\hat{y}/\hat{k}$ must be constant in steady state. The time derivative of $\hat{y}/\hat{k}$ is

$$\frac{d(\hat{y}/\hat{k})}{dt} = \frac{\hat{k}.\hat{y}'(\hat{k})\dot{\hat{k}} - \hat{y}(\hat{k})\dot{\hat{k}}}{\hat{k}^2} = -\left[\frac{\hat{y} - \hat{k}.\hat{y}'}{\hat{k}}\right]\left(\frac{\dot{\hat{k}}}{\hat{k}}\right).$$

The expression of $-\left[(\hat{y} - \hat{k}.\hat{y}')/\hat{k}\right]$ equals the marginal product of an effective labor and is positive, $\dot{\hat{k}}/\hat{k}$ must be equal to zero in steady state as long as $\hat{k}$ is finite.

$$(2.5) \qquad \hat{k}^* = \left(\frac{s}{n+g+\delta}\right)^{1/(1-\alpha)}$$

Substituting equation (2.5) into the production function, equation (2.3) and taking logs, we find following expression for steady state per capita income:

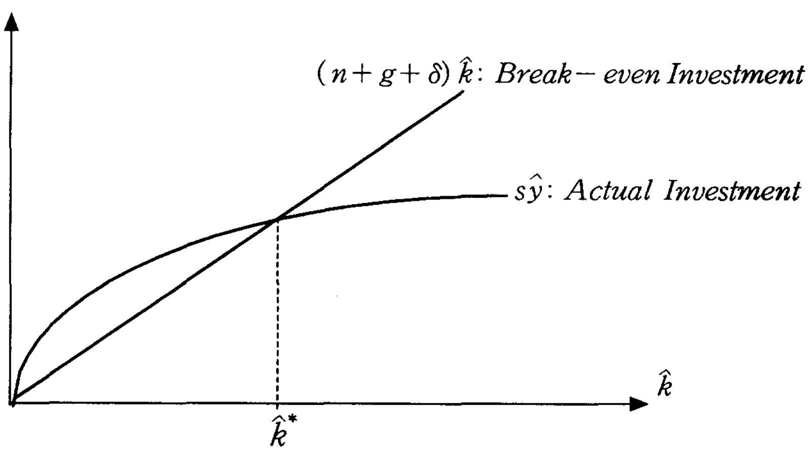
$$(2.6) \quad \ln(y_t^*) = \ln A_t + \alpha \ln(\hat{k}^*)$$

$$= \ln A(0) + gt + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n+g+\delta)$$

$$= \ln(y_0^*) + gt$$

It is obvious that per capita output in steady state grows at the constant rate, g.

FIGURE 3. Actual and Break-even Investment



It is important to know the speed of the transitional dynamics. If convergence is rapid, then we can focus on steady-state behavior, because most economies would typically be close to their steady state. Conversely, if convergence is slow, then economies would be far from their steady state, and hence, their growth experiences would be dominated by the transitional dynamics. The neoclassical model also implies a speed of convergence to equilibrium which is determined by the model's parameters. From the equation (2.4), the growth rate of k, γ_k is given by

$$(2.7) \quad \gamma_k = \frac{\dot{\hat{k}}}{\hat{k}} = s.\frac{\hat{y}}{\hat{k}} - (n+g+\delta) = s.(\hat{k})^{-(1-\alpha)} - (n+g+\delta)$$

Now consider a log-linear approximation of Eq.(2.7) in the neighborhood of the steady state[4];

$$(2.8) \quad \gamma_k = d[\ln(\hat{k})]/dt \cong -\lambda[\ln(\hat{k}/\hat{k}^*)] \text{ where } \lambda = (1-\alpha).(n+g+\delta).$$

The coefficient λ determines the speed of convergence fromfrom k to $\hat{k}^*$. For known $(n+g+\delta)$, estimates of λ will imply a value for α; in particular $\lambda=0$, no convergence, implies $\alpha=1$, which is inconsistent with the Solow model. The time it takes to reach equilibrium also depends on the proportionate distance from steady state, k/k^*.[5] This applies also to the growth rate of $\hat{y}$. Since $\gamma_y = \alpha\gamma_k$ from equation (2.3), we have $\ln(\hat{y}/\hat{y}^*) = \alpha\ln(\hat{k}/\hat{k}^*)$. Substituting these formulas into equation (2.8) yields

$$(2.9) \quad \gamma_y \cong -(1-\alpha)(n+g+\delta)\ln(\hat{y}/\hat{y}^*),$$

which has the same form as equation (2.8). That is, the convergence coefficient, λ, for $\hat{y}$, is the same as that for $\hat{k}$.

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4 Rewrite Eq.(2.7) in terms of $\ln\hat{k}$. Note that γk is just the time derivative of $\ln\hat{k}$ and $(\hat{k})^{-(1-\alpha)}$ can be written $\exp[-(1-\alpha)\ln\hat{k}]$. The steady-state value of s.(k)-(1-α) equals (n+g+δ). Now take a first-order Taylor expansion of $\ln\hat{k}$ around $\ln\hat{k}^*$ to get Eq.(2.8).

5 Note that savings rate, s, does not affect the speed of convergence. This result reflects two offsetting forces that exactly cancel in the Cobb-Douglas case. [Refer to Barro and Sala-I-Martin, Economic Growth, pp37].

Thus the term λ indicates how rapidly and economy's income per effective worker approaches its steady-state value, $\hat{y}^*$. For example, if $\lambda = 0.05$ per year, then 5 percent of the gap between $\hat{y}$ and $\hat{y}^*$ vanishes in one year.

