Neoclassical Convergence Versus Technological Catch-Up: A Contribution for Reaching a Consensus[1]

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Abstract

New macro empirical evidence is provided to assess the relative importance of object and idea gaps in explaining the world income distribution dynamics over a benchmark period of 1960-1985. Results are then extended through 1995. Formal statistical hypothesis tests allow us to discriminate between two competing growth models: (i) the standard neoclassical growth model similar to that employed by Mankiw, Romer, and Weil (1992), and (ii) an endogenous growth model closely related to the Nelson and Phelps' approach (1966) that emphasizes the importance of technology transfer in addition to factor accumulation as an opportunity to catch up. First, the latter can hardly be rejected and reveals itself to be either a reliable alternative or a complementary model, depending on the sample under study. Second, taking into consideration the impact of the technological catch-up phenomenon allows us to better capture and locally fit the pattern of income distribution dynamics that took place over the period of 1960-1995.

Key words: endogenous growth, neoclassical convergence, technological catch-up, and income dynamics.

JEL Classification: C12-C14-C21-O33-O40-O50

''We could produce statistical evidence that all growth came from capital accumulation, with no room for anything called technological change. But we could not believe it.''

Romer (1993; p. 562)

1. Introduction

In the neoclassical theory, technology is assumed to be an exogenous pure public good that is available to everyone, everywhere, and is free of charge. On the contrary, an alternative view suggests that poorer countries may suffer from a technological gap. This requires technology to be considered less public. Total factor productivity growth may thus differ across countries, at least for a transitional period, depending, for instance, on both the technological gap and the absorption capacity of a nation. Both approaches may exhibit an opportunity for countries lagging behind catch-up, though for different reasons. In the neoclassical theory, poorer countries may converge with rich ones because there are diminishing returns to capital. In the technology-gap approach, a high absorption capability makes it easier for a poor country to catch up due to the opportunity for faster growth through the adoption and implementation of the leading-edge technology. Because both approaches are not mutually exclusive, I investigate the relative importance of both these phenomena at an aggregate level within a unified theoretical and empirical framework.

The first alternative has been empirically investigated in a seminal contribution by Mankiw, Romer, and Weil (1992) over the period of 1960-1985. They consider a human capital augmented version of the Solow (1956) growth model and conclude that (p. 433): ''...our results indicate that the Solow model is consistent with the international evidence if one acknowledges the importance of (the accumulation of) human as well as physical capital.'' In particular, there is conditional

[1] Research on this paper was carried out in part in the Sonderforschungsbereich 373 at Humboldt-Universität zu Berlin whose hospitality is gratefully acknowledged. It is also part of a CNRS' research program on "Les Enjeux Economiques de l'Innovation". I thank without implications Stéphane Adjemian, Cecilia Garcia-Penalosa, Jérôme Glachant, Ferhat Mihoubi, and Muriel Roger. A previous version has been presented in 2000 at the T2M Conference (Nanterre-France), at the Annual Meetings of the Society for Economic Dynamics (San José-Costa Rica), at the Conference on "Growth and Business Cycles in Theory and Practice" (Manchester-UK), and at the Annual Meeting of the Latin American and Caribbean Economic Association (Rio de Janeiro-Brazil). All graphs and calculations have been realized using XploRe, http://www.xplore-stat.de. I am alone, of course, responsible for shortcomings and errors.

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convergence in that lower initial values of output per worker generate higher transitional growth rates, once the determinants of the steady state are controlled for.

Nelson and Phelps (1966) provide an early example of a formal model that incorporates the idea that a country may benefit from its technological backwardness depending on its absorption capability that can be approximated by its stock of human capital. They suggest that the growth of total factor productivity is a function both of the level of human capital and of the technological gap because an educated labor force is expected to be better at adopting foreign technologies, thereby generating growth (see also Abramowitz (1986) for a more recent but less formal contribution to this line of research, and Romer (1990)). Benhabib and Spiegel (1994) take this alternative seriously and provide an interesting empirical criticism of Mankiw, Romer, and Weil's conclusions. Within a growth accounting exercise, they find that growth remains essentially uncorrelated with the change in educational attainment when one considers an augmented neoclassical production function model where human capital is nothing but an input in the aggregate production function, but educational attainment levels become significantly correlated with growth when one assumes as in Nelson and Phelps that the stock of human capital may positively affect the rate of technology transfer.

Aghion and Howitt (1998) stress how important it is to distinguish between these two frameworks because they deliver different insights as to the growth effects of various educational policies. Romer (1993) also emphasizes how important it is to assess the relative importance of what he calls ''object gaps'' versus ''idea gaps'' because each imparts a distinctive thrust to the analysis of economic development. This article aims precisely at providing new international macroeconomic empirical evidence on the relative importance of ideas versus objects in international growth differences.

In a manifesto for a growth econometrics, Durlauf (2001, p. 65) argues: ''...It is only through an econometrics that can link theory to data analysis and hypothesis testing that a synergy (between the theoretical and empirical growth literatures) can be achieved''. To assess the relative importance of the opportunity to catch up because of diminishing returns to reproducible factors as in a neoclassical framework and the opportunity to catch up because of differences in technology, I therefore present a simple growth model characterized by a neoclassical production function that exhibits constant returns to scale, but where total factor productivity differences evolve endogenously according to the endogenous version of growth favored by Nelson and Phelps. Following De la Fuente (1995), I then explicitly derive and estimate a convergence equation through a (log) linear approximation around the steady state, whose fit and specification which incorporates both the neoclassical convergence effect and the technological catch-up effect, can be directly compared to the empirical results originally found by Mankiw, Romer, and Weil (see also Barro and Sala & Martin (1992)). In particular, statistical specification testing allows us to choose among the two competing theoretical frameworks. Proceeding this way also allows us to solve the problem of how to map data on education into growth models within an unified empirical framework. Traditionally, researchers that focus on total factor productivity adopt an approach based on growth accounting (see for instance, the insightful survey on technology and international growth differences by Fagerberg (1994), and for more recent studies, Hall and Jones (1999), and Klenow and Rodriguez-Clare (1997) among many others). A more recent nonparametric approach, as exemplified in Kumar and Russel (2002), proposes to decompose the growth of labor productivity into technological change, technological catch-up, and capital accumulation by constructing, through Data Envelopment Analysis, a worldwide production frontier and associated levels of individual economies. In order for my results to be directly comparable to the Mankiw, Romer, and Weil's contribution, I voluntarily choose to use their approach, that is, one of estimation. Thus, we become able to fully appreciate whether the data is consistent with the view that there are only object gaps as in an augmented human capital Solow model, or with the view that both idea and object gaps are important to explain the world income dynamics.

If idea and object gaps are correlated, which seems very likely to happen, then, it is well-known that the estimation of the augmented human capital model as provided by Mankiw, Romer, and Weil yields biased estimates as a consequence of omitted variables. This motivated part of the literature that studies growth empirics to turn to panel data methods while estimating a traditional convergence equation similar to that in MRW (see, among others, Islam (1995), Caselli, Esquivel, and Lefort (1996)). However, as emphasized by Durlauf and Quah (1999), even though these methods allow us to uncover country-specific heterogeneity, possibly in the level of initial technological efficiency, this heterogeneity remains empirically unobserved and is not motivated by economic theory. The simple growth model and its associated convergence equation presented below are only slightly more difficult than in Mankiw, Romer, and Weil's article. But, they allow us to overtake this major drawback faced by panel data estimation of a MRW convergence equation type. A recent notable exception is Dowrick and Rogers (2002) whose unified framework explicitly captures both capital deepening and technological catch-up by adopting panel estimation, but within a production function model, i.e., not through a MRW convergence equation type.

This article is organized as follows. In Section 2, I present a descriptive growth model that allows for both the neoclassical convergence and the technological catch-up effects, and explicitly derive a convergence equation from it. In Section 3, I discuss data and specification issues. In Section 4, I first estimate the model over a benchmark period of 1960-1985, and compare it to a Mankiw, Romer, and Weil's specification by associating with each model estimated loss functions after having explicitly addressed country-specific heterogeneity at initial efficiency levels, i.e., omitted variable bias, heteroscedasticity, and potential outliers issues. In addition, formal specification tests allow us to discriminate between the two rival models. A key finding when the absorption capability of a nation is proxied by its stock of human capital, is that the Mankiw, Romer, and Weil's specification should be either discarded as compared to a Nelson and Phelps' specification when a large set of non-oil countries is considered, or, at least extended by explicitly including technological catch-up whatever the sample of countries under study. Human capital can therefore not be viewed, at least entirely, as a factor of production. Moreover, our estimates suggest a much lower speed of convergence due to decreasing returns once one controls for technological catch-up opportunities. Following both De Long and Summers (1991) international evidence and Parente and Prescott's (1994) view of technology adoption investment, Section 4 also provides, first, robust empirical evidence that the high social product of equipment investment reflects technology transfer mediated through capital goods and, second, various tests of specification which suggest that technological catch-up relies on different types of absorptive capabilities depending on the stage of development of the economy. In Section 5, results are extended through 1995. The technological catch-up effect remains substantially significant except in the OECD sample, and again, for a worldwide set of countries, the Nelson and Phelps' estimation framework reveals itself to be a reliable complementary model compared to the human capital augmented neoclassical growth model. Moreover, counterfactual income density estimates which provide a visually clear local representation of where in the income distribution the different models exert the greatest impact, reveal that taking into account the impact of technological backwardness enables us to better capture and fit the ‘‘twin-peakedness’’ expression of the world income distribution dynamics as identified, for instance, in the work of Quah (1996, 1997). Section 6 concludes the paper.

2. A Growth Model with Factor's Accumulation and Technological Diffusion

In this section, I present a simple growth model and following De la Fuente, I then explicitly derive a conditional convergence equation where an exogenous stock of human capital speeds up technological diffusion throughout the economy. The role of technological catch-up in economic convergence has often been overlooked, while the opposite is true for the capital-deepening component of convergence. Similar to Mankiw, Romer and Weil (1992) and more recently Howitt (2000), the model discussed below must be viewed as a useful tool for thinking about the empirics of convergence.

Let us start from an aggregate Cobb-Douglas production function exhibiting constant returns in labor and reproducible capital of the form:

$$Y(t) = K(t)^{\alpha}(A(t)L(t))^{1-\alpha}, \tag{1}$$

where A is an index of labor-augmenting technological progress, K may denote a broad physical capital aggregate, and L is the labor force, where $L(t) = L(0).e^{nt}$, with n as an exogenous constant growth rate of the labor force.

Define k as the stock of capital per unit of effective labor. Then, output per worker is:

$$y(t) = A(t)k(t)^{\alpha}. \tag{2}$$

Taking logarithms of (2) and differentiating with respect to time, the rate of growth of output per worker can be written as the sum of two terms that reflect, respectively, growth in total factor productivity and the accumulation of reproducible factors:

$$\frac{\dot{y}(t)}{y(t)} = \frac{d[\log y(t)]}{dt} = \gamma_y(t) = \gamma_A(t) + \alpha\gamma_k(t) \cdot \tag{3}$$

The problem consists of specifying the immediate determinants of γ_A and γ_k. Let us start with the second factor. The evolution of physical capital is given by:

$$\gamma_k(t) = sk(t)^{\alpha-1} - (n + \gamma_A(t) + \delta), \tag{4}$$

where s is a constant exogenous fraction of gross income invested in physical capital and δ is the rate of depreciation.

