Cross-Country Growth Empirics and Model Uncertainty: An Overview

Bülent Ulaşan

Central Bank of the Republic of Turkey

Abstract The aim of this paper is to provide an overview of empirical cross-country growth literature. The paper begins with describing the basic framework used in recent empirical cross-country growth research. Even though this literature was mainly inspired by endogenous growth theories, the neoclassical growth model is still the workhorse for cross-country growth empirics. The second part of the paper emphasises model uncertainty, which is indeed immense but generally neglected in the empirical cross-country growth literature. The most outstanding feature of the literature is that a large number of factors have been suggested as fundamental growth determinants. Together with the small sample property, this leads to an important problem: model uncertainty. The questions which factors are more fundamental in explaining growth dynamics and hence growth differences are still the subject of academic research. Recent attempts based on general-to-specific modeling or model averaging are promising but have their own limits. Finally, the paper highlights the implications of model uncertainty for policy evaluation.

Published as Survey and Overview

Correspondence Bülent Ulaşan, Research and Monetary Policy Department, Central Bank of the Republic of Turkey, Istiklal Cad. No:10, Ulus, 06100, Ankara, Turkey; e-mail: Bulent.Ulasan@tcmb.gov.tr

When I finished that 1956 paper, I had no idea that it would still be alive and well 50 years later, more or less part of the folklore.

— Robert M. Solow (2007, p.4)

1 Introduction

Why do growth rates vary across countries? Why are some countries growing rapidly and some are not growing at all? Do countries converge or diverge in terms of per capita income? Which factors are effective in promoting economic growth? These questions are the central motivation of the recent empirical cross-country growth literature. Following the seminal studies by Kormendi and Meguire (1985), Barro (1991) and Mankiw, Romer and Weil (1992), a large number of empirical works have emerged over the last few decades. Undoubtedly, this renewed interest arose from recent developments in the theory of endogenous growth and the increasing availability of multi-country growth data sets, e.g. the Penn World Tables, (Summers and Heston (1988, 1991)).

Endogenous growth theories largely developed from the contributions of Romer (1986) and Lucas (1988) stress the role of knowledge (or ideas) as a production factor on the long-run economic growth. In contrast to the neoclassical growth model, these theories conclude that growth rate can constantly increase over time since accumulation of knowledge is not subject to diminishing returns and thus help us for understanding why the world economy as a whole has been growing indefinitely in per capita terms. However, endogenous growth theories have less explanatory power for cross-country growth differences relative to the neoclassical growth model. The recent empirical cross-country growth studies are, therefore, mainly based on the extended versions of the neoclassical growth model in spite of the contribution of endogenous growth theories. For instance Barro (1997, p.8) argues that "[I]t is surely an irony that one of the lasting contributions of endogenous growth theory is that it stimulated empirical work that demonstrated the explanatory power of the neoclassical growth model." In

short, the neoclassical growth model firstly developed by Solow (1956) and Swan (1956) is a starting point of most cross-country growth studies.

In this respect, the pioneering work by Mankiw, Romer and Weil (1992) augments the neoclassical growth model with the inclusion of human capital. The prominent aspect of this study is that it provides a coherent theoretical framework for empirical cross-country growth studies and a large body of empirical cross-country growth literature is based on Mankiw, Romer and Weil (1992). Islam (1995) and others further adapt the framework of Mankiw, Romer and Weil (1992) for panel estimation.

Conceptually, there are two main empirical approaches in the literature, namely growth accounting and growth regression, quantifying the following relation:

$$Output = F(Production\ Factors,\ Technology)$$

It is obvious that the accumulation of production factors (namely physical and human capital and population) and technological progress (whether exogenous or endogenous) are *proximate* determinants of economic growth. In other words, even though these factors explain a considerable part of cross-county growth differences and in spite of the common consensus concerning these factors as potential growth determinants, these facts bear a pertinent question: *Why are countries different in terms of proximate growth determinants?* That is why beyond the proximate determinants, explaining the *fundamental* sources of growth differences across economies is the main objective of the empirical cross-country growth literature. In doing so, the cross-country growth studies apply a wide range of new growth theories. A typical study, firstly presents a new growth theory, then suggests a proxy variable for that theory and finally concludes a cross-country growth regression including this new theory as well as the proximate determinants.[1]

---

[1] Typically such cross-country growth regressions include the initial income level, the rate of population growth, the investment ratio and a measure of human capital such as primary and secondary school enrolment rate, as well as some proxy variables for the new theory. Regression of this kind is also known as "Barro type regression" due to the pioneering work by Barro (1991).