Equation (2.9) is a differential equation in $\ln(\hat{y}_t)$ with the solution,

$$(2.10) \quad \ln \hat{y}(t_2) = (1 - e^{-\lambda\tau}) \ln \hat{y}^* + e^{-\lambda\tau} \ln \hat{y}(t_1),$$

where $y(t_1)$ is income per effective worker at some initial point of time and $\tau = (t_2 - t_1)$. Subtracting $\ln \hat{y}(t_1)$ from both sides yields

$$(2.11) \quad \ln \hat{y}(t_2) - \ln \hat{y}(t_1)$$
$$= (1 - e^{-\lambda\tau}) \ln \hat{y}^* - (1 - e^{-\lambda\tau}) \ln \hat{y}(t_1)$$

This equation represents a partial adjustment model, the "optimal" or "target" value of the dependent variables is determined by the explanatory variables of the current period. In the present case, $\hat{y}^*$ is determined by s and n, which are assumed to be constant for the entire intervening time period between t_1 and t_2 hence represent the values for the current year as well. Substituting for $\hat{y}^*$ gives

$$(2.12) \quad \ln \hat{y}(t_2) - \ln \hat{y}(t_1)$$
$$= (1 - e^{-\lambda\tau}) \frac{\alpha}{1-\alpha} \ln(s) - (1 - e^{-\lambda\tau}) \frac{\alpha}{1-\alpha} \ln(n + g + \delta)$$
$$- (1 - e^{-\lambda\tau}) \ln \hat{y}(t_1)$$

Thus, in the Solow model the growth of income is a function of the determinants of the ultimate state and initial level of income. M-R-W and Islam used this equation to study the process of convergence across different samples of countries. In M-R-W's treatment t_1 was 1960, and t_2 was 1985, while in Islam those were 1960 and 1965. They all assumed $(g + \delta)$ to be the same for all countries and equal to 0.05.

In actual implementation, M-R-W and Islam worked with income per capita. Note that income per effective labor is

$$(2.13)\quad \hat{y}(t) = \frac{Y(t)}{A(t)L(t)} = \frac{Y(t)}{L(t)A(0)e^{gt}}$$

so that

$$\ln \hat{y}(t) = \ln \frac{Y(t)}{L(t)} - \ln A(0) - gt = \ln y(t) - \ln A(0) - gt,$$

where $y(t)$ is the per capita income. Substituting for $y(t)$ into the equation (2-11), we get the usual "growth-initial level" equation;

$$(2\text{-}14)\ \ln y(t_2) - \ln y(t_1) = -(1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s)$$

$$-(1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta) - (1-e^{-\lambda\tau})\ln y(t_1)$$

$$+(1-e^{-\lambda\tau})\ln A(0) + g(t_2 - e^{-\lambda\tau} t_1)$$

If we collect terms with $\ln y(t_1)$ on the right hand side, we get the equation in the following form;

$$(2\text{-}15)\quad \ln y(t_2)$$

$$= (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s) - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta)$$

$$+(e^{-\lambda\tau})\ln y + (1-e^{-\lambda\tau})\ln A(0) + g(t_2 - e^{-\lambda\tau} t_1)$$

Now, it can be seen that above equation represents a dynamic panel model with $(1-e^{-\lambda\tau})\ln A(0)$ as the time-invariant individual country-effect term. Note that if countries have permanent differences in their production functions - that is, different $A(0)$'s - then these $A(0)$'s would enter as part of the error term and would be positively correlated with initial income. Hence, a panel approach can be a proper method for testing for convergence hypothesis. We may use the following conventional notation of the panel date literature;

$$(2\text{-}16) \quad y_{it} = \gamma y_{it-1} + \sum_{j=1}^{2} \beta_j x_{it}^j + \eta_t + \mu_i + \varepsilon_{it}$$

where $y_{it} = \ln y(t_2)$, $y_{it-1} = \ln y(t_1)$, $\gamma = e^{-\lambda\tau}$

$\beta_1 = (1 - e^{-\lambda\tau})\frac{\alpha}{1-\alpha}$, $\beta_2 = -(1 - e^{-\lambda\tau})\frac{\alpha}{1-\alpha}$, $x_{it}^1 = \ln(s)$,

$x_{it}^2 = \ln(n+g+\delta)$, $\mu_i = (1 - e^{-\lambda\tau})\ln A(0)$, $\eta_t = g(t_2 - e^{\lambda\tau} t_1)$,

and ε_{it} is the transitory error term that varies across countries and time periods and has mean equal to zero. Panel data estimation of this equation now provides the kind of environment necessary to control for the individual country effect.

III. Dynamic Error Components Model[6]

1. The Importance of the Initial Observations in Dynamic Error Component Model.

One of the main advantages of panel data is that it allows one to study the dynamics of economic behavior at an individual level. Unfortunately, when dynamic models are estimated using time-series of cross sections data, the usual least squares methods do not lead to consistent estimates for the parameters of the two most commonly used models for panel data(i.e., the fixed effects model and error component models).

A Simple dynamic linear model can be written as

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[6] This section is extensively based on the Sevestre and Trognon [1996] and Nerlove[1996].

(3-1) $Y_{it} = \gamma Y_{it-1} + \beta X_{it} + u_{it}$, i=1,...N, and t=1,...,T.,

where u_{it} can be decomposed as $u_{it} = \mu_i + \varepsilon_{it}$. If we treat the individual effects μ_i as fixed parameters, this model will be the fixed effects model and if not, this will be the random effect of error components model. The usual assumptions on the disturbance terms are;

(i) The random variables μ_i and ε_{it} are independent for all i and t.