With $\alpha \in]0,1[$, the behavior of the dynamical system described by (4) is such that the system is stable, and the stock of capital per unit of effective labor converges to its stationary path k^*, characterized by:

$$\gamma_k(t) = 0 \Rightarrow k^*(t) = \left(\frac{s}{n + \gamma_A(t) + \delta}\right)^{1/(1-\alpha)}. \tag{5}$$

In the Mankiw, Romer, and Weil's estimation framework, $\gamma_A(t)$ is assumed to be constant over time, exogenous, and identical to all countries. Instead, I rather specify the determinants of the rate of technological progress as in Nelson and Phelps, where the rate of technological progress of a country is endogenous and driven by its individual stock of human capital, which in turn affects a country's ability to catch up with more advanced economies.

Define a technological distance between $A(t)$ and the best-practice level of technology $T(t)$, that would prevail if technological diffusion were completely instantaneous. Nelson and Phelps then define $T(t)$ as 'a measure of the stock of knowledge or body of techniques that is available to innovators' at time t and assume that it expands at a strictly positive exogenous constant rate, g. Improved technological practice is assumed to depend on educational attainment (H) and upon the gap between the theoretical level of technology and the level of technology in practice. More specifically:

$$\gamma_A(t) = \Phi(H).\log\left(\frac{T(t)}{A(t)}\right) \text{ with } \Phi(0) = 0, \text{ and } \Phi'(H) > 0. \tag{6}$$

Following Howitt (2000), $A(t)$ may be more precisely interpreted as an average productivity parameter across the different sectors of an economy, and $T(t)$ as an average productivity parameter across all those sectors which make use of the leading-edge technology. If one assumes that no country can be on the frontier in all sectors at the same time, then, no country can ever be on the technology frontier, except if $T(t)$ were to remain unchanged.

Substituting (6) into (4) yields:

$$\gamma_k(t) = sk(t)^{\alpha-1} - (n + \Phi(H).\log\left(\frac{T(t)}{A(t)}\right) + \delta). \tag{7}$$

The transitional dynamics can now be quantified by using a log linear approximation of (7) around the steady state. The solution for $\log k(t)$ given the above Cobb-Douglas technology is:

$$\gamma_k(t) \cong -\beta\tilde{k}(t) - \Phi(H)\tilde{b}(t), \tag{8}$$

with $\beta = (1-\alpha)(n+g+\delta)$ that determines the speed of convergence from $k(t)$ to $k^*(t)$. $\tilde{k}(t)$, respectively $\tilde{b}(t)$, is equal to $\log(k(t)/k^*(t))$, respectively $b(t)-b^*$, and denotes the deviation of the stock of capital per unit of effective labor, in respect to the technological gap, i.e., $b(t) = \log(T(t)/A(t))$, from its steady state value.

Given (2), (3), and (8) we have:

$$\gamma_y(t) \cong \gamma_A(t) - \beta(\log y(t) - \log A(t)) + \alpha(\beta \log k^*(t) - \Phi(H)\tilde{b}(t)). \tag{9}$$

It remains to incorporate in (9) the behavior of the technological variable. Note that $db(t)/dt = g - \Phi(H)b(t)$, the time path of $b(t)$ is therefore given by:

$$b(t) = b(0)e^{-\Phi(H)t} + b^*(1-e^{-\Phi(H)t}) \text{ or } \tilde{b}(t) = \tilde{b}(0)e^{-\Phi(H)t}. \tag{10}$$

It becomes now clear that there is a positive equilibrium gap for every g and H, where:

$$\frac{db(t)}{dt} = 0 \Rightarrow \gamma_{A^*} = g \text{ and } b^* = \frac{g}{\Phi(H)}. \tag{11}$$

That is, the equilibrium gap is an increasing function of g and a decreasing function of the index of educational attainment. Moreover, in a stagnant economy ($g = 0$), the gap, defined as $b(t) = \log(T(t)/A(t))$, approaches zero for every $H > 0$.

Substituting (10) into (6) and using (11), the rate of technological progress at time s is given by:

$$\gamma_A(s) = \Phi(H)b(s) = \Phi(H)\left[b(0)e^{-\Phi(H)s} + \frac{g}{\Phi(H)}(1-e^{-\Phi(H)s})\right] = \Phi(H)\left[\tilde{b}(0)e^{-\Phi(H)s}\right] + g \cdot \tag{12}$$

Thus, education influences the growth of total factor productivity only in the short run. Integrating (12) from 0 to t, we obtain the time path of the logarithm of the productivity index:

$$\log A(t) = \log A(0) + gt + \tilde{b}(0)(1-e^{-\Phi(H)t}). \tag{13}$$

Notice that $\tilde{b}(0) = b(0) - b^* = \log(T(0)/A(0)) - g/\Phi(H)$. If we define $\lambda \equiv \Phi(H)/(n+g+\delta)$, and substitute (10), (12), and (13) into (9), this yields the following convergence equation:

$$\gamma_y(t) = \beta \log T(0) + g(1+\beta t) - \beta \log y(t) + \frac{\alpha\beta}{1-\alpha}\log s - \frac{\alpha\beta}{1-\alpha}\log(n+g+\delta) - \beta\frac{g}{\Phi(H)} + \beta\left[\log\left(\frac{T(0)}{A(0)}\right) - \frac{g}{\Phi(H)}\right](\lambda-1)e^{-\Phi(H)t} . \quad (14)$$

Following the traditional conditional convergence literature, the growth rate of output per worker is an increasing function of investment in physical capital and decreases with the log of the contemporaneous level of income, and with the growth rate of the labor force; that is, across a set of economies that approach the same steady state, poor countries should grow faster on average than rich ones because of diminishing returns to capital accumulation. However, in contrast to the previous literature, education does not enter as another ordinary factor of production that affects growth through its rate of accumulation.

Instead, Equation (14) is consistent with, for instance, Howitt (2000) who captures in a closely related growth model very similar transitional and long run dynamics. Another important reason why convergence should occur in this model is technology diffusion. The larger the technological gap is, the faster the backward countries' growth rate is once one controls differences in factors' accumulation as well as differences in the absorption capability. The stock of human capital influences growth during transition in two specific ways. On the one hand, the growth of output per worker is a decreasing function of the equilibrium gap (b) that is itself a decreasing function of the stock of human capital. On the other hand, for a given stock of human capital, the growth rate of output per worker increases with the deviation of the initial technological gap from the equilibrium gap. However, the contribution of the catch-up process also decreases with time as its productivity level converges towards the technological frontier and the rate at which it converges to zero also depends positively on the stock of human capital.

Differences in education are therefore important to explain differences in growth rates. However, in contrast to the Mankiw, Romer, and Weil's approach, growth is not driven by the accumulation of human capital, where differences in the rates at which countries accumulate can explain why growth rates differ. Instead, growth is driven by the stock of human capital, which in turn affects a country's ability to absorb new technologies and therefore to catch up.

3. Data and Specification

To investigate and assess the relative importance of the technological catch-up process and of the neoclassical convergence effect as proposed in the model above, and for ease of comparison with most contributions I refer to, I first use data from Mankiw, Romer, and Weil (1992), human capital stocks data constructed by Nehru, Swanson, and Dubey (1995), and equipment investment to GDP ratios from De Long and Summers (1993). Thus, I choose to first focus on the period of 1960-1985. In Section 4, this data is used to compare the model above where, following Nelson and Phelps (1966) and Parente and Prescott's (1994) arguments, either human capital or equipment investment in GDP enhances an economy's ability to implement new technologies, and the Mankiw, Romer, and Weil's human capital augmented version of the Solow model. In Section 5 which is dedicated to the analysis of counterfactual income distribution dynamics, I extend some of the results through 1995 by using updated data collected by Bernanke and Gürkaynak (2001) except for the average stock of human capital which comes from the Barro and Lee (2001) database on school attainment levels.

Three aspects of the choice of variables deserve some discussion. First, Nehru et al. provide education stocks for a large sample of 73 countries that intersect with both the original Mankiw, Romer, and Weil's ''non-oil'' sample of developing and industrialized countries and with the De long and Summers data on equipment investment. (Countries included in our sample over the period of 1960-1985 are available in Appendix A.) The human capital stocks data available in Benhabib and Spiegel cover a much smaller number of countries, and the choice of these specific data sets allows us to best thwart the possible presence of multicollinearity. However, because Nehru et al.'s human capital stocks are available only up to 1987 for a worldwide set of countries, I then turn to the well-known dataset constructed by Barro and Lee which provides observations up to 1995. Although this yields a slightly different sample of 79 countries (see Appendix C), to be convincing, results should be robust to the use of different samples and different measures of human capital stocks.

Second, following Benhabib and Spiegel, the technological catch-up effect is captured via an interactive term that involves the average either secondary-school education stock (H) or equipment investment output ratio (Eq/GDP) over the period and the gap of a country behind the leader at the beginning of the period in terms of the level of initial output per working-age person ($\ln(Y60_{max}/Y60)$). This specification also follows Barro and Sala-i-Martin (1992) who acknowledge in their conclusion the possibility that the convergence observed from the estimation of a convergence equation similar to that of Mankiw, Romer, and Weil should be broken down into at least two components, reflecting both diminishing returns to capital and effects that involve the spread of technology. Much of the technological catch-up literature also includes per worker output as a proxy for the scope for catch-up. The choice of this proxy must be seen as a good point from which to start to assess the relative importance of object and idea gaps at an aggregate level if initial output per worker is highly correlated with the initial level of technological development[1]. Third, the absorbing capability also acts independently of any other variables in the convergence equation because it also determines the equilibrium technological gap that may influence contemporaneous growth. It is therefore, also introduced in the growth regression estimated below. More specifically, I specify the following convergence equation:

$$Growth_i^{60-85} = c + \beta_1 \ln(Y60)_i + \beta_2 (X_i.\ln(Y60_{\max}/Y60)_i + \beta_3 \ln(I/GDP)_i + \beta_4 \ln(n+g+\delta) + \beta_5 X_i + \varepsilon_i \,, \quad (15)$$

where X_i is either H_i or $(Eq/GDP)_i$, and ε_i is a normally distributed error term. The dependent variable is the difference in the logs of output per working-age person over the period. $Y60$ is GDP per working-age person in 1960. The shares of investment in real GDP and labor force growth rates are averages for the period under study, and $(n+g+\delta)$ is assumed to be equal to 0.05 as in Mankiw, Romer, and Weil. Results obtained by the estimation of Equation (15) can, therefore, be directly compared to results obtained with a Mankiw, Romer, and Weil specification where the rate of human capital accumulation is proxied by the average percentage of the working-age population in secondary school ($school$) for the period under study.