The most outstanding characteristic of these new growth theories is that they are open-ended, such that the inclusion of one growth theory does not preclude the validity of others, as pointed out by Brock and Durlauf (2001). This means that unlike the proximate determinants of growth, there is no common consensus among the new growth theories. Whilst almost all studies include the same proximate determinants, the new growth theories change from study to study. In other words, there is no clear answer as to which of these new growth theories is more important. Wacziarg (2002, p. 907) nicely summarises this phenomenon:

> All-encompassing hypotheses concerning the sources of economic growth periodically surface, and with the support of adequately chosen cross-country correlations, enjoy their fifteen minutes of fame. Over the last few decades, the list of proposed panaceas for growth in per-capita income has included high rates of physical-capital investment, rapid human-capital accumulation, low income inequality, low fertility, being located far from the equator, a low incidence of tropical diseases, access to the sea, favorable weather patterns, hands-off governments, trade-policy openness, capital-market developments, political freedom, economic freedom, ethnic homogeneity, British colonial origins, a common-law legal system, the protection of property rights and the rule of law, good governance, political stability, infrastructure, market-determined prices (including exchange rates), foreign direct investment, and suitably conditioned foreign aid. This is a growing and non-exhaustive list.

As a consequence of open-ended nature of new growth theories, a vast number of explanatory variables appears in the empirical cross-country growth literature.[2] This implies that identification of explanatory variables

---

[2] Another reason for this proliferation is the difficulties arising from construction of proxy variables for new growth theories. For instance, a theory pointing out that openness to international trade is important for economic growth does not provide a clear answer as to how we measure openness.

in a growth regression is an important task in order to highlight the exact contribution of new theories to economic growth. It is, however, statistically infeasible to run a cross-country growth regression encompassing all variables suggested by new growth theories due to the degrees-of-freedom problem. Put differently, given the large number of proposed growth variables and small number of countries in the world, it is highly likely that the number of possible regressors is very close to number of observations, or even more. Furthermore, when running cross-country growth regressions, we are missing observations of many countries due to the data availability and this makes the degrees-of-freedom problem more severe. Therefore, a typical cross-country growth regression includes a subset of potential growth variables. Under these circumstances, the results of empirical cross-country growth studies are obviously very sensitive to model selection and hence presenting results of a single preferred model is often misleading about the sources of economic growth. This means that the problem of model uncertainty is an important econometric problem in cross-country growth studies and has also serious implications for providing strong policy recommendations.

The objectives of this overview are threefold: First, it describes the general theoretical framework which constitutes the basis for the most empirical cross-country growth works. Second, it addresses the model uncertainty problem which is indeed immense but generally ignored in the empirical cross-country growth literature. Third, the paper highlights the importance of model uncertainty for policy evaluation.

The rest of the paper is organised as follows. Section 2 describes the basic framework for the recent cross-country growth literature. Section 3 deals with the model uncertainty problem and discusses its possible solutions. Section 4 briefly evaluates the policy implications that can be drawn from cross-country growth studies in the presence of model uncertainty. Section 5 concludes.

2   Theoretical Foundation of Growth Regressions

In this section, we provide an overview of theoretical basis for most cross-country growth work. Special emphasis is focused on Mankiw, Romer and Weil (1992) since this study develops a solid theoretical foundation for a linear growth model, which is widely used in the subsequent cross-country growth studies.