(ii) $E(\mu_i) = E(\varepsilon_{it}) = 0$

(iii) $E(\varepsilon_{it}\varepsilon_{js}) = \begin{cases} \sigma_\varepsilon^2, & i=j,\ t=s \\ 0, & otherwise \end{cases}$

(iv) $E(\mu_i\mu_j) = \begin{cases} \sigma_\mu^2, & i=j, \\ 0, & otherwise \end{cases}$

(v) X_{it} is non-stochastic

Since a panel date set has generally two dimensions, it is possible to increase the size of the sample and this has two notable implications on the works with dynamic model such as (3-1). One is that the stationary assumption (i.e., $|\gamma|<1$) is not necessary as long as T is finite and the other is that **the generating process of the initial value Y_{io} must be specified.**

(3-2)[7] $Y_{it} = \gamma^t Y_{i0} + \sum_{j=0}^{t-1} \gamma^j \beta X_{it-j} + _{it,} \frac{1-\gamma^t}{1-\gamma}\mu_i + \nu_{it}$ where $\nu_{it} = \sum_{j=0}^{t-1} \gamma^j \varepsilon_{it-j}$.

It is clear that the initial observations Y_{io}, i=1,2,...,N affect the asymptotic behavior of estimators as long as the time dimension is finite. That is, if we consider the third or last term in this

[7] The ν_{it} is an autoregressive process with fixed initial values; $\nu_{it} = \gamma\nu_{it-1} + \varepsilon_{it}$ if $t \geq 1$ and $\nu_{it}=0$ if t=0.

equation (3-2), we know that it does not make sense to assume that the initial value Y_{io} are not correlated with either μ_i or X_{io}. Thus, let us consider that these initial values depend on the individual effects μ_i and on the past of the exogenous variables X_{it-j}, and on a serially uncorrelated disturbance term ε_{i0}[8];

(3-3) $Y_{io} = f(X_{it-j},\ \mu_i,\ \varepsilon_{i0})$.

Then if the individual effects are fixed, the lagged X's are given, then the initial observations are exogenous, since they are obviously uncorrelated with ν_{it}. But if the individual effects are assumed to be random, the initial values are no longer exogenous since they are correlated with μ_i and ν_{it} as they now enter the disturbance term. Therefore, it is essential to specify the process of the initial observation correctly in the dynamic error component model.

2. The Inconsistency of the LSDV (Least Square Dummy Variable) Estimator.

As Sevestre and Trognon (1996) notes, the autoregressive fixed effects model cannot be consistently estimated by OLS as long as T is finite. By Frisch-Waugh theorem, the estimation of the coefficients γ and β in the fixed effects model can be done by applying OLS to the following transformed model;[9]

(3-4) $Qy = Qy_{-1} + Q\beta x + Q\varepsilon$, where $Q = I_N \otimes (I_T - l_T l'_T / T)$

[8] To assume that these initial observations are fixed and do not depend on the individual effect is too strong. In that case, they are clearly exogenous since $E[Y_{i0} | \mu_i] = 0$, $E[Y_{i0} | \nu_{it}] = 0$. But, this assumption is strong as the date of the beginning of the sample is most often arbitrary and does not justify such a different treatment of the initial and subsequent observations.

[9] Note that $Q\mu = 0$, where $\mu = [\mu_1, \mu_2, \ldots, \mu_N]$

I_N denotes the(N×N) identity matrix, $\otimes$ denotes the Kronecker product, and l_T is (T×1) unit vector. The, OLS estimators of γ and β can be written as the Within estimator:

$$(3\text{-}5)\quad \begin{pmatrix} \hat{\gamma} \\ \hat{\beta} \end{pmatrix} = \begin{pmatrix} y'_{-1}Qy_{-1} & y'_{-1}Qx \\ x'_{-1}Qy_{-1} & x'_{-1}Qx \end{pmatrix} \begin{pmatrix} y'_{-1}Qy \\ x'_{-1}Qy \end{pmatrix},$$

since the transformation matrix Q is a symmetric and idempotent. Dividing by NT and taking probability limits as N→∞, holding T fixed yields

$$(3\text{-}6)\quad Plim \begin{pmatrix} \hat{\gamma} \\ \hat{\beta} \end{pmatrix} = \begin{pmatrix} \gamma \\ \beta \end{pmatrix}$$

$$+ \begin{pmatrix} Plim\frac{1}{NT}y'_{-1}Qy_{-1} & Plim\frac{1}{NT}y'_{-1}Qy_{-1} \\ Plim\frac{1}{NT}x'_{-1}Qy_{-1} & Plim\frac{1}{NT}x'_{-1}Qy_{-1} \end{pmatrix} \begin{pmatrix} Plim\frac{1}{NT}y'_{-1}Q\varepsilon \\ Plim\frac{1}{NT}x'_{-1}Q\varepsilon \end{pmatrix}$$

The inconsistency of this estimator depends on the fact that, given the assumption about the disturbances, one has *P*lim $\frac{1}{NT}x'Q\varepsilon = 0$ but

$$(3\text{-}7)\quad P\text{lim}\frac{1}{NT}y'_{-1}Q\varepsilon$$

$$= P\text{lim}\frac{1}{NT}\sum_i\sum_t (Y_{it-1} - \overline{Y}_{i-1})(\varepsilon_{it} - \overline{\varepsilon}_i)$$

$$= E\left(\frac{1}{T}\sum_t (Y_{it-1} - \overline{Y}_{i-1})(\varepsilon_{it} - \varepsilon_{i.})\right)$$

$$= -\frac{1}{T^2}\frac{T-1-T\gamma+\gamma^T}{(1-\gamma)^2}\sigma_\varepsilon^2 \neq 0\ ,$$

where $\overline{Y}_{i.-1} = \frac{1}{T}\sum_t Y_{it-1}$, $\overline{\varepsilon}_i = \frac{1}{T}\sum_t \varepsilon_{it}$, and σ_ε^2 is the variance of ε_{it}. Then, as long as T is fixed, the OLS estimator of an autoregressive fixed effects model is not consistent. This semi-inconsistency is due to the asymptotic correlation that exists between $(Y_{it-1} - \overline{Y}_{i.-1})$ and $(\varepsilon_{it} - \overline{\varepsilon}_i)$ when N→∞ ; though