Notice that in the Mankiw, Romer, and Weil 's specification, the term $\beta_2(X_i.\ln(Y60_{\max}/Y60)_i + \beta_5 X_i + \varepsilon_i$ is nested within their error term. If $X_i.\ln(Y60_{\max}/Y60)_i$ and/or X_i are correlated with the other right-hand side independent variables, then their conditional convergence regressions should provide biased estimates. This led numerous authors such as Islam (1995) to suggest the use of panel data methods that allow us to uncover country-specific heterogeneity. Another simpler approach, advocated by Temple (1998a-b), consists of carefully specifying regional dummies within cross-country growth regressions. In this study, I rather follow Benhabib and Spiegel, and choose to explicitly specify initial efficiency heterogeneity within a growth model as discussed in the previous section (see also Dowrick and Rogers (2002)). Thus, Equation (15) provides a specification within a convergence equation which potentially reduces possibilities for misspecification that may arise in traditional cross-country growth regressions which do not explicitly consider country-specific effects associated with differences in total factor productivity. Moreover, in contrast to a traditional convergence equation estimated by panel data methods, it has the key advantage to be directly motivated by economic theory. (For a discussion of advantages and drawbacks of the use of panel data methods in growth empirics, see, for instance, Durlauf and Quah (1999).)

Besides the individual specific effect problem discussed above, our estimates explicitly deal with two other problems that have been recognized to affect cross-country growth regres-

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[1] Whether the (log) difference in output per worker is a good proxy for technological heterogeneity remains an open question that I do not explicitly address in the present study.

sions, namely, heteroscedasticity and outliers. First, according to Benhabib and Spiegel, I compute the heteroscedasticity robust standard error of White (1980). Second, following Temple (1998a), I also look for outlying observations and present results issued by applying the reweighted least squares estimation (RWLS) as recommended by Rousseew and Leroy (1987); that is, I first detect highly influential observations by using the so-called Least Trimmed Squares estimator and then apply a classical estimation procedure on the ‘‘cleaned’’ data[1].

Finally, Caselli, Esquivel, and Lefort (1996) claim that there is a crucial role for endogeneity in driving standard results in traditional cross-country growth regressions. Many authors, including Mankiw (1995), have also stressed this potential drawback. To deal with this problem, Caselli et al. propose, as an appropriate estimation procedure, to use generalized method of moments (GMM) as developed by Arellano and Bond (1991) and to estimate a dynamic panel data model. First, Bernanke and Gürkaynak (2001) explicitly test the conjecture that cross-country growth regressions may indeed face endogeneity biases associated, for instance, with a Ramsey type growth model, and conclude (p. 16): ‘‘one cannot reasonably account for the observed correlation of saving and growth as reflecting the endogenous response of the former to the latter.’’ Moreover, they also estimate an Uzawa-Lucas (1988) type model where the rate of human capital formation in the steady state is assumed to be endogenous. However, they find that this type of model must be rejected as literal description of the data. To conclude, they add (p. 29): ‘‘... Future research should consider variants of endogenous growth models to see which if any provide a more complete and consistent description of the cross-country data’’. This article aims to go through that direction. Second, GMM requires the use of instruments which, by definition, must be uncorrelated with the error term. Usually, lags of the regressors are used. As emphasized, for instance, by Durlauf and Quah (1999), and Temple (1999), the problem is that if saving rates and the rate of labor force growth are persistent in the course of the study, then their GMM’s estimator can be expected to perform badly. (See for instance, Easterly et al. (1993) who find that country characteristics, and especially rates of factor accumulation display high persistence, with cross-decade correlations ranking from 0.6 to 0.9 between the 60s and 70s and between the 70s and 80s.) More generally, Durlauf (2001) while discussing what he calls the ‘‘open-ended’’ feature of growth theories, argues (p. 66): ‘‘...Yet, those studies which attempt to use instrumental variables to address regressor endogeneity have not yet been persuasive in that the choices of instruments have not met the necessary exogeneity requirements for instrument validity.’’ For ease of comparison with most studies I refer to, I therefore choose to concentrate on results issued by traditional cross-country growth regressions following a specification as described by Equation (15).

4. Growth Regressions Over a Benchmark Period: 1960-1985

4.1. Rates of Accumulation Versus Levels of Human Capital

The results of estimating Equation (15) are presented in Table 1 for three samples that intersect with the non-oil, the intermediate and the OECD samples of countries analyzed by Mankiw, Romer, and Weil along with an estimation of their augmented Solow model. From now on, I call them the MRW and the NP models. The MRW estimations are used as benchmark regressions that I compare to the regressions obtained with the above competing NP model. Although, the MRW model is initially estimated on a sample of 73 non-oil countries instead of 98 in the original contribution, estimations by using these two samples provide very similar results. This is equally true for the intermediate and OECD samples. (See Table V, p. 426, of Mankiw, Romer, and Weil’s (1992) article and results reported in columns 1, 5, and 9 of Table 1.)

The goodness of fit as measured by the adjusted-R^2 and the Akaike information criterion (AIC) that take into account the trade-off between the goodness of fit and the complexity of the

[1] A key parameter that is needed in that procedure is the trimming constant that determines the breakdown point of the LTS estimator. For both the non-oil and the intermediate samples, respectively the OECD sample, it is set to about two-thirds, respectively three-quarters, of the total number of observations present in the original sample of countries as listed in Appendices A and C.

models, does not allow us to discriminate between both models or to choose the best model among the two, whatever OLS or RWLS estimations are used.

Before I turn to formal specification test, it is however worth stressing that the main finding of conditional convergence, that is, a low initial level of income is associated with a high subsequent growth rate, still holds for both the MRW and the NP specifications whatever the sample used, and as long as we rely on results provided by the RWLS procedure. The coefficient, however, is smaller in the NP as compared to the MRW specification, therefore suggesting a lower speed of convergence because of decreasing returns once one controls technological catch-up opportunities. Second, and more important for our discussion, is the positive relationship between our interactive term which is intended to capture technological catch-up, and growth in all three samples. It is interesting that despite the inclusion of the neoclassical convergence term in the NP specification, it is significantly different from zero with at least a 5% level of confidence in both the intermediate and OECD samples. Still, it loses significance when one considers the larger sample of non-oil countries (p-values are equal to 0.06 (0.15) when issued by OLS (RWLS) estimation). Finally, although not significantly different from zero, the coefficients associated with the stock of human capital are always positive. These results are in sharp contrast with those obtained by Benhabib and Spiegel (see their Table 5, p. 162).

It is well-known that multicollinearity is an essential feature of international data at an aggregated level and that results obtained from almost all cross-country growth regressions remain very sensitive to the chosen specification (see Levine and Renelt (1992))[1]. In the light of the correlation matrices available in Appendix B and as the conditional figures available in Table 1 indicate, multicollinearity is a more serious problem in the NP when compared to the MRW specification. However, suggestion that the results might be different if the data were not collinear has little practical value. Once the largest available set of observations is introduced in the estimation, there is no satisfying remediation to multicollinearity. Dropping troublesome variables leads to begging the problem of specification error which is exactly what we try to overcome with the NP specification. Using a principal components estimator involves using a weighted average of the dependent variables. This would result in the inability to discriminate between the individual magnitude of the effect of the independent variables. Another alternative regression technique is ridge regression, but it yields biased estimators. If multicollinearity reduces the precision with which coefficients are estimated by inflating their variance when OLS are used, it, however, yields unbiased estimates. Moreover, multicollinearity does not invalidate a theoretical model.

Notice that the main effect and the interaction effect of both the log of GDP per working-age person in 1960 and the average secondary-school education stock on economic growth as they are specified in Equation (15), in no instance represent a constant effect of the corresponding independent variable on the dependent variable. The inclusion of the interaction term indeed leads the effect of the log of GDP per working-age person in 1960 to vary according to each value of the average secondary-school education stock, meaning that its associated relevant p-value can only be derived at a particular value of H. In Table 2, I therefore provide summary statistics of these distributions; that is, both the mean and variance of the parameter estimates of the marginal effect of ln(Y60) and H, as well as the average marginal significance level of a two-tailed test of the hypothesis that the marginal effect is equal to zero with both its variance and the number of observations for which this null hypothesis cannot be rejected at the 10 (respectively 5) percent significance level.

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[1] A novel approach which explicitly deals with model uncertainty, namely, Bayesian Averaging of Classical Estimates (BACE), has recently been proposed by Doppelhofer, Miller, and Sala-i-Martin (2000). At issue is to check the importance of explanatory variables in cross-country growth regressions. Among 11 explanatory variables which are found to be robustly partially correlated with long run growth, the strongest evidence appears to be for the initial level of real GDP per capita. Unfortunately for our purpose, neither an interaction term that captures the technological catch-up effect as specified in Equation 15 is included yet among their 32 explanatory variables under study, nor Levine and Renelt introduce it in their set of estimated growth equations.

Table 1

Tests for neoclassical convergence and technological catch-up where the absorption capability of a nation is approximated by its stock of education at secondary levels

[a]Dependent variable: difference in the logs of GDP per working-age person (1960-1985)

Sample	Non-oil				Intermediate				OECD			
	[b]OLS		[c]RWLS		OLS		RWLS		OLS		RWLS	
Observations	N=73		N=69		N=65		N=61		N=21		N=17	
	[d]MRW	[d]NP	MRW	NP	MRW	NP	MRW	NP	MRW	NP	MRW	NP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	2.58	2.06	2.63	2.53	3.01	1.71	2.96	2.23	3.05	-0.03	1.41	-0.28
	[e](0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.02)	(0.98)	(0.01)	(0.44)
ln(Y60)	-0.27	-0.19	-0.24	-0.21	-0.36	-0.18	-0.31	-0.20	-0.38	-0.05	-0.33	-0.16
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.58)	(0.00)	(0.00)
$H.\ln(Y60_{max}/Y60)$		0.14		0.09		0.18		0.13		0.27		0.21
		(0.06)		(0.15)		(0.02)		(0.03)		(0.01)		(0.00)
ln(I/GDP)	0.57	0.57	0.70	0.68	0.48	0.51	0.62	0.63	0.28	-0.04	-0.09	-0.22
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.83)	(0.31)	(0.01)
$\ln(n+g+\delta)$	-0.57	-0.29	-0.45	-0.27	-0.73	-0.37	-0.60	-0.34	-0.74	-0.40	-0.92	-0.66
	(0.02)	(0.21)	(0.02)	(0.19)	(0.00)	(0.14)	(0.00)	(0.11)	(0.00)	(0.10)	(0.00)	(0.00)
ln(school)	0.15		0.06		0.27		0.16		0.27		0.23	
	(0.09)		(0.39)		(0.01)		(0.03)		(0.03)		(0.00)	
H		0.07		0.06		0.04		0.03		-0.13		0.03
		(0.36)		(0.41)		(0.59)		(0.65)		(0.17)		(0.51)
Adj. R^2	0.465	0.477	0.603	0.620	0.448	0.423	0.590	0.592	0.638	0.720	0.873	0.955
AIC	41.2	40.7	10.7	8.7	30.3	34.1	0.7	1.4	-18.1	-22.4	-38.1	-46.4
[f]κ	3.62	4.62	3.69	4.64	3.62	4.50	3.70	4.52	1.68	6.37	1.90	7.08

Sample		Unrepresentative observations dropped in RWLS
Non-oil	MRW	Chile, Morocco, Singapore, Zambia
(N=69)	NP	Chile, Morocco, Singapore, Zambia
Intermediate	MRW	Chile, Morocco, Singapore, Zambia
(N=61)	NP	Chile, Morocco, Singapore, Zambia
OECD	MRW	Ireland, Japan, Norway, United Kingdom
(N=17)	NP	Ireland, Norway, Spain, United Kingdom

Notes:

a. All variables are borrowed from Mankiw, Romer, and Weil's (1992), except for the average education stock over the period (H) which is calculated with data provided by Nehru et al. (1995).

b. Ordinary Least Squares estimation.

c. Reweighted Least Squares estimation as recommended by Rousseeuw and Leroy (1987).

d. MRW corresponds to the Mankiw, Romer, and Weil specification. NP is for Nelson and Phelps and corresponds to the specification as described by Equation (15) in the text.

e. p-values, i.e., the marginal significance level of a two-tailed test of the hypothesis that the coefficient is equal to zero, are in parenthesis under coefficient estimates. White's heteroscedasticity correction used.

f. κ is the conditional number measuring collinearity.