Following the standard notation, we denote the level of output by $Y(t)$, labour stock by $L(t)$ and level of labour-augmenting technology by $A(t)$ at time t. Assuming that production function exhibits constant returns to scale and labour and technology grow exogenously at rates n and g such that $L(t) = L(0)e^{nt}$ and $A(t) = A(0)e^{gt}$, output per unit of labour; $y(t) = Y(t)/L(t)$ and output per unit of effective labour; $\tilde{y}(t) = Y(t)/A(t)L(t)$ are defined. As indicated by many authors both Solow-Swan or Ramsey-Cass-Koopmans versions of the neoclassical growth model for closed economies conclude that the growth rate of per capita output is inversely related to initial level of per capita output.[3] This implies that

$$\lambda = -\frac{\partial(\dot{\tilde{k}}(t)/\tilde{k}(t))}{\partial \log \tilde{k}(t)} \tag{1}$$

where a dot over the variable indicates the derivative of that variable with respect to time, $\tilde{k}$ denotes the physical capital stock per unit of effective labour and λ measures the speed of convergence (defined as how much the growth rate decreases when the capital stock increases proportionally). Notice that in equation (1), the speed of convergence is defined with a negative sign since the derivative is negative due to the marginal diminishing return to capital. Therefore, λ must be positive, and its size depends on the parameters of the model. The other important point is that λ is not constant. This means that λ decreases monotonically while capital stock converges to its steady-state value. Put differently λ is implicitly a function of $\tilde{k}(t)$ and becomes zero when the capital stock reaches its steady-state level. Therefore,

---

[3] See, for instance, Barro and Sala-i-Martin (1992), Mankiw et al. (1992), Mankiw (1995), Islam (1995), Durlauf et al. (2005).

we denote speed of convergence in the neighborhood of steady-sate by λ^*. Since the production function is assumed to have constant returns to scale, equation (1) can be applied for the output per unit of effective labour, i.e. speed of convergence can be alternatively defined for $\tilde{y}(t)$:

$$\lambda = -\frac{\partial(\dot{\tilde{y}}(t)/\tilde{y}(t))}{\partial \log \tilde{y}(t)} \tag{2}$$

Equation (1) implies that the first-order Taylor approximation of $\log \tilde{k}(t)$ around the steady state yields

$$\dot{\tilde{k}}(t)/\tilde{k}(t) \cong -\lambda^*[\log(\tilde{k}(t)/\tilde{k}(t)^*)] \tag{3}$$

Similarly, equations (2) and (3) imply that

$$\dot{\tilde{y}}(t)/\tilde{y}(t) \cong -\lambda^*[\log(\tilde{y}(t)/\tilde{y}(t)^*)] \tag{4}$$

As can be seen, equations (3) and (4) are first-order differential equations. Equation (4) can be written more explicitly as follows

$$\frac{d \log \tilde{y}(t)}{dt} = \lambda^* \log \tilde{y}(t)^* - \lambda^* \log \tilde{y}(t) \tag{5}$$

Solving (5) gives

$$\log \tilde{y}(t) = (1 - e^{-\lambda^* t}) \log \tilde{y}(t)^* + e^{-\lambda^* t} \log \tilde{y}(0) \tag{6}$$

Equation (6) can be expressed for output per labour instead of output per unit of effective labour as follows

$$\log y(t) - \log A(t) = (1 - e^{-\lambda^* t}) \log \tilde{y}(t)^* + e^{-\lambda^* t} \log y(0) - e^{-\lambda^* t} \log A(0) \tag{7}$$

and so

$$\log y(t) = gt + (1 - e^{-\lambda^* t}) \log \tilde{y}(t)^* + (1 - e^{-\lambda^* t}) \log A(0)) + e^{-\lambda^* t} \log y(0) \tag{8}$$

Subtracting the logarithm of the initial level of output per capita from both sides of equation (8) and dividing by time t yields the following growth equation

$$t^{-1}(\log y(t) - \log y(0)) = g + \eta[\log \tilde{y}(t)^* + \log A(0) - \log y(0)] \qquad (9)$$

where $\eta = t^{-1}(1 - e^{-\lambda^* t})$. The left-hand-side of equation (9) shows the growth rate of output per labour between 0 and t.[4] As seen in equation (9), the growth rate of per capita output may be decomposed into two main factors. The first one is the growth rate of technological progress, g. The second one is the distance between initial level of output per unit of effective labour and its steady state value, $\log \tilde{y}(t)^* - \log \tilde{y}(0)$. In order to show the second factor more explicitly, equation (9) can be written as

$$t^{-1}(\log y(t) - \log y(0)) = g + \eta[\log \tilde{y}(t)^* - \log \tilde{y}(0)] \qquad (10)$$

As shown in equation (10), the growth rate of per capita output is inversely related to the initial level of output per unit of effective labour while it is positively related to the steady state level of output per unit of effective labour and hence its determinants. As time approaches infinity, i.e. as an economy converges to its steady state, the effect of the second factor vanishes, and at the steady state, is equal to zero. This means that in the long run, the growth rate of per capita output is determined by the rate of technological progress, g.