Y_{it-1} and ε_{it} are uncorrelated, their respective individual means are correlated with each other (Sevestre and Trognon (1996), pp124). As it is clear from the equation (3-7), when $N \to \infty$, $T \to \infty$, this estimator is consistent and hence, if the number of time periods in the sample is large enough, the asymptotic bias of this estimator is likely to be rather small.

3. The Unconditional Maximum Likelihood

The transition from fixed effects to random effects yields the error components models. For dynamic models the random effect creates serial correlation which interacts with the autoregressive part of the model. When the disturbance is normal, it is natural to apply the ML principle to the estimation problem. This was first explored in the seminal paper by Balestra and Nerlove (1966). At that time they used a conditional likelihood function in which the initial values were assumed to be fixed. Such ML estimators are, as Sevestre and Trognon (1996) pointed out, for wide range of combinations of the parameters, equal to the OLS estimators and hence they are not consistent. This important drawback does not occur when the likelihood function takes into account the density function of the first observations, i.e., when the likelihood function is unconditional. Provided the marginal distribution of the initial values Y_{i0} $i=1,...,N$, can be correctly specified, the unconditional density of Y_{iT},,...., Y_{i1}, Y_{i0} conditional only on the observed exogenous variables gives rise to a likelihood function which has an interior maximum with probability one.(Nerlove[1996]). Thus, the key is a correct specification of the marginal distribution of the initial observations.

Even though there are various alternative specifications on the initial observation, for considerable simplification, I assume that the X_{it} is stationary and $|\gamma|<1$. Under this assumption, consider the equation (3-2) for initial observation Y_{i0} and infinite past. Then, (3-9) $Y_{i0} = \sum_{j=0}^{\infty} \gamma^j \beta X_{i-j} + \frac{1}{1-\gamma} \mu_i + \nu_{i0}$,

where $\nu_{iT} = \gamma \nu_{iT-1} + \varepsilon_{iT}$.[10]

If $\beta = 0$, so that the relationship to be estimated is a pure autoregression for each Y_{it}, the vector of initial observations, $Y_0 = (Y_{10}, \ldots, Y_{N0})$ has a joint normal distribution with means 0 and variance -covariance matrix as following;

$$Var(Y_0) = \left(\frac{\sigma_\mu^2}{(1-\gamma)^2} + \sigma_\nu^2 \right) I_N = \left(\frac{\sigma_\mu^2}{(1-\gamma)^2} + \frac{\sigma_\varepsilon^2}{1-\gamma^2} \right) I_N{}^{11}.$$

Now, consider when β is not equal to zero. Let the first term in the equation (3-9) be $\varphi_{it} = \beta \sum_{j=0}^{\infty} \gamma^j X_{i,-j}$. Then, for any stationary processes X_{it}, which may be serially correlated, the $\frac{\varphi_{jt}}{\beta} = \gamma \frac{\varphi_{jt-1}}{\beta} + X_{it}$ has a variance $\sigma_\phi^2 = \beta^2 \frac{\sigma_{Xi}^2}{1-\gamma^2}$.[12] Since the variance of X_{it} is assumed to be same for all i, then the random variable φ_{it} has a well defined variance which is the same for all

[10] From the equation (3-2), taking a particular time period T and the infinite past gives
$Y_{iT} = \gamma^\infty Y_{i,-\infty} + \sum_{j=0}^{\infty} \gamma^j \beta X_{iT-j} + \frac{1-\gamma^\infty}{1-\gamma} \mu_i + \nu_{iT}$, where $\nu_{iT} = \sum_{j=1}^{\infty} \gamma^j \varepsilon_{iT-j}$
Since $|\gamma| < 1$ and $\nu_{iT} = \sum_{j=1}^{\infty} \gamma^j \varepsilon_{iT-j}$ is MA form of a first-order autoregression with white noise, the equation (3-9) is derived.

[11] Refer to footnote 12.

[12] Under the assumption that Xit is a white noise but with constant variance
σ_X^2, the infinite one-side moving average $\{\varphi_{it}\}$, where $\varphi_{it} = \sum_{j=0}^{\infty} \gamma^j X_{i,t-j}$ and $\sum_{j=0}^{\infty} (\gamma^j)^2 < \infty$ is well defined stationary process with mean zero and variance $\sum_{j=0}^{\infty} (\gamma^j)^2$.

i and a function of β, γ, and σ_x^2. The unconditional likelihood function[13] is, therefore,