Table 2

Marginal effect of both the convergence rate and the stock of education at secondary levels on economic growth over the period of1960-1985

[a]Marginal effect of both the convergence rate and the stock of human capital on economic growth (1960-1985)

Sample	Non-oil				Intermediate				OECD			
	N=73		[b]N=69		N=65		[b]N=61		N=21		[b]N=17	
ln(Y60)	[c]m.e.	[d]p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value
Mean	-0.27	(0.00)	-0.26	(0.00)	-0.29	(0.00)	-0.29	(0.00)	-0.40	(0.01)	-0.42	(0.00)
Variance	0.007	0.000	0.003	0.000	0.013	0.000	0.006	0.000	0.032	0.001	0.018	0.000
n.s. obs.		0(0)		0(0)		0(0)		0(0)		0(1)		0(0)
H	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value
Mean	0.31	(0.02)	0.21	(0.04)	0.32	(0.03)	0.23	(0.05)	0.07	(0.43)	0.18	(0.05)
Variance	0.016	0.003	0.007	0.005	0.024	0.009	0.012	0.015	0.018	0.154	0.013	0.016
n.s. obs.		4(6)		6(12)		5(10)		11(13)		14(14)		1(3)

Notes:

a. Given Equation (15), the marginal effect of ln(Y60), respectively of H, on growth rates, is β_1-β_2H, respectively $\beta_5+\beta_2$ ln($Y60_{max}$/Y60).

b. Sample used after an outlier detection. Unrepresentative observations dropped out from the procedure are listed in Table 1.

c. Both mean and variance of the parameter estimates of the marginal effect of ln(Y60) for different values of H, respectively of H for different values of ln($Y60_{max}$/Y60).

d. p-values, i.e., the average marginal significance level of a two-tailed test of the hypothesis that the marginal effect is equal to zero, are in parenthesis with, below, both the associated variance and the number of observations for which the null hypothesis cannot be rejected at the 10 (5) percent significance level. White's heteroscedasticity correction used.

First, it is interesting that the impact of ln(Y60) on economic growth is significantly different from zero at the 5% level for all values of H in all three samples with only one exception in the OECD sample. Second, the effect of H conditional upon values of ln($Y60_{max}$/Y60) is now, on average, significant at least at the 5% level; being non significant for only 5 to 20% of the values of ln($Y60_{max}$/Y60), except for the OECD sample when an OLS estimation procedure is used. Finally, the average marginal effect of the convergence rate in the NP specification now gets closer to the neoclassical convergence rate in the MRW model, therefore strengthening the conjecture that indeed, not only convergence reflects diminishing returns to capital but it also involves the spread of technology. In other words, the world is not composed of economies that all benefit from the state of the art of technology which is considered in a neoclassical framework as a pure public good, but of economies that do not have access to the same level of technology, and that may benefit from their lagging behind according to their absorption capability as proxied, for instance, by their stock of human capital.

In order to discriminate between our two competing specifications, I now turn to testing between the MRW and the NP models that are nonnested models as they are characterized by non-overlapping independent variables. (See also Bleaney and Nishiyama (2002) for a contest of seminal empirical growth models.) I apply a JA-test which has the advantage over, for instance, the J-test developed by Davidson and MacKinnon (1981), to remain valid for small samples and to be a robust test when the number of variables specified in each model is quite similar[1].

[1] The JA-test is a nonnested test derived by Fisher and McAleer (1981). It is based on artificial regressions. Suppose we have two competing models of the form: H_0: $E(Y)=X_1\beta_1$ vs H_1: $E(Y)=X_2\beta_2$.
The question is: to what extent the model specified under the null hypothesis is capable of predicting the performance of the model specified under the alternative hypothesis? And the procedure is as follows:
(i) obtain the predictions Y_0 of Y from the model specified in the null hypothesis by applying the Least Squares method;
(ii) obtain the predictions $Y_{0,1}$ of Y_0 from the model specified in the alternative hypothesis;
(iii) augment the model specified in the null hypothesis by the single variable $Y_{0,1}$ and test the significance of its coefficient;
(iv) the null hypothesis is rejected if the coefficient is significantly different from zero.

Results of the test are provided in Table 3 where the p-values give the probability of being wrong when rejecting the model specified in the null hypothesis. Concerning the non-oil sample, when the MRW model is specified as the null hypothesis and the NP model as the alternative hypothesis, it cannot be rejected at a 5% significance level. However, this does not mean that it must necessarily be preferred to the NP model or that the latter is not also capable of predicting the performance of the MRW model[1]. Once the models are reversed with the previous alternative hypothesis becoming the null, the testing procedure tends to reject the MRW model with a much smaller probability (12% compared to 41%) of committing a first error type, i.e., to reject it though it is the true model. Hence, there is no evidence that the NP model is misspecified. What is more, it may be preferred to the MRW model given the type one error probabilities. Notice however that the opposite holds when the intermediate sample is considered.

Given that the same outlying observations have been dropped out from the RWLS estimation in both the non-oil and intermediate samples, I also test how both models match up against one another when outlying observations are removed from the original samples. Once the testing procedure is applied to the cleaned data, it yields an unambiguous result for the non-oil sample where one would be wrong with a 90% probability in rejecting it against the MRW model. For the intermediate sample, the result is now mixed: the probabilities to be wrong in rejecting one of the models against the other are indeed very close. There is no longer clear evidence that one model dominates the other. The same non nested test between the MRW and NP estimation frameworks applied to the OECD group of countries are also available in Table 3. When considering the original sample of 21 countries, the test fails to reject any of the candidate models. On the contrary, when Ireland, Norway, and the United Kingdom, three outliers shared by both estimation frameworks, are dropped, the test tends to reject both models at a 10% significance level. Therefore, each model may represent a partial truth of the transition pattern experienced by OECD countries or, equivalently, each model may significantly improve the other.

On the one hand, while the neoclassical revival left no room to technological knowledge disparities, it seems that human capital cannot be viewed, at least entirely, as a factor of production. On the other hand, the above empirical evidence supports the importance of human capital as a factor which facilitates the adoption and dissemination of technical advances. It also suggests that the MRW model is very likely to be misspecified, its error structure being contaminated by omitted variables. In a broader perspective, and following Romer's comment on Mankiw's (1995) article, ''The Growth of Nations'', one may argue that the neoclassical model does indeed not go far enough and that there is some room to enrich it. For instance, it may be seen as a model nested within an encompassing specification that includes both the human-capital augmented model of Mankiw, Romer, and Weil and the endogenous approach favored by Nelson and Phelps. To test the empirical validity of such an argument, I make use of nested specification testing as proposed by Breusch and Pagan (1980)[2]. The results of such a test procedure are provided in Table 4. Again, in this table, p-values give the probability to be wrong when rejecting the nested model specified under the null. Notice that because the rationale behind both the JA and the LM tests is that of the encompassing principle and that the set of variables specified in each model (MRW and NP) is

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[1] Nonnested hypothesis tests do not formulate the hypothesis in a complementary way as in nested hypothesis tests because one model cannot be obtained from the other by imposing a restriction. There are therefore four possible outcomes: (i) both models are rejected, (ii) both models are accepted, (iii) the NP model is accepted and the MRW model is rejected, (iv) the MRW model is accepted and the NP model is rejected.

[2] The Lagrange Multiplier test for nested models applied here has been derived by Breusch and Pagan (1980) who have shown that for linear hypothesis on linear models, the LM principle involves only two OLS regressions. The test procedure is as follows:

(i) the null hypothesis specifies either the MRW or the NP model as a restricted version of the alternative hypothesis that specifies a more general specification that encompasses both estimation frameworks;

(ii) estimate the residuals from the nested model;

(iii) regress them on the original variables from the model under the alternative hypothesis;

(iv) calculate the statistic NR^2 from this second regression, where N is the number of observations;

(v) compare it with the critical 5 percent value of a chi(2,M) where M is the number of constraints implied by the null hypothesis. If NR^2 is greater than chi(2,M), we reject the null hypothesis with a 5 percent first error type probability; i.e., to reject the null when it is true.

quite similar, it is not surprising that results provided in Tables 3 and 4 essentially deliver the same information when applied to identical samples of non-oil and intermediate countries whatever OLS or RWLS is used. Still, in contrast to Table 3, when we focus on OECD countries, the test now tends to reject the MRW specification as a special case of our extended model with an almost zero probability to be wrong while the NP specification cannot be rejected at a 5% confidence level.

Table 3

Nonnested hypothesis test: MRW versus NP

[a]JA-test (1960-1985)

Sample		Non-oil		Intermediate		OECD	
		N=73	[b]N=69	N=65	[b]N=61	N=21	[b]N=18
H0	H1						
MRW	NP	0.12	0.10	0.34	0.26	0.42	0.07
NP	MRW	0.41	0.93	0.04	0.26	0.20	0.05
		[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value

Notes:

a. The JA-test performs a test of specification of non nested models as described in the text.

b. Sample used after an outlier detection. Unrepresentative observations dropped out from the procedure are listed in Table 1. For the OECD sample, Ireland, Norway, and the United Kingdom, the three common outliers to both the MRW and NP specifications have been removed.

c. The p-values give the probability of being wrong when rejecting the model specified under the null hypothesis. White's heteroscedasticity correction used.