If we assume that the rate of technological progress, g and the determinants of the steady state level of output per unit of effective labour are constant across countries, then each economy approaches the same steady state in the long run. That is why countries with a lower initial level of

---

[4] Notice that the growth rate in equation (9) is defined per unit of time. If the unit of time is a year, the left-hand side of equation (9) measures the average growth rate of output per labour *annually*. On the other hand one can construct the growth rate as the log difference between initial and end of period values such that $\log y(t) - \log y(0)$ since equation (9) is based on the log-linear approximation of output per unit of effective labour in the vicinity of steady state. As long as it is explicitly expressed, both approaches are in essence the same, and choosing between these two depends on the researchers' preferences.

output per unit of effective labour grow faster than those with a higher initial level of output per unit of effective labour during the transition period due to the diminishing returns to capital. This result is known as the *absolute convergence hypothesis* and predicts that poor countries tend to catch up with rich ones. However, if the countries have different values of g and determinants of steady state value of output per unit of effective labour, then steady states will be different across countries. Therefore, each economy will converge to its own steady state rather than a common steady state, and the speed of this convergence will be inversely related to the distance of the initial level from the steady state. This property is again a result of the assumption of diminishing returns to capital, so that economies which have less capital per head relative to its steady state level tend to have higher rates of return and so faster growth. In this situation, the neoclassical growth model implies *conditional convergence* instead of absolute convergence in the sense that an economy with a lower initial value of per capita output tends to generate higher growth rate of per capita output if g and determinants of the steady state value of output per unit of effective labour are the same across countries or their effects are controlled.

If the convergence hypothesis defined above is true, then we expect a negative association between the level of initial income and subsequent growth rate across countries. In order to test the convergence hypothesis, researchers run the growth-initial income regressions. Therefore, in the literature both absolute and conditional convergence are sometimes referred as β-convergence due to the coefficient of the initial income level (namely β) in the cross-country growth regression (see, for instance, Sala-i-Martin (1996)). Notice that both absolute β-convergence and conditional β-convergence imply that the initial conditions of countries do not matter for their steady state levels of income. The only difference between these two convergence concepts is that the latter also allows the structural heterogeneity across countries, that is structurally similar countries converge to the similar income level in the long run. Hence, absolute convergence and conditional convergence coincide if all countries are structurally the same. On the other hand, Quah (1996) criticises the concept of β-convergence and suggest to the concept of σ-convergence measuring the relative dispersion of per capita income

level across countries. Whilst the sentiment of Quah (1996) rings true, β-convergence is still an important concept since it is a necessary condition for σ-convergence.[5]

Equations (9) and (10) are the basis for the estimation of cross-country growth regressions in the empirical growth literature. Adding an error term μ, which is independent from all right-hand-side variables, yields the following cross-country growth regression

$$t^{-1}(\log y_i(t) - \log y_i(0)) = g_i + \eta \log \tilde{y}_i(t)^* - \eta \log y_i(0) + \eta \log A_i(0) + \mu_i \quad (11)$$

where subscript i denotes the country i. This last equation is the basic cross-country growth regression in discrete time which is derived from continuous time neoclassical Solow-Swan growth model.

In this context, the seminal study by Mankiw, Romer and Weil (1992, MRW hereafter) augments the Solow-Swan version of neoclassical growth model by adding the accumulation of human capital. They assume a Cobb-Douglas production function such that production at time t in country i is given by

$$Y_i(t) = K_i(t)^\alpha H_i(t)^\beta (A_i(t) L_i(t))^{1-\alpha-\beta} \quad (12)$$

where the notation here is again standard such that Y is output, K is physical capital, H is the stock of human capital, L is labour, and A is level of technology. MRW (1992) assumes that $\alpha + \beta < 1$, which means that there are decreasing returns to both kinds of capital. Labour stock and the level of technology are assumed to grow exogenously at rates n and g, respectively as before.