(3-10)

$$\log L(\beta, \gamma, \sigma_\mu^2 \sigma_\varepsilon^2, \sigma_x^2 \mid Y_{11}, \ldots, Y_{1T}, \ldots Y_{NT}; X_{11}, \ldots X_{NT}; Y_{10}, \ldots, Y_{N0})$$

$$= -\frac{N(T+1)}{2}\log 2\pi - \frac{NT}{2}\log\sigma^2 - \frac{N}{2}\log\xi - \frac{N(T-1)}{2}\log\eta$$

$$-\frac{1}{2\sigma^2}\sum_i\sum_t (y_{jt}^* - \gamma y_{-1}^* - \beta x_{jt}^*)^2 - \frac{N}{2}\log\left\{\frac{\beta^2\sigma_x^2}{1-\gamma^2} + \frac{\sigma_\mu^2}{(1-\gamma)^2} + \frac{\sigma_\varepsilon^2}{1-\gamma^2}\right\}$$

$$-\left[\frac{\sum_{i=1}^{N} Y_{i0}{}^2}{2\left\{\frac{\beta^2}{1-\gamma^2} + \frac{\sigma_\mu^2}{(1-\gamma)^2} + \frac{\sigma_\varepsilon^2}{1-\gamma^2}\right\}}\right],$$

where $\rho = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\varepsilon^2} = \frac{\sigma_\mu^2}{\sigma^2}$, $\xi = 1 - \rho + T\rho, \eta = 1 - \rho$, y^*, x^*,

and y_{-1}^* are transformed variables and are defined as

$$y_{it}^* = \xi^{-1/2}\,\overline{Y}_{i\cdot} + \eta^{-1/2}(Y_{it} - \overline{Y}_{i\cdot}),\; x_{it}^* = \xi^{-1/2}\overline{X}_{i\cdot} + \eta^{-1/2}(X_{it} - \overline{X}_{i\cdot})$$

$$y_{-1}^* = \xi^{-1/2}\,\overline{Y}_i - 1 + \eta^{-1/2}(Y_{i-1} - \overline{Y}_{i,-1}),\quad \overline{Y}_{i\cdot} = \frac{1}{T}\sum_{t=1}^{T} Y_{it},$$

$$\overline{X}_{i\cdot} = \frac{1}{T}\sum_{t=1}^{T} X_{it}\;, \text{ and }\; \overline{Y}_{i-1} = \frac{1}{T}\sum_{t=1}^{T} Y_{it-1}\;.$$

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13 Although I do not review the conditional likelihood function in this section, its form is;

$$\log L(\beta, \gamma, \sigma_\mu^2, \sigma_\varepsilon^2, \Big| Y, X) = -\frac{NT}{2}\log 2\pi - \frac{NT}{2}\log\sigma^2 - \frac{N}{2}\log\xi$$

$$-\frac{N(T-1)}{2}\log\eta - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{jt}^* - \gamma y_{-1}^* - \beta x_{jt}^*)^2$$

Ⅳ. Data, Samples, and Estimation Results

1. Data and Samples

One of the reasons for the recent surge in work on growth empirical analysis has been the availability of the Summers-Heston (1988) data set. Since the Summers-Heston data set also includes various measures of the GDP and its components for different countries over several decades, it is possible to analyze growth empirics by using a panel approach. Basically, Islam (1995) as well as Barro (1989) and M-R-W (1992) used the this data set to construct the variables. The data comes from the Penn World Tables 5.6, publicly available from the NBER web site at ftp://nber.harvard.edu/pub/[14].Since I want to compare my estimation results with those obtained by Islam, I kept the country samples similar to those used by him. The three samples that Islam considered were (i) NONOIL (96 countries), (ii) INTER (74 countries), and (iii) OECD (22 countries)[15]. The counties are listed in the Appendix 1. The value of $(g+\delta)$ is assumed to be constant as 0.05 and same for all countries and for all years[16]. Five-year time interval data like Islam were used for the estimation of model and so considering the period 1960-1985, five data points for each country; 1985, 80, 75, 70, and 1960. When $t=1965$, for example, $(t-1)$ denotes 1960, and savings rate and population growth rate are an average value of five years. Finally all econometric results are calculated by

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[14] PWT5.6. is most recent version of Summers-Heston data.

[15] NONOIL means countries that oil production is not the dominant industry. Actually we can not expect standard growth model to account for measured GDP in these countries. INTER are countries whose data receive a grade of "D" from Summers and Heston or whose populations in 1960 were less than one million. Summers and Heston use the "D" grade to identify countries whose real income figures are based on extremely little primary data. Third sample consists of the 22 OECD countries with populations greater than one million.

[16] This assumption follows M-R-W and Islam's assumption.

using the GAUSS 3.02.

2. Estimation Results

2.1. Single Cross-section Results

To see how much results of this paper differ from those of Islam and M-R-W, single cross-section regressions were first run. For this regression y_{it} is the log of per capita GDP for 1985 and y_{it-1}, same for 1960. s and n are averages of savings and population growth rate for 1960-1985. Table 1 includes these results. The first panel of the table denotes results of estimation in unrestricted form, while the second panel contains restricted case which the coefficient of the investment and population growth variables are equal in magnitude but opposite sign[17]. All estimates are very similar in each case except constant term.

In the comparison with Islam and M-R-W, the estimates of initial GDP for three subsample are -0.168. -0.212, and -0.318, respectively. Corresponding estimates of Islam and M-R-W are -0.127, -0.218, -0.328 and -0.141, -0.228, -0.351. Also for estimates of λ my results are 0.0073, 0.0095, and 0.0153, respectively, while those of Islam and M-R-W are 0.0054, 0.0098, 0.0159 and 0.0061, 0.0104, 0.0173.

In general, the results from restricted estimation allow us unique estimates of λ and α and these results show a very slow rate of convergence. On the other hand, the estimates of α, implying an elasticity of output with respect to capital, are unusually high in each case because these estimates imply such a high capital share.