Table 4

Nested hypothesis test: MRW and NP versus a more general specification which includes both the MRW and the NP models

[a]LM test (1960-1985)

Sample	Non-oil		Intermediate		OECD	
	N=73	[b]N=69	N=65	[b]N=61	N=21	[b]N=18
H0						
MRW	0.17	0.14	0.30	0.24	0.03	0.00
NP	0.38	0.92	0.04	0.23	0.14	0.07
	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value

Sample	Unrepresentative observations dropped in RWLS
Non-oil (N=69)	Chile, Morocco, Singapore, Zambia
Intermediate (N=61)	Chile, Morocco, Singapore, Zambia
OECD (N=18)	Ireland, Norway, United Kingdom

Notes:

a. The LM-test performs a test of specification of nested models as described in the text.

b. The test procedure is issued by the use of RWLS; that is, unrepresentative observations identified within the general specification have been dropped.

c. The p-values give the probability of being wrong when rejecting the nested model specified under the null hypothesis.

The extended theoretical framework provided above is only slightly more complicated than the neoclassical model with exogenous technological change. Nevertheless, it reveals itself to be either a reliable alternative or a complementary model depending on the sample of countries under study, compared to the human capital augmented neoclassical growth model originally proposed by Mankiw, Romer, and Weil.

4.2. ''Idea Gaps and Object Gaps in Economic Development'' Revisited

First, Parente and Prescott (1994) provide a theory of economic development in which technology adoption and barriers to such adoptions depend on how much a firm invests to advance its technology. Second, a key finding of the ''new'' empirics of economic growth is the importance of investment in equipment as an exceptional source of economic growth. In seminal contributions, De long and Summers (1991, 1993) argue that implied social returns to equipment investment are far above the private returns (see also Temple (1998b) who checked on the robustness of this relationship to outliers). However, De Long and Summers (1991) also find that this result is not robust to tests for interaction with an income gap variable for high-income countries. As a consequence, they suggest that their high estimate may, to some extent, reflect catching up. More specifically, they note (p. 467-468):

> *''We find very attractive the idea that a high social product of equipment investment reflects technology transfer mediated through capital goods, and thus that the social product is higher for poorer countries with more of a technology gap to bridge. But the data do not speak reliably enough on this point for us to be willing to do more than point out that the question is intriguing and potentially very important, and the evidence is not conclusive.''*

If De Long and Summers are so cautious in suggesting that their high estimates may indeed reflect technological catch up, this is because their results are not robust to sample expansion. In this section, I follow this line of research and re-estimate Equation (15), but where the absorption capacity of a nation is now approximated by the average share of equipment investment in output (henceforth OIG for Object and Idea Gaps model). Results are provided in Table 5 and are directly comparable to those obtained in Tables 1 and 2.

Note first that the goodness-of-fit criteria are better for the non-oil and intermediate samples compared to those obtained with the estimations of both the MRW and NP models in Table 1, but are slightly inferior in the case of the OECD sample, especially in comparison with the NP specification.

Results for the non-oil and intermediate samples may intrigue the reader. When ordinary least squares are applied, the interaction term fails to be significantly different from zero, while conditional convergence is significantly at work, therefore partially corroborating the results found by De Long and Summers (1991). Moreover, the term Eq/GDP is significant at about a 10% confidence level despite the inclusion of the investment ratio whose coefficient is on the other hand always associated with a close to zero p-value. However, these results are not robust to outliers. Results issued by reweighted least squares, offer a different explanation of cross-country economic growth. Indeed, once unrepresentative observations are dropped, the interaction term becomes substantively significant while the neoclassical convergence term now fails to be significantly different from zero anymore (its p-values are equal to 0.32 (0.14) for the non-oil (intermediate) sample). Finally, while the investment share term remains highly significant, the term Eq/GDP is now statistically insignificant, changing sign in the case of the non-oil sample.

In the light of the correlation matrices available in Appendix B, it is worth noticing that besides creating high variances of coefficients estimates, we can expect multicollinearity to yield large changes in parameter estimates once a set of observations are removed from the original sample. First, given the presence of the product term in the OIG specification, it is interesting that the marginal impact of the log of GDP per working-age person in 1960 is substantively significant for almost all values of the equipment investment output ratio except for the OECD sample when the RWLS estimation procedure is used.

Second, the marginal impact of Eq/GDP for different values of the initial output per worker also reveals itself to be significantly different from zero at the 5% level for, at least, 75% of the observations for the non-oil and intermediate samples, therefore, supporting De Long and Summers alternative view that equipment investment may indeed accompany technology transfer.

Table 5

Tests for neoclassical convergence and technological catch-up where the absorption capability of a nation is approximated by its equipment investment output ratio

[a]Dependent variable: difference in the logs of GDP per working-age person (1960-1985)

Sample	Non-oil		Intermediate		OECD	
	[b]OLS	[b]RWLS	OLS	RWLS	OLS	RWLS
Observations	N=73	N=65	N=65	N=58	N=21	N=18
Constant	1.30	1.26	1.18	1.15	-1.68	3.39
	[c](0.18)	(0.10)	(0.25)	(0.16)	(0.26)	(0.06)
ln(Y60)	-0.17	-0.06	-0.19	-0.09	0.09	-0.87
	(0.03)	(0.32)	(0.02)	(0.14)	(0.65)	(0.00)
Eq/GDP.ln($Y60_{max}$/Y60)	2.22	4.26	1.77	3.73	6.83	-11.03
	(0.18)	(0.01)	(0.31)	(0.01)	(0.04)	(0.01)
ln(I/GDP)	0.42	0.58	0.35	0.50	-0.13	-0.35
	(0.00)	(0.00)	(0.03)	(0.00)	(0.50)	(0.02)
ln(n+g+δ)	-0.37	-0.22	-0.44	-0.27	-0.41	-1.47
	(0.09)	(0.22)	(0.06)	(0.13)	(0.11)	(0.00)
Eq/GDP	3.42	-0.76	4.07	0.50	-0.63	10.73
	(0.11)	(0.73)	(0.06)	(0.81)	(0.84)	(0.00)
Adj. R^2	0.537	0.719	0.480	0.699	0.743	0.835
AIC	31.77	-8.31	27.45	-14.21	-24.23	-40.55
[d]κ	6.10	6.27	6.02	6.20	9.19	15.12

[e]Marginal effect of both the convergence rate and equipment investment output ratio

		[f]m.e.	[g]p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value
ln(Y60)	Mean	-0.26	(0.00)	-0.24	(0.02)	-0.27	(0.01)	-0.26	(0.00	-0.43	(0.00)	-0.06	(0.24)
	Vari-	0.006	0.000	0.022	0.003	0.004	0.000	0.016	0.000	0.023	0.000	0.054	0.096
	n.s. obs.		0(0)		3(6)		0(0)		0(1)		0(0)		9(10)
Eq/GDP	Mean	7.16	(0.01)	6.25	(0.12)	6.84	(0.01)	6.30	(0.07)	4.40	(0.20)	3.37	(0.11)
	Vari-	3.914	0.000	13.67	0.060	2.279	0.000	10.21	0.023	12.17	0.079	27.60	0.058
	n.s. obs.		1(1)		14(14)		0(1)		11(13		10(11		3(5)

	Unrepresentative observations dropped in RWLS
Non-oil (N=65)	CHL, CMR, ETH, JAM, MAR, UGA, VEN, ZMB
Intermediate (N=58)	CHL, CMR, JAM, MAR, PRY, VEN, ZMB
OECD (N=18)	GBR, GRC, JPN

Notes:

a. All variables are borrowed from Mankiw, Romer, and Weil's (1992), except for the equipment investment data (Eq/GDP) which comes from De Long and Summers (1993).

b. Ordinary Least Squares estimation and Reweighted Least Squares estimation as recommended by Rousseeuw and Leroy (1987).

c. p-values, i.e., the marginal significance level of a two-tailed test of the hypothesis that the coefficient is equal to zero, are in parenthesis under coefficient estimates. White's heteroscedasticity correction used.

d. κ is the conditional number measuring collinearity.

e. Given the interaction effect, the marginal impact of ln(Y60), respectively of Eq/GDP , on growth rates, is β_1-β_2(Eq/GDP), respectively β_5+$\beta_2$ln($Y60_{max}$/Y60).

f. Both mean and variance of the parameter estimates of the marginal effect of ln(Y60) for different values of Eq/GDP , respectively of Eq/GDP for different values of ln($Y60_{max}$/Y60).

g. p-values, i.e., the average marginal significance level of a two-tailed test of the hypothesis that the marginal effect is equal to zero, are in parenthesis with, below, both the associated variance and the number of observations for which the null hypothesis cannot be rejected at the 10 (5) percent significance level. White's heteroscedasticity correction used.

Observations dropped in RWLS are quite different in the OIG model compared to the MRW and NP models. Therefore, I only estimate whether improvements can be made by combining all the independent variables from the different models in an encompassing model which either nests the MRW and the OIG models or includes the NP and the OIG models (Table 6). Let us first focus on an extended MRW specification which explicitly incorporates technological catch-up where the absorption capability of a nation is approximated by its equipment investment in output. It is interesting that, in contrast to Table 4, whatever the sample under study and whatever OLS or RWLS, the MRW model is now always rejected as a nested model within the more general specification with an almost zero probability to be wrong in doing so. While the same is true for the non-oil and intermediate samples in the case of OLS regressions when the OIG model is specified under the null, the test does not allow us to reject the OIG model as nested when RWLS estimation is used. Again, this constitutes evidence that the MRW model can be significantly improved by taking into consideration technological differences in a large cross-section of nations. Technological catch-up indeed takes place and reveals itself to be a key factor which underlies the world income distribution dynamics. Still, the opposite remains true for the OECD sample. The OIG model specified under the null cannot be rejected in the OLS regression, while it is with only a 1% probability to be wrong in the RWLS estimation.

As a consequence, despite the high correlation between both the stock of human capital and the share of equipment investment in output, I now ask whether both capture different and independent notions of the absorption capacity of a nation to implement the successive advances in the best-practice technology? In other words, can technological catch-up depend upon a combination of both proxies for the absorption capability of a nation? While the NP model can be rejected as a nested model with an infinitesimal probability to commit a first error type, the opposite holds for the OIG model in the non-oil and intermediate samples. In contrast, the importance of human capital as a proxy for the absorption capability of an economy cannot be rejected at a 10% significance level in the OECD sample, therefore suggesting that the technological catch-up phenomenon may rely more strongly on different types of absorption capability depending on the stage of economy development. In other words, and as results available in both Tables 4 and 6 suggest, it seems likely that the above competing theories may well fit different sets of countries. This corroborates Durlauf (2001) who argues (p. 68): ‘‘...Empirical growth studies virtually always assume that one theory is equally valid for all countries, whereas it is far more natural to think that a given theory will explain the growth experience of each country more or less well depending on the country’s individual characteristics’’. Quah (1996, 1997) provides interesting patterns of the evolution of cross-section income distributions. I now turn to estimate counterfactual income distributions issued by the different above estimated models.

5. Counterfactual Income Dynamics Over the Period of 1960-1995

A question that originally motivated the convergence literature is: what will the distribution of output per worker look like in the future? In this section, following Di Nardo, Fortin, and Lemieux (1996), I rather look at counterfactual dynamics of the world income distribution implied by either the MRW and NP frameworks or a more general specification that nests both the MRW and NP models over the period of 1960-1995.