The production function in equation (12) can be written in its intensive form. More clearly, it can be expressed in terms of per unit of effective labour as it shows constant returns to scale property.

$$\tilde{y}(t) = \tilde{k}(t)^\alpha \tilde{h}(t)^\beta \quad (13)$$

---

[5] Closely related to β-convergence, another concept of convergence is *club convergence* suggested by Durlauf and Johnson (1995) and Galor (1996). This concept says that initially and structurally similar countries converge to similar steady states. See, Durlauf (1996), Islam (2003) and Durlauf et al. (2009a) for nice surveys on convergence debate.

where $\tilde{h}$ is the stock of human capital per unit of effective labour and the remaining variables are as before. The model assumes that a constant fraction of output is invested in both physical and human capital such that s_K is the fraction of income invested in physical capital and s_H is the fraction of income invested in human capital. Defining δ as the depreciation rate of both physical and human capital, yields

$$\dot{\tilde{k}}(t) = s_K \tilde{y}(t) - (n + g + \delta)\tilde{k}(t) \tag{14}$$

$$\dot{\tilde{h}}(t) = s_H \tilde{y}(t) - (n + g + \delta)\tilde{h}(t) \tag{15}$$

Equations (14) and (15) imply that the economy converges to a steady state defined as follows

$$\tilde{k}(t)^* = \left(\frac{s_K^{1-\beta} s_H^{\beta}}{n + g + \delta} \right)^{1/1-\alpha-\beta} \tag{16}$$

$$\tilde{h}(t)^* = \left(\frac{s_K^{\alpha} s_H^{1-\alpha}}{n + g + \delta} \right)^{1/1-\alpha-\beta} \tag{17}$$

Substituting equations (16) and (17) into the production function gives the steady state level of output per unit of effective labour:

$$\tilde{y}(t)^* = \left[\frac{s_K^{\alpha} s_H^{\beta}}{(n + g + \delta)^{\alpha+\beta}} \right]^{1/1-\alpha-\beta} \tag{18}$$

Using the definition of speed of convergence expressed in equation (2) with the equations from (13) to (18), the convergence coefficient in the vicinity of the steady state can be defined by[6]

$$\lambda^* = (1 - \alpha - \beta)(n + g + \delta) \tag{19}$$

---

[6] Since the derivation of convergence coefficient in the augmented neoclassical growth model is available elsewhere, we do not need to elaborate it here. The reader can refer to, *inter alia*, Mankiw (1995) or Barro and Sala-i-Martin (2004) for details in derivation.

λ^* measures how rapidly a country's output per unit of effective labour approaches its steady state value in the neighbourhood of the steady state. For instance, if we assume that the sum of rates of population growth, technological progress and depreciation is seven percent and capital shares are one-third, then λ^* would be equal to 0.023. This means that 2.3 percent of the gap between a country's steady state and its current income level is eliminated each year and halfway convergence to the steady state takes approximately 30 years, in the absence of any other shocks.[7]

In order to get a cross-country growth regression, we need to substitute expression (18), i.e. steady state level of output per unit of effective labour into equation (11). This produces

$$t^{-1}(\log y_i(t) - \log y_i(0)) = g + \eta \frac{\alpha}{1-\alpha-\beta} \log s_{i,K} + \eta \frac{\beta}{1-\alpha-\beta} \log s_{i,H}$$
$$- \eta \frac{\alpha+\beta}{1-\alpha-\beta} \log(n_i + g + \delta) - \eta \log y_i(0)$$
$$+ \eta \log A_i(0) + \mu_i$$

$$(20)$$

As can be seen from the last equation, MRW assume that rates of technological progress and of depreciation are constant across countries. On the other hand, logarithm of initial level of technology is assumed to be different across countries and to be equal to the sum of a fixed parameter, a and a country specific shock, ε_i such that

$$\log A_i(0) = a + \varepsilon_i \qquad (21)$$

According to MRW, the level of initial technology represents not only the technology but also the resource endowment, institutions, climate and so

---

[7] According to the equation (6), the halfway convergence to steady state requires the condition $1 = 2e^{-\lambda^* t}$. Therefore, the time that a country spends to eliminate half of the distance between its initial position and its steady state is $\log(2)/\lambda^*$. Similarly, elimination of a three-quarter gap must satisfy the condition $1 = 4e^{-\lambda^* t}$, and takes $2\log(2)/\lambda^*$. For instance in the example above, three-quarters of convergence to the steady state takes $2\log(2)/0.023 = 60.3$ years.