2.2. Pooled Estimation

Next, a pooled regression (OLS) is implemented on the basis of our five-year span data is implemented. The Table 2 reports these results. Because of differences in the value of τ, the reduced

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[17] Such restriction on the coefficients of ln(s) and ln $(n+g+\delta)$is derived from the assumption of the constant returns to scale.

form coefficients are not directly comparable to single cross-section results. Therefore, consider the implied values of the structural parameters. The values of λ from the unrestricted pooled estimation are 0.0105, 0.0128, and 0.0243 for NONOIL, INTER, and OECD. Unlike Islam's result, these are different from the corresponding estimates in Table 1. While the implied values of α are very similar in two regressions, these results, still, show very low estimates of the rate of convergence and relatively high estimates of the elasticity parameter α; 0.708 for NONOIL sample, 0.690 for INTER, and 0.607 for OECD.

2.3. LSDV Estimation with Fixed Effects

The result of the LSDV estimation is presented in Table 3. The implied rates of convergence and output elasticity for NONOIL, INTER, and OECD samples are 0.0660, 0.0597, 0.0537, and 0.3719, 0.4122, 0.4096, respectively[18]. These are very different from the previous corresponding estimates and relatively high as before two regressions. Therefore, the adoption of the panel approach leads to a two-fold change in the results. First, we obtain much higher rates of the convergence, and second, we obtain more empirically plausible estimates of the elasticity of output with respect to capital. However, as we have seen, these estimates are not consistent.

2.4. Feasible GLS and ML Estimation

In order to compare various estimates based on different assumptions, a feasible GLS with a random effects is run and is used for starting values for conditional and unconditional maximum likelihood estimates. The results report Table 4 and Table 5. In the process of FGLS, Nerlove (1971)'s method[19] is applied for the calculation of rho ρ, that is intra-correlation

[18] These results are almost same to that of Islam.

[19] Actually, there are three alternatives in calculation of the estimates intra-correlation coefficient; Nerlove (1971) estimate, Balestra and Nerlove estimate, and Green-Jurge estimate. These provide different value of ρ.Refer to Nerlove[1996]

coefficient. A sample variance of X is replaced for σ_x^2 in obtaining he unconditional maximum likelihood estimators.

The implied rates of convergence and output elasticity for NONOIL, INTER, and OECD samples are 0.0402, 0.0394, 0.0462, and 0.4966, 0.5157, 0.4718 in the FGLS. In the case of unconditional ML, these are 0.0127, 0.0151, 0.0425 and 0.6846, 0.6713, 0.4865, respectively. Note that considering the downward bias in the coefficient of the lagged dependent variable in a dynamic fixed effects model suggest that other coefficients will be biased upwards.

V. Conclusion

We have seen in Section II that the speed of convergence to equilibrium is proportional to the value of λ, and so γ. The relationship between λ and γ is given by $\lambda = -\frac{1}{\tau}\ln(\gamma)$.[20] Thus, a higher value of γ leads to a lower value of λ, implying a slow speed of convergence. Table 6 shows that relationships between λ and the T, which means the time period required for convergence to equilibrium.[21]

As Islam notes, higher rate of convergence over the whole sample can be obtained by adoption of a panel data approach, which allows for difference in the aggregate production function not only across groups of countries but also across individual countries. This is obviously good news for the Solow model. However, his LSDV approach with fixed effect's model has an incline to increase the estimate of the speed of convergence. The unconditional ML estimator of lambda shows it clear.

Even though we do not consider the fact that the estimator of the coefficient of the lagged variable in the dynamic fixed

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[20] Note that τ is $(t_2 - t_1)$ and so constant.

[21] Note that our data is consist of 5-year span for 1965, 70, 75, 80, and 1985.

effects model γ, biases to downward, so the estimates of λ is overestimated, it hardly seems to say that there exists a reasonable evidence of rapid convergence if we see the time period required for the convergence.

TABLE 1. Single Cross-Section Results, 1960-85

Coefficient	NONOIL	INTER	OECD	NONOIL	INTER	OECD
		Islam's Results			This Paper	
			Unrestricted			
Constant	0.9448	1.1075	1.7433	0.8885	1.2196	2.6793
	(0.8724)	(0.8975)	(1.2655)	(0.8163)	(0.8412)	(1.0877)
ln(y60)	0.8733	0.7822	0.6722	0.8119	0.7689	0.6849
	(0.0611)	(0.0667)	(0.0694)	(0.0607)	(0.0625)	(0.0571)
ln(s)	0.6585	0.6431	0.4114	0.4980	0.5221	0.6694
	(0.0926)	(0.1121)	(0.1845)	(0.0622)	(0.0819)	(0.1900)
ln(n+g+d)	-0.6122	-0.8144	-0.8021	-0.7481	-0.7718	-0.5791
	(0.3667)	(0.3717)	(0.4187)	(0.3563)	(0.3555)	(0.3521)
R-square*	0.9006	0.8915	0.8499	0.9051	0.9024	0.8917
Lambda	0.0054	0.0098	0.0159	0.0083	0.0105	0.0151
	(0.0004)	(0.0008)	(0.0016)	(0.0030)	(0.0033)	(0.0033)
			Restricted			
Constant	0.8475	1.4565	2.6689	1.3921	1.7265	2.4758
	(0.3429)	(0.3798)	(0.5715)	(0.3632)	(0.3778)	(0.5001)
ln(y60)	0.8701	0.7945	0.6817	0.8328	0.7882	0.6827
	(0.0547)	(0.0599)	(0.0678)	(0.0524)	(0.0553)	(0.0547)
ln(z)	0.6554	0.6610	0.4847	0.5061	0.5378	0.6461
	(0.0884)	(0.1034)	(0.1602)	(0.0609)	(0.0782)	(0.1511)
R-square	0.9037	0.8927	0.8524	0.9057	0.9032	0.8972
Lambda	0.0056	0.0092	0.0153	0.0073	0.0095	0.0153
	(0.0004)	(0.0007)	(0.0015)	(0.0025)	(0.0028)	(0.0032)
Alpha	0.8346	0.7628	0.6036	0.7517	0.7175	0.6706
	(0.1126)	(0.1193)	(0.1995)	(0.0225)	(0.0295)	(0.0517)

Figures in parentheses are standard errors and ln(z) denotes ln(s)-ln(n+g+d) and R-square represents adjusted R-square.