5.1. Rates of Accumulation Versus Levels of Human Capital Over the Period of 1960-1995

In the previous section, our aim was to evaluate whether a simple growth model that explicitly takes into consideration technological catch-up could help us to understand economic growth. I did so by focusing on a period of 19601985, which has been the reference of most influential contributions on the empirics of growth over the last decade. Worldwide international data have now been updated to 1995. Thus, before analyzing the world income dynamics, I first replicate results obtained in the previous section and reassess the empirical relevance of the two competing models by extending the results through 1995. Data are from the same sources as Mankiw, Romer, and Weil and are those collected and used by Bernanke and Gürkaynak (2001), except for the average stock of human capital variable (H) which now consists in the educational attainment at the secondary level series provided by Barro and Lee (2001). This leads the sample under study to be slightly different compared to the previous section (see Appendix C). However, to be reliable, the above results should be robust to the choice of both the sample of countries under study and to the variable used as a proxy for the stock of human capital[1]. Table 7 provides the results.

First, both models still explain a significant part of the variation of economic growth across countries. The goodness of fit as measured by the adjusted-R^2 even improves compared to the period of 1960-1985 whatever the sample under study and whatever OLS or RWLS estimation is used, except in the case of the NP model for the OECD sample. Second, in contrast to results in Table 1, the technological catch-up effect on growth is now always significantly positive in both the non-oil and the intermediate samples whatever OLS or RWLS estimation is used, but not anymore in the group of OECD countries.

Third, in Section 4, I have already discussed some consequences of estimating a non additive model as specified in Equation (15). Hence, Table 8 provides information on the marginal impact of both the convergence rate and the stock of human capital upon the value of H, respectively of $\ln(Y60_{max}/Y60)$. Similarly to results obtained in Table 2, the marginal impact of ln(Y60) is highly significant with the expected sign for all countries whatever both the sample under study and the estimation procedure, and the effect of H is also always significant at a 5% level for, at least, 75% of the observations except for the OECD sample.

Table 6

Nested hypothesis test: (i) MRW and OIG versus a more general specification which nests both the MRW and the OIG models, (ii) NP and OIG versus a more general specification that includes both the NP and the OIG models

[a]**LM test (1960-1985)**

Sample	Non-oil		Intermediate		OECD	
	N=73	[b]N=63	N=65	[b]N=55	N=21	[b]N=18
H0						
MRW	0.00	0.00	0.00	0.00	0.03	0.00
OIG	0.05	0.81	0.00	0.22	0.71	0.01
	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value
	Unrepresentative observations dropped in RWLS					
Non-oil (N=63)	ARG, BGD, CHL, CMR, ETH, JAM, MAR, UGA, VEN, ZMB					
Intermediate (N=55)	ARG, BGD, CHL, CMR, ETH, JAM, MAR, PRY, VEN, ZMB					
OECD (N=18)	AUT, GBR, PRT					
	N=73	[b]N=66	N=65	[b]N=59	N=21	[b]N=18
H0						
NP	0.01	0.01	0.01	0.00	0.10	0.11
OIG	0.22	0.56	0.12	0.44	0.22	0.01
	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value	[c]p-value
	Unrepresentative observations dropped in RWLS					
Non-oil (N=66)	BGD, CHL, CMR, JAM, MAR, UGA, ZMB					
Intermediate (N=59)	CHL, CMR, JAM, MAR, MLI, ZMB					
OECD (N=18)	GBR, IRL, NOR					

Notes:

a. The LM-test performs a test of specification of nested models as described in the text.

b. The test procedure is issued by the use of RWLS; that is, unrepresentative observations identified within the general specification have been dropped.

c. The p-values give the probability of being wrong when rejecting the nested model specified under the null hypothesis.

d. World Bank country codes and associated country names are available in Appendix A.

[1] The estimation procedure used for estimating human capital stock in Barro and Lee (2001) differs from the technique used by Nehru et al. (1995). Therefore, unless one spheres data before hand, underlying differences in location and scale in both series naturally yield completely different coefficient estimates in Tables 7 and 8 compared to Tables 1 and 2. (See both the above references for details).

Table 7

Tests for neoclassical convergence and technological catch-up where the absorption capability of a nation is approximated by its stock of education at secondary levels

[a]Dependent variable: difference in the logs of GDP per working-age person (1960-1995)

Sample	Non-oil				Intermediate				OECD			
	[b]OLS		[c]RWLS		OLS		RWLS		OLS		RWLS	
Observations	N=79		N=73	N=76	N=66		N=63	N=64	N=21		N=17	
	[d]MRW	[d]NP	MRW	NP	MRW	NP	MRW	NP	MRW	NP	MRW	NP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	3.40	1.55	3.14	2.11	5.13	2.23	4.98	3.03	4.59	2.95	5.58	5.76
	[e](0.00)	(0.20)	(0.00)	(0.08)	(0.00)	(0.09)	(0.00)	(0.02)	(0.00)	(0.12)	(0.00)	(0.00)
ln(Y60)	-0.42	-0.25	-0.41	-0.24	-0.53	-0.28	-0.56	-0.31	-0.55	-0.45	-0.55	-0.57
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
H.ln($Y60_{max}$/Y60)		0.03		0.03		0.02		0.02		0.01		0.00
		(0.00)		(0.00)		(0.01)		(0.03)		(0.64)		(0.77)
ln(I/GDP)	0.56	0.60	0.58	0.76	0.70	0.74	0.68	0.81	0.30	0.35	-0.14	-0.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.17)	(0.15)	(0.29)	(0.17)
ln(n+g+δ)	-1.02	-0.81	-1.10	-0.69	-0.97	-0.78	-1.08	-0.65	-1.02	-0.91	-0.25	-0.06
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.03)	(0.01)	(0.03)	(0.21)	(0.75)
ln(school)	0.30		0.28		0.42		0.41		0.43		0.18	
	(0.01)		(0.00)		(0.01)		(0.00)		(0.04)		(0.10)	
H		0.00		0.00		0.00		0.00		0.00		0.00
		(0.95)		(0.58)		(0.76)		(0.72)		(0.97)		(0.47)
Adj. R^2	0.553	0.574	0.690	0.654	0.568	0.544	0.669	0.626	0.746	0.681	0.919	0.915
AIC	83.01	80.13	34.90	55.60	53.81	58.34	24.76	38.65	-14.18	-8.40	-37.70	-35.74
[f]κ	3.57	4.52	3.57	4.52	3.24	4.30	3.33	4.27	2.03	5.33	1.77	4.95

Sample		Unrepresentative observations dropped in RWLS
Non-oil	MRW	Botswana, Hong Kong, Jamaica, Uganda, Zaire, Zambia
	NP	Mozambique, Uganda, Zambia
Intermediate	MRW	Hong Kong, Jamaica, Zambia
	NP	Zambia, Zimbabwe
OECD	MRW	Japan, New Zealand, Norway, Turkey
	NP	Japan, New Zealand, Norway, Turkey

Notes:

a. All variables are borrowed from Bernanke and Gürkaynak (2001), except for the average education stock over the period (H) which is calculated with secondary-school attainment data provided by Barro and Lee (2001).

b. Ordinary Least Squares estimation.

c. Reweighted Least Squares estimation as recommended by Rousseeuw and Leroy (1987).

d. MRW corresponds to the Mankiw, Romer and Weil specification. NP is for Nelson and Phelps and corresponds to the specification as described by Equation (15) in the text.

e. p-values, i.e., the marginal significance level of a two-tailed test of the hypothesis that the coefficient is equal to zero, are in parenthesis under coefficient estimates. White's heteroscedasticity correction used.

f. κ is the conditional number measuring collinearity.

Table 8

Marginal effect of both the convergence rate and the stock of education at secondary levels on economic growth over the period of 1960-1995

[a]Marginal effect of both the convergence rate and the stock of human capital on economic growth (1960-1995)

Sample	Non-oil				Intermediate				OECD			
	N=79		[b]N=76		N=66		[b]N=64		N=21		[b]N=17	
ln(Y60)	[c]m.e.	[d]p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value
Mean	-0.46	(0.00)	-0.45	(0.00)	-0.49	(0.00)	-0.50	(0.00)	-0.53	(0.01)	-0.60	(0.00)
Variance	0.042	0.000	0.042	0.000	0.033	0.000	0.024	0.000	0.002	0.00	0.000	0.000
n.s. obs.		0(0)		0(0)		0(0)		0(0)		0(0)		0(0)
H	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value	m.e.	p-value
Mean	0.04	(0.05)	0.03	(0.09)	0.03	(0.10)	0.02	(0.13)	0.01	(0.57)	0.01	(0.18)
Variance	0.000	0.026	0.000	0.045	0.000	0.048	0.000	0.061	0.000	0.034	0.000	0.016
n.s. obs.		11(11)		12(15)		12(16)		16(17)		21(21)		12(15)

Notes:

a. Given Equation (15), the marginal effect of ln(Y60), respectively of H, on growth rates, is β_1-β_2H, respectively β_5+β_2 ln(Y60$_{max}$/Y60).

b. Sample used after an outlier detection. Unrepresentative observations dropped out from the procedure are listed in Table 7.

c. Both mean and variance of the parameter estimates of the marginal effect of ln(Y60) for different values of H, respectively of H for different values of ln(Y60$_{max}$/Y60).

d. p-values, i.e., the average marginal significance level of a two-tailed test of the hypothesis that the marginal effect is equal to zero, are in parenthesis with, below, both the associated variance and the number of observations for which the null hypothesis cannot be rejected at the 10 (5) percent significance level. White's heteroscedasticity correction used.

5.2. Counterfactual Income Density Estimates

The effect of the different theoretical frameworks on the world income dynamics are estimated by applying kernel density methods (see for instance, Silverman (1986)). Practical application of kernel density estimation is crucially dependent on the choice of the smoothing parameter. In the following analysis, I use the plug-in method of Sheather and Jones (1991) as bandwidth selector that is also chosen by Di Nardo, Fortin, and Lemieux.

In the upper boxes of Figure 2, both univariate and bivariate density estimates of the world real output per working-age person are displayed. Notice that the so-called phenomenon of twin peaks distribution dynamics across countries is still at work over the period of 1960-1995. The dynamics of the cross-section distribution of countries exhibit polarization. The middle-income class vanishes leading to a group of rich countries which tends to collect together and to the formation of a development trap (see Quah, 1996).

Notice that for the larger set of non-oil countries, the MRW (NP) specification could (not) be rejected at a 5% significance level as nested within a more general specification that includes both the MRW and the NP theoretical frameworks whatever OLS or RWLS is used. Is this more general specification better able to fit such distribution dynamics compared to the standard neo-classical model as proposed by Mankiw, Romer, and Weil? To answer this question, I estimate counterfactual income distribution issued by standard growth regressions over the period of 1960-1995 and applied to the ‘‘cleaned’’ sample of non-oil countries (N=73) as estimated in Table 7 for the MRW specification.