on. Therefore, initial differences across countries are reflected by the term ε_i. Substituting equation (21) into equation (20) yields the following cross-country growth regression;

$$t^{-1}(\log y_i(t) - \log y_i(0)) = g + \eta a - \eta \log y_i(0) - \eta \frac{\alpha + \beta}{1 - \alpha - \beta} \log(n_i + g + \delta)$$
$$+ \eta \frac{\alpha}{1 - \alpha - \beta} \log s_{i,K} + \eta \frac{\beta}{1 - \alpha - \beta} \log s_{i,H}$$
$$+ \mu_i + \eta \varepsilon_i$$
$$(22)$$

The most critical assumption of MRW (1992, p.411) is that "[t]he rates of saving and population growth are independent of country-specific factors shifting the production function." This means that $s_{i,K}$, $s_{i,H}$, and n_i are independent from the country specific shocks ε_i and thus, a cross-country growth regression expressed as in equation (22) can be estimated by OLS.

The cross-country growth regression in equation (22) can be written in its reduced form as follows

$$\varrho_i = \pi_0 + \pi_1 \log y_i(0) + \pi_2 \log(n_i + g + \delta) + \pi_3 \log s_{i,K} + \pi_4 \log s_{i,H} + \upsilon_i \quad (23)$$

where

$$\varrho_i = t^{-1}(\log y_i(t) - \log y_i(0))$$
$$\pi_0 = g + \eta a$$
$$\pi_1 = -\eta$$
$$\pi_2 = -\eta \frac{\alpha + \beta}{1 - \alpha - \beta}$$
$$\pi_3 = \eta \frac{\alpha}{1 - \alpha - \beta}$$
$$\pi_4 = \eta \frac{\beta}{1 - \alpha - \beta}$$
$$\upsilon_i = \mu_i + \eta \varepsilon_i$$

Equation (22) and its reduced form in (23) are the basis of the augmented neoclassical growth model. MRW estimated the augmented neoclassical growth model for 98 countries (oil producing countries are excluded) over the 1960-1985 period. The share of investment in GDP and the fraction of working-age population enrolled in secondary school are used as proxy variables for s_K and s_H, respectively. All right-hand-side variables, except the initial level of GDP per worker are entered into the regression as period averages instead of their initial value. It should be noted that theory does not provide a clear answer for choosing between period averages and initial values, since these variables are considered as constant over the period and exogenous. Yet, the common practice in the literature is to use average values over the period. Regression results show that the average growth rate of GDP per worker is positively correlated with the investment to GDP ratio and secondary school enrolment rate and negatively with the initial income level and population growth. Moreover, MRW estimate the augmented neoclassical model imposing the restriction that coefficients on $\log(n+g+\delta)$, $\log s_K$ and $\log s_H$ add up to zero. Finding that this restriction is not rejected, MRW conclude the regression estimates of $\lambda^* = 0.0142$, $\alpha = 0.48$ and $\beta = 0.23$, which denote the convergence rate, physical and human capital shares in the vicinity of the steady-state, respectively. According to MRW, their estimation results produce a lower convergence rate than the standard neoclassical growth model excluding human capital and remove some anomalies which are not captured by the standard model. In other words, with the inclusion of human capital, differences in saving, education and population growth produce a consistent explanation for cross-country growth variations.

Even though MRW provide a coherent framework to explain cross-country growth differences, it is subject to a number of criticisms. The most important one is that it is unlikely that variations in the initial level of technology across countries are uncorrelated with the right-hand-side variables. As mentioned before, the initial level of technological efficiency capturing the country-specific technology shift term (ε_i) is omitted from the cross-country regression since it is not observed. Yet, on the contrary to MRW, it is not plausible to assume that the initial technological efficiency

is uncorrelated with the initial level of income, saving rates and population growth. Furthermore, since MRW define the term of initial level of technology in a broader way, including the resource endowment, institutions, climate and so on as well as the production technology, this variable will be highly likely to be correlated with the right-hand-side variables. Hence, the coefficient estimates of regressors by OLS will be biased. As suggested by Islam (1995), one solution to this problem is to employ panel data estimation methods.