TABLE 2. POOLED REGRESSION RESULTS OF 5-YEAR SPAN DATA

Coefficient	NONOIL	INTER	OECD	NONOIL	INTER	OECD
	Islam's Results			This Paper		
			Unrestricted			
ln(y-1)	0.9764	0.9636	0.9228	0.9490	0.9385	0.8892
	(0.0101)	(0.0107)	(0.0147)	(0.0091)	(0.0091)	(0.0131)
ln(s)	0.1386	0.1396	0.1047	0.1255	0.1440	0.1934
	(0.0153)	(0.1172)	(0.0313)	(0.0114)	(0.0139)	(0.0350)
ln(n+g+d)	-0.1291	-0.1300	-0.1799	-0.1150	-0.1070	-0.1183
	(0.0584)	(0.0566)	(0.0653)	(0.0319)	(0.0295)	(0.0626)
R-square*	0.9848	0.9861	0.9807	0.9817	0.9839	0.9796
Lambda	0.0048	0.0074	0.0161	0.0105	0.0127	0.0235
	(0.0001)	(0.0001)	(0.0003)	(0.0019)	(0.0019)	(0.0029)
			Restricted			
ln(y-1)	0.9758	0.9628	0.9248	0.9487	0.9382	0.8857
	(0.0012)	(0.0098)	(0.0147)	(0.0091)	(0.0091)	(0.0127)
ln(z)	0.1381	0.1388	0.1184	0.1244	0.1374	0.1764
	(0.0151)	(0.0165)	(0.0286)	(0.0108)	(0.0126)	(0.0313)
R-square	0.9848	0.9861	0.9901	0.9817	0.9839	0.9795
Lambda	0.0059	0.0095	0.0146	0.0105	0.0128	0.0243
	(0.0001)	(0.0002)	(0.0002)	(0.0019)	(0.0019)	(0.0029)
Alpha	0.8338	0.7736	0.6150	0.7080	0.6897	0.6067
	(0.0912)	(0.0924)	(0.1486)	(0.0179)	(0.0197)	(0.0423)

Figures in parentheses are standard errirs and ln(z) denotes ln(s)-ln(n+g+d) and R-square represents adjusted R-square.

TABLE 3. LSDV Estimation with Fixed Effects Model

Coefficient	NONOIL	INTER	OECD	NONOIL	INTER	OECD
		Islam's Results			This Paper	
			Unrestricted			
ln(y-1)	0.7762	0.7935	0.5864	0.7127	0.7272	0.7636
	(0.0353)	(0.0388)	(0.0532)	(0.0235)	(0.0211)	(0.0203)
ln(s)	0.1595	0.1709	0.1215	0.2090	0.2686	0.1617
	(0.0237)	(0.0256)	(0.0586)	(0.0230)	(0.0251)	(0.0660)
ln(n+g+d)	-0.4092	-0.2466	-0.0698	-0.0753	-0.0687	-0.1713
	(0.1024)	(0.1007)	(0.1007)	(0.0329)	(0.0283)	(0.0912)
R-square	0.7404	0.8254	0.9659	0.9900	0.9920	0.9900
Lambda	0.0507	0.0462	0.1067	0.0677	0.0637	0.0539
	(0.0091)	(0.0098)	(0.0181)	(0.0066)	(0.0058)	(0.0053)
			Restricted			
ln(y-1)	0.7919	0.7954	0.6294	0.7204	0.7419	0.7645
	(0.0349)	(0.0387)	(0.0495)	(0.0237)	(0.0219)	(0.0187)
ln(z)	0.1634	0.1726	0.0954	0.1656	0.1809	0.1634
	(0.0238)	(0.0254)	(0.0581)	(0.0193)	(0.0198)	(0.0577)
R-square	0.7368	0.8251	0.9642	0.9890	0.9910	0.9900
Lambda	0.0467	0.0458	0.0926	0.0660	0.0597	0.0537
	(0.0088)	(0.0097)	(0.0157)	(0.0066)	(0.0059)	(0.0049)
Alpha	0.4398	0.4575	0.2047	0.3719	0.4122	0.4096
	(0.0545)	(0.0575)	(0.1042)	(0.0312)	(0.0471)	(0.0886)

TABLE 4. Feasible GLS Estimation with Random Effects Model

Coefficient	NONOIL	INTER	OECD
ln(y-1)	0.8179	0.8212	0.7939
	(0.0174)	(0.0165)	(0.0166)
ln(z)	0.1796	0.1904	0.1841
	(0.0166)	(0.0175)	(0.0481)
R-square	0.8700	0.9020	0.9560
Lambda	0.04021	0.03940	0.04617
	(0.00425)	(0.00403)	(0.00418)
Alpha	0.49656	0.51565	0.47179
	(0.02636)	(0.02632)	(0.06788)

Figures in parentheses are standard errors and ln(z) denotes ln(s)-ln(n+g+d).