Such counterfactual income density estimates are plotted in the lower left-hand box of Figure 2 where I superimpose both counterfactual income density estimates that would have been observed at the end of the period of 1960-1995 if the growth model was either the MRW (solid line) or the nested (dotted line) model and the true income density estimate in 1995 (thick line). Following Di Nardo, Fortin, and Lemieux, I also plot in the lower right-hand box of this figure the difference between the density estimate of the world income distribution in 1995 and each counterfactual density implied by either the MRW (solid line) or the nested (dotted line) model. The closer to the zero line and the flatter the estimated line is, the better the counterfactual density estimate fits the shape of the observed income distribution at the end of the period. The local impact of each model on the evolution of the world income distribution can now be clearly seen.

First, taking into consideration the impact of technological backwardness associated with the absorption capacity of a nation enables us to better capture the formation of the development trap as illustrated by the lower tail of the true distribution at the end of the period under study. There is indeed more mass at the bottom of the counterfactual income density estimate implied by the nested specification compared to the MRW model. Second, the impact of the technological catch-up phenomenon also allows us to better fit the vanishing of the middle-income class, as well as the bump that took place in the upper tail of the true income density estimate in 1995. Finally, even though we now explicitly take into consideration the opportunity to catch up which substantially contributes to a better understanding the worldwide income dynamics, the U-shape in the lower right-hand box reveals that the twin-peakedness expression of the income distribution still remains partially unexplained. Indeed, none of them are able to completely pick up the mechanism which drives the convergence phenomenon, respectively the development trap formation, occurring in the upper tail, respectively the lower tail, of the income density estimate observed at the end of the period. However, the final impact of the technological catch-up effect substantively improves the local fit and reveals itself to contribute to the polarization of the world income distribution.

6. Conclusion

In this article, I take seriously two alternative theoretical models that have been proposed to explain international growth rates' differences. These differences led to dramatic inequalities in the quality of life that is feasible to the world population. As both approaches have different implications in terms of the development policies and strategies that should be undertaken to lead poorer countries to catch up with richer ones, it is important that growth researchers focus on finding a consensus about the relative importance of the different mechanisms that may offer to poorer countries the opportunity to catch up.

In the mid-80s, because growth rates were not converging to similar levels, growth researchers developed models in which technological progress is endogenous (see, for instance, Lucas (1988) and Romer (1986)). Romer, for instance, argues that capital accumulation leads to technological progress in the form of learning-by-doing that offsets the decline of the marginal productivity of capital. Within this kind of framework, convergence does not occur anymore: the poor stays poor, and the rich stays rich. However, there is also clear empirical evidence that some poorer countries have been able to catch up while others fell into a poverty trap. The middle-income group vanished over the post World War II period leading to a polarization of the world income distribution. It is, therefore, important to assess whether this convergence phenomenon is the result of diminishing returns to reproducible factors or the result of a technological catch-up effect, or both. Similarly, it is important to know whether the poverty trap arises because of differences in the rates of accumulation, or because countries lack the absorbing capability that would allow them to benefit from their technological backwardness. This paper aims precisely at re-assessing the relative importance of the neoclassical convergence effect and the technological catch-up effect.

It stands out from other papers that have addressed on this topic for a worldwide set of countries by making use of formal growth models, but without using estimated measures of the technology based on total factor productivity, and of specification hypothesis tests in an integrated framework where both object and idea gaps are allowed to play a role in the evolution of the world income distribution. It also provides a counterfactual exercise that allows us to distinguish the marginal impact of both capital deepening and technological catch-up issued by a traditional convergence equation on the world income distribution dynamics (see also Kumar and Russel (2002) for such an exercise within a Data Envelopment Analysis).

First, and as already found by various researchers who focused on the determinants of total factor productivity within growth accounting exercises, the above empirical analysis confirms but within a different both theoretical and empirical environment that technology diffusion opportunities are a significant and robust determinant of the world income distribution dynamics. It should be seen as complementary evidence to that strand of literature that traditionally makes use of production function models, and which also argues in favor of endogenous growth. In other words, and as Solow originally argued (and as Mankiw, Romer, and Weil did not necessarily rule out), both capital deepening and technological catch-up appear to play an important role in explaining growth rates differences. Second, and more specific to the present paper, our results suggest a lower speed of convergence associated with capital deepening once one controls the spread of technology. Moreover, within this framework, we cannot reject the hypothesis that there is a significant negative marginal impact of the initial output per worker on growth in almost all countries but it may differ according to the associated level of technological absorption capability. This yields a highly non linear pattern of convergence. Similarly, the marginal impact of the technological capability of a nation reveals itself to be positively and significantly related to economic growth for about three-quarters of the countries available in the larger sample.

Finally, our results also suggest that the technological catch-up phenomenon may rely more strongly on different types of absorption capability depending on the stage of development of the economy as proxied by its initial level of income. The normative question of which absorptive capability proxy most enhances economic growth, possibly according to a non linear pattern or sequence of development stages is of course essential and should definitely be investigated further.

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Appendix A

Country List for Section 4 (1960-1985, N=73)

Country name	(N, I, O)	Country name	(N, I, O)	Country name	(N, I, O)
AFRICA		*ASIA*		*NORTH AMERICA*	
Algeria (DZA)	(1, 1, 0)	Bangladesh (BGD)	(1, 1, 0)	Canada (CAN)	(1, 1, 1)
Angola (AGO)	(1, 0, 0)	India (IND)	(1, 1, 0)	Costa Rica (CRI)	(1, 1, 0)
Cameroon (CMR)	(1, 1, 0)	Israel (ISR)	(1, 1, 0)	El Salvador (SLV)	(1, 1, 0)
Ethiopia (ETH)	(1, 1, 0)	Japan (JPN)	(1, 1, 1)	Guatemala (GTM)	(1, 1, 0)
Ghana (GHA)	(1, 0, 0)	Jordan (JOR)	(1, 1, 0)	Haiti (HTI)	(1, 1, 0)
Ivory Coast (CIV)	(1, 1, 0)	Korea (KOR)	(1, 1, 0)	Honduras (HND)	(1, 1, 0)
Kenya (KEN)	(1, 1, 0)	Malaysia (MYS)	(1, 1, 0)	Jamaica (JAM)	(1, 1, 0)
Madagascar (MDG)	(1, 1, 0)	Pakistan (PAK)	(1, 1, 0)	Mexico (MEX)	(1, 1, 0)
Malawi (MWI)	(1, 1, 0)	Philippines (PHL)	(1, 1, 0)	Panama (PAN)	(1, 1, 0)
Mali (MLI)	(1, 1, 0)	Singapore (SGP)	(1, 1, 0)	United States (USA)	(1, 1, 1)
Mauritius (MUS)	(1, 0, 0)	Sri Lanka (LKA)	(1, 1, 0)		
Morocco (MAR)	(1, 0, 0)	Thailand (THA)	(1, 1, 0)	*SOUTH AMERICA*	
Mozambique (MOZ)	(1, 0, 0)			Argentina (ARG)	(1, 1, 0)
Nigeria (NGA)	(1, 1, 0)	*EUROPE*		Bolivia (BOL)	(1, 1, 0)
Rwanda (RWA)	(1, 0, 0)	Austria (AUT)	(1, 1, 1)	Brazil (BRA)	(1, 1, 0)
Senegal (SEN)	(1, 1, 0)	Belgium (BEL)	(1, 1, 1)	Chile (CHL)	(1, 1, 0)
Sierra Leone (SLE)	(1, 0, 0)	Denmark (DEN)	(1, 1, 1)	Colombia (COL)	(1, 1, 0)
Tanzania (TZA)	(1, 1, 0)	Finland (FIN)	(1, 1, 1)	Ecuador (ECU)	(1, 1, 0)
Tunisia (TUN)	(1, 1, 0)	France (FRA)	(1, 1, 1)	Paraguay (PRY)	(1, 1, 0)
Uganda (UGA)	(1, 0, 0)	Germany, West (DEU)	(1, 1, 1)	Peru (PER)	(1, 1, 0)
Zaire (ZAR)	(1, 0, 0)	Greece (GRC)	(1, 1, 1)	Uruguay (URY)	(1, 1, 0)
Zambia (ZMB)	(1, 1, 0)	Ireland (IRL)	(1, 1, 1)	Venezuela	(1, 1, 0)
Zimbabwe (ZWE)	(1, 1, 0)	Italy (ITA)	(1, 1, 1)		
		Netherlands (NDL)	(1, 1, 1)	*OCEANIA*	
		Norway (NOR)	(1, 1, 1)	Australia (AUS)	(1, 1, 1)
		Portugal (PRT)	(1, 1, 1)		
		Spain (ESP)	(1, 1, 1)		
		Sweden (SWE)	(1, 1, 1)		
		Switzerland (CHE)	(1, 1, 1)		
		Turkey (TUR)	(1, 1, 1)		
		United Kingdom (GBR)	(1, 1, 1)		

Temple (1998a & b) who first applied RWLS technique to cross-country growth regressions found a number of unrepresentative observations that are not initially included in the above sample of countries, namely: Botswana, Chad, Egypt, Hong Kong, Indonesia, Mauritania, Papua New Guinea, and Somalia.

Appendix B

Correlation Matrices (1960-1985)

Correlation matrix - Non-oil sample (N=73)

ln(Y60)	1.00							
H.ln($Y60_{max}$/Y60)	0.13	1.00						
(Eq/GDP).ln($Y60_{max}$/Y60)	-0.06	0.44	1.00					
ln(I/GDP)	0.64	0.35	0.41	1.00				
ln(n+g+S)	-0.52	-0.23	0.01	-0.39	1.00			
ln(school)	0.76	0.48	0.17	0.68	-0.36	1.00		
H	0.68	0.59	0.14	0.55	-0.61	0.63	1.00	
Eq/GDP	0.64	0.36	0.61	0.72	-0.48	0.58	0.68	1.00

Correlation matrix - Intermediate sample (N=65)

ln(Y60)	1.00							
H.ln($Y60_{max}$/Y60)	0.06	1.00						
(Eq/GDP).ln($Y60_{max}$/Y60)	-0.17	0.45	1.00					
ln(I/GDP)	0.58	0.29	0.35	1.00				
ln(n+g+S)	-0.54	-0.23	0.04	-0.39	1.00			
ln(school)	0.76	0.44	0.10	0.62	-0.36	1.00		
H	0.66	0.57	0.09	0.51	-0.61	0.62	1.00	
Eq/GDP	0.60	0.35	0.58	0.70	-0.47	0.56	0.66	1.00

Correlation matrix - OECD sample (N=21)

ln(Y60)	1.00							
H.ln($Y60_{max}$/Y60)	-0.50	1.00						
(Eq/GDP).ln($Y60_{max}$/Y60)	-0.81	0.85	1.00					
ln(I/GDP)	0.09	0.39	0.34	1.00				
ln(n+g+S)	-0.05	-0.10	-0.07	-0.04	1.00			
ln(school)	0.40	0.19	-0.03	0.25	-0.09	1.00		
H	0.34	0.52	0.09	0.21	-0.02	0.60	1.00	
Eq/GDP	0.22	0.45	0.35	0.69	-0.02	0.63	0.54	1.00

Appendix C

Country List for Section 5 (1960-1995, N=79)

Country name	(N, I, O)	Country name	(N, I, O)	Country name	(N, I, O)
AFRICA		*ASIA*		*NORTH AMERICA*	
Algeria (DZA)	(1, 1, 0)	Bangladesh (BGD)	(1, 1, 0)	Canada (CAN)	(1, 1, 1)
Benin (BEN)	(1, 0, 0)	Hong Kong (HKG)	(1, 1, 0)	Costa Rica (CRI)	(1, 1, 0)
Botswana (BWA)	(1, 1, 0)	India (IND)	(1, 1, 0)	Dominican Rep. (DOM)	(1, 1, 0)
Cameroon (CMR)	(1, 1, 0)	Indonesia (IDN)	(1, 1, 0)	El Salvador (SLV)	(1, 1, 0)
Central Af. Rep. (CAF)	(1, 0, 0)	Israel (ISR)	(1, 1, 0)	Guatemala (GTM)	(1, 1, 0)
Congo (COG)	(1, 0, 0)	Japan (JPN)	(1, 1, 1)	Honduras (HND)	(1, 1, 0)
Ghana (GHA)	(1, 0, 0)	Jordan (JOR)	(1, 1, 0)	Jamaica (JAM)	(1, 1, 0)
Kenya (KEN)	(1, 1, 0)	Korea (KOR)	(1, 1, 0)	Mexico (MEX)	(1, 1, 0)
Malawi (MWI)	(1, 1, 0)	Malaysia (MYS)	(1, 1, 0)	Nicaragua (NIC)	(1, 1, 0)
Mali (MLI)	(1, 1, 0)	Nepal (NPL)	(1, 0, 0)	Panama (PAN)	(1, 1, 0)
Mauritius (MUS)	(1, 0, 0)	Pakistan (PAK)	(1, 1, 0)	Trinidad & Tobago (TTO)	(1, 1, 0)
Mozambique (MOZ)	(1, 0, 0)	Philippines (PHL)	(1, 1, 0)	United States (USA)	(1, 1, 1)
Niger (NER)	(1, 0, 0)	Singapore (SGP)	(1, 1, 0)		
Rwanda (RWA)	(1, 0, 0)	Sri Lanka (LKA)	(1, 1, 0)	*SOUTH AMERICA*	
Senegal (SEN)	(1, 1, 0)	Syria (SYR)	(1, 1, 0)	Argentina (ARG)	(1, 1, 0)
South africa (ZAF)	(1, 1, 0)	Thailand (THA)	(1, 1, 0)	Bolivia (BOL)	(1, 1, 0)
Togo (TGO)	(1, 0, 0)			Brazil (BRA)	(1, 1, 0)
Tunisia (TUN)	(1, 1, 0)	*EUROPE*		Chile (CHL)	(1, 1, 0)
Uganda (UGA)	(1, 0, 0)	Austria (AUT)	(1, 1, 1)	Colombia (COL)	(1, 1, 0)
Zaire (ZAR)	(1, 0, 0)	Belgium (BEL)	(1, 1, 1)	Ecuador (ECU)	(1, 1, 0)
Zambia (ZMB)	(1, 1, 0)	Denmark (DEN)	(1, 1, 1)	Paraguay (PRY)	(1, 1, 0)
Zimbabwe (ZWE)	(1, 1, 0)	Finland (FIN)	(1, 1, 1)	Peru (PER)	(1, 1, 0)
		France (FRA)	(1, 1, 1)	Uruguay (URY)	(1, 1, 0)
		Greece (GRC)	(1, 1, 1)	Venezuela (VEN)	(1, 1, 0)
		Ireland (IRL)	(1, 1, 1)		
		Italy (ITA)	(1, 1, 1)	*OCEANIA*	
		Netherlands (NLD)	(1, 1, 1)	Australia (AUS)	(1, 1, 1)
		Norway (NOR)	(1, 1, 1)	New Zealand (NZL)	(1, 1, 1)
		Portugal (PRT)	(1, 1, 1)	Papua New Guinea (PNG)	(1, 0, 0)
		Spain (ESP)	(1, 1, 1)		
		Sweden (SWE)	(1, 1, 1)		
		Switzerland (CHE)	(1, 1, 1)		
		Turkey (TUR)	(1, 1, 1)		
		United Kingdom (GBR)	(1, 1, 1)		

Notice that Chad, Egypt, Mauritania, and Somalia are not included in the above sample (see Temple (1998a & b)).

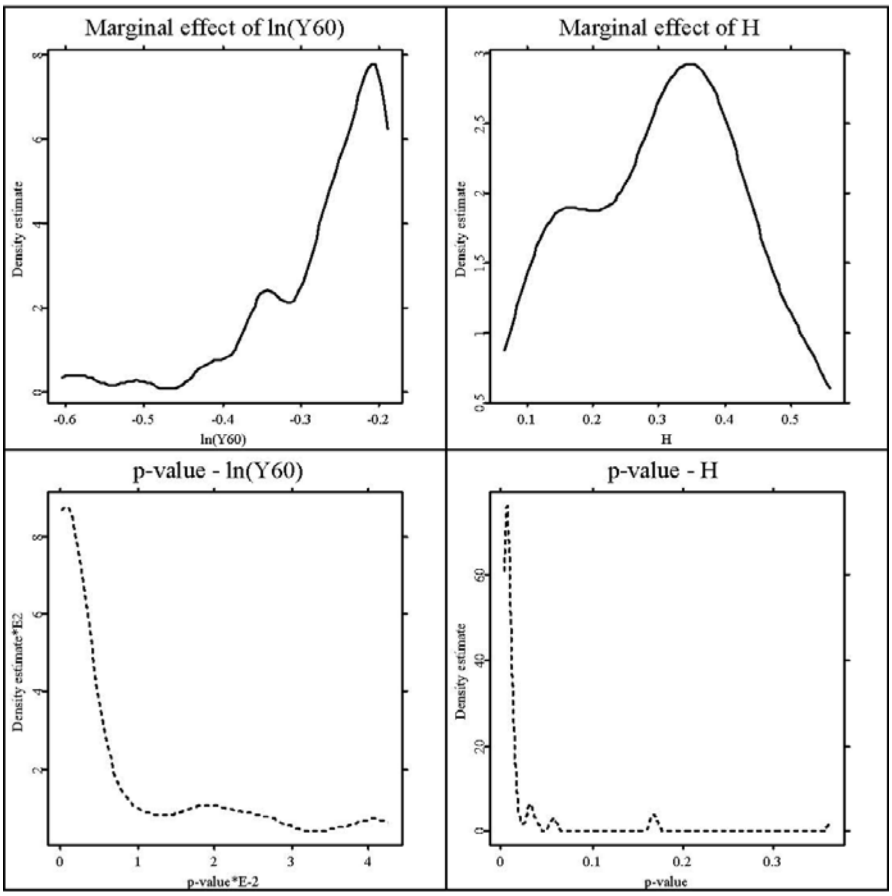

Figure 1: The kernel density estimate of the marginal effect on economic growth over the period of 1960-1985 of ln(*Y*60) according to values of *H*, respectively of *H* according to values of ln($Y60_{max}$/*Y*60) is displayed in the left, respectively right, upper box (solid line). In the corresponding lower box, the associated relevant p-value's kernel density estimate is depicted(dotted line). (A Gaussian kernel has been used and the amount of smoothing is issued by the Sheather and Jones plug-in method (1991)).

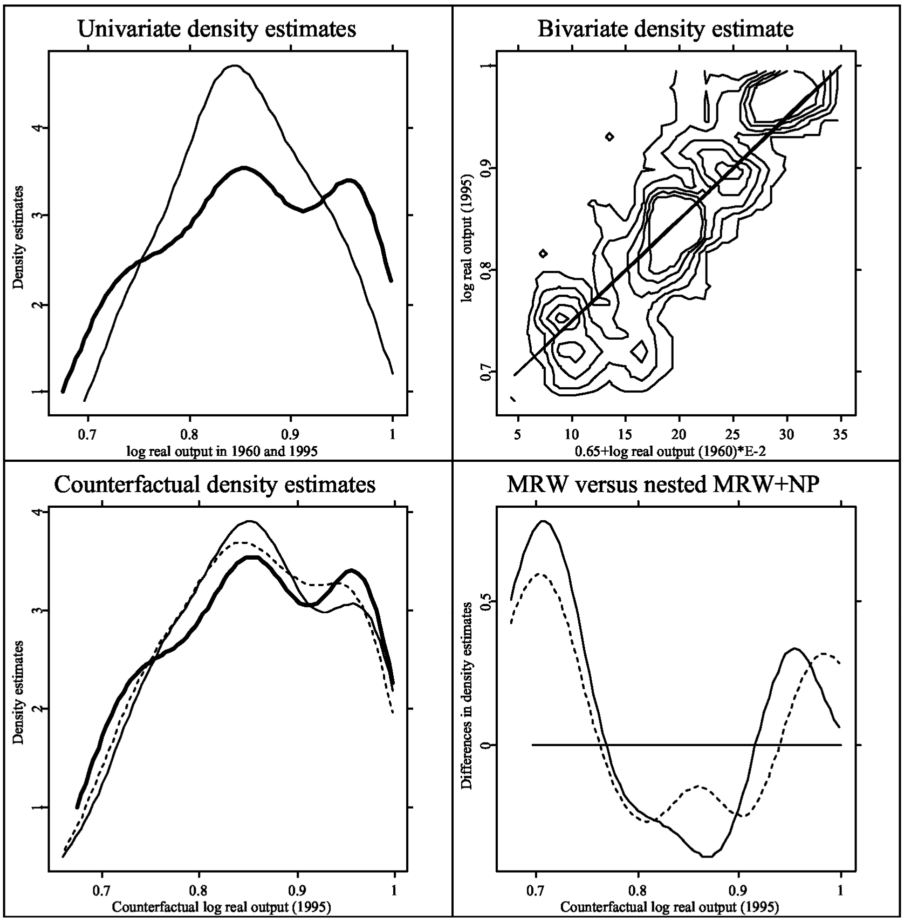

Figure 2: In the left-hand upper box, univariate kernel density estimates for the log real output per working-age person in 1960 (solid line) and 1995 (thick line). In the right-hand upper box, equal probability contours of bivariate kernel density estimate for the log real output per-working-age person in 1960 (x-axis) and 1995 (y-axis). In the left-hand lower box, counterfactual real output per working-age person density estimates in 1995 issued by the MRW (solid line) and the more general specification that nests both the MRW and the NP theoretical models (dotted line), and true output density estimate in 1995 (thick line). In the right-hand lower box, differences between the true density estimate in 1995 and counterfactual density estimates implied by the MRW (solid line) and the nested MRW+NP (dotted line) models over the period of 1960-1995. Data have been normalized relative to their maximum. The smoothing parameter is issued by the Sheather and Jones plug-in method and is equal to 0.035.