TABLE 5. Conditional and Unconditional ML Estimates

Coefficient	NONOIL	INTER	OECD	NONOIL	INTER	OECD
	Conditional MLE			Unconditional MLE		
ln(y-1)	0.9339	0.9156	0.8189	0.9385	0.9271	0.8085
	(0.0122)	(0.0135)	(0.0245)	(0.0105)	(0.0118)	(0.0228)
ln(z)	0.1370	0.1580	0.1908	0.1334	0.1488	0.1815
	(0.0131)	(0.0158)	(0.0438)	(0.0124)	(0.0154)	(0.0521)
Lambda	0.0137	0.0176	0.0400	0.0127	0.0151	0.0425
	(0.0026)	(0.0053)	(0.0060)	(0.0022)	(0.0025)	(0.0056)
Alpha	0.6744	0.6518	0.5131	0.6846	0.6713	0.4865
	(0.0289)	(0.0909)	(0.0664)	(0.0277)	(0.0276)	(0.0791)

Figures in parentheses are standard errors and ln(z) denotes ln(s)-ln(n+g+d).

TABLE 6. The Speed of Convergence

Estimation Method	NONOIL		INTER		OECD	
	λ	T	λ	T	λ	T
Pooled Estimation	.0105	331.8	.0128	272.5	.0243	144.3
Fixed Effects Model	.0660	54.2	.0597	59.8	.0537	66.3
Feasible GLS	.0402	87.9	.0394	89.7	.0462	76.7
Unconditional MLE	.0127	274.6	.0151	231.2	.0425	83.3

The Unit of T is year.

Annex 1. Countries used in this study.

OECD(22): Japan, Austria, Belgium, Denmark, Finland, France, Germany(FRG), Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, U.K., Canada, U.S., New Zealand

INTER(74): OECD 22 Countries + Algeria, Botswana, Cameroon, Ethiopia, Ivory Coast, Kenya, Madagascar, Malawi, Mali, Morocco, Nigeria, Senegal, South Africa, Tanzania, Zambia, Zimbabwe, Costa Rica, Dominican Rep., El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad & Tobogo, Argentina, Bolivia, Chile, Colombia, Ecuador, Paraguay, Peru,Uruguay, Venezuela, Bangladesh, Hong Kong, India, Israel, Jordan, Korea, Malaysia, Burma, Pakistan, Philippines, Singapore, Sri Lanka, Syria, Thailand

NONOIL(94): INTER(74) + Angola, Benin, Burundi, Central African Rep., Chad, Congo, Egypt, Ghana, Liberia, Mauritania, Mauritius, Mozambique, Niger, Rwanda, Somalia, Togo, Uganda, Zaire, Nepal, Papua New Guinea

REFERENCES

Balaestra, Pietro. 1996. "Fixed Effect Models and Fixed Coefficient Models." pp.34-49 in L. Matyas and P. Sevestre. *The Economics of Panel Data.* 2nd ed.

Balestra, P. and M. Nerlove. 1966. "Pooling Cross-Section and Time-Series Data in the Estimation of a Dynamic Economic Model: The Demand for Natural Gas." *Econometrica* 34: 585-612.

Barro, R.J. 1991. "Economic Growth in a Cross Section of Countries." *Quarterly Journal of Economics* 106(May): 407-443.

Barro, R.J. and X. Sala-I-Martine. 1992. "Convergence." *Journal of Political Economy* 100(April): 223-51.

Barro, R.J. and X. Sala-I-Martine. 1995. *Economic Growth,* New York: McGraw-Hill.

Bernard, A.B., and S.N. Durlauf. 1996. "Interpreting Tests of the Convergence Hypothesis." *Journal of Econometrica,* 71: 161-173;

Islam, N. 1995. "Growth Empirics: A Panel Data Approach." *Quarterly Journal of Economics* 110: 1127-1170.

Mankiw. N.G., D. Romer and D. Weil. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107: 407-37.

Matyas, L. and P. Sevestre. 1992[1996]. *The Econometrics of Panel Data: A Handbook of the Theory with Applications.* Boston: Kluwer Academic Publishers. 2nd. ed.

Matyas, Laszlo. 1996. "Error Components Models." pp. 50-99 in L. Matyas and P. Sevestre. *The Economics of Panel Data.* 2nd ed. Boston: Kluwer Academic Publishers.

Nerlove, M. 1971. "Further Evidence on the Estimation of Dynamic Economic Relations from a Time Series of Cross-Sections." *Econometrica* 39: 359-382

Nerlove, M. 1996. "Economic Growth: Testing Conditional Convergence." *Lecture Note.*

Nerlove, M. 1996. "Panel Data." Forthcoming in *Econometrics for Applied Economists.* Academic Press.

Nerlove, M. and L.K. Raut. 1996. "Growth Models with Endogenous Population: A General Framework." Forthcoming in M.R. Rosenzweig and O. Dtark (eds.). *The Handbook of Family and Population Economics.* New York: Elsevier Scientific Publishers.

Nerlove, M. and P. Balestra. 1996. "Formulation and Estimation of Econometric Models for Panel Data." pp. 3-22 in L. Matyas and P. Sevestre. *The Economics of Panel Data.* 2nd ed. Boston: Kluwer Academic Publishers.

Nickell, S. 1981. "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49: 1417-1426.

Rebelo, S. 1991. "Long-run Policy Analysis and Long-run Growth." *Journal of Political Economy* 99: 500-21.

Romer, P.M. 1990. "Endogenous Technological Change." *Journal of Political Economy* 98: 71-102.

Sevestre, Patrick and Alain Trognon. 1996. "Linear Dynamic Models." pp. 120-144 in L. Matyas and P. Sevestre. *The Economics of Panel Data.* 2nd ed.

Solow, R.M. 1956. "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics* 70: 65-94.

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