We can specify the cross-country growth regression expressed in equation (23) in panel form in which growth rate and all right-hand-side variables averaged over time periods with duration τ as follows:

$$\varrho_{it-\tau} = \gamma_0 + \gamma_1 \log y_{it-\tau} + \gamma_2 \log(n_{it-\tau} + g + \delta) + \gamma_3 \log s_{it-\tau,K} + \gamma_4 \log s_{it-\tau,H} + \varphi_t + \nu_{it}$$
$$(24)$$

where

$$\varrho_{it-\tau} = \log y_{it} - \log y_{it-\tau}$$
$$\phi = (1 - e^{-\lambda^*\tau})$$
$$\gamma_0 = \phi a$$
$$\gamma_1 = -\phi$$
$$\gamma_2 = -\phi \frac{\alpha + \beta}{1 - \alpha - \beta}$$
$$\gamma_3 = \phi \frac{\alpha}{1 - \alpha - \beta}$$
$$\gamma_4 = \phi \frac{\beta}{1 - \alpha - \beta}$$
$$\varphi_t = g(t - e^{-\lambda^*\tau}(t - \tau))$$
$$\nu_{it} = \mu_{it} + \phi \varepsilon_i$$

In the last equation, the term φ_t denotes a time specific effect and the term ν_{it} indicates the composite error term, defined as the sum of a zero-mean error term, μ_{it} and an initial country-specific shock or effect, $\phi \varepsilon_i$. Hence, it is easy to rewrite the last equation as a dynamic panel model with

an unobserved time-constant country-specific effect more explicitly as:

$$\log y_{it} = \gamma_0 + (1 + \gamma_1)\log y_{it-\tau} + \gamma_2 \log(n_{it-\tau} + g + \delta) + \\ \gamma_3 \log s_{it-\tau,K} + \gamma_4 \log s_{it-\tau,H} + \xi_i + \varphi_t + \mu_{it} \tag{25}$$

where $\xi_i = \phi\varepsilon_i$ denotes a time-invariant country-specific effect. By assuming that the time periods, from t to $t - \tau$ are normalised so that the time subscript t denotes a time interval of duration τ, we can express equation (25) in the conventional notation of the panel data literature as follows:

$$\log y_{i,t} = (1 + \gamma_1)\log y_{i,t-1} + \gamma X_{i,t} + \xi_i + \varphi_t + \mu_{i,t} \tag{26}$$

for $i = 1,..,N$ and $t = 2,...,T$, where N and T denote the number of countries and time periods in the panel growth model, respectively, X_{it} represents a vector of augmented neoclassical growth variables (except the initial level of income), and γ is the vector of corresponding coefficients of these variables.[8] In the context of cross-country growth model, a time-constant country effect, ξ_i is treated as a country-specific fixed effect since it is highly likely to be correlated with the explanatory variables, at least with the level of initial income, as mentioned above.[9]

---

[8] More precisely, we define $X_{i,t} = [1, \log(n_{it} + g + \delta), \log s_{it,K}, \log s_{it,H}]$ and $\gamma = [\gamma_0, \gamma_2, \gamma_3, \gamma_4]$. As mentioned earlier, these variables enter the regression model as averages over the time period of duration τ. Akin to the single cross-country growth model, the initial income level, denoted by $y_{i,t-1}$ shows the income level at the beginning of time period t while the dependent variable indicates the income level at the end of that period.

[9] It is evident that the initial income level, $\log y_{i,t-1}$, must be correlated with the unobserved country-specific effects, ξ_i, since the dependent variable, $\log y_{it}$ is a function of ξ_i and the lagged dependent variable, $\log y_{i,t-1}$ is also a function of ξ_i. In order to show more explicitly, lagging equation (26) by one period yields the following equation:

$$\log y_{it-1} = (1 + \gamma_1)\log y_{it-2} + \gamma X_{it-1} + \xi_i + \varphi_{t-1} + \mu_{it-1}$$

As seen easily in the last equation, the assumption that the differences in the level of initial technology across countries is uncorrelated with the right-hand-side variables in the baseline cross-country growth specification is clearly violated. Put differently, as long as the cross-country growth specification includes the level of initial income as a right-hand-side variable, the country-specific effect must be correlated with the other explanatory variables. This is not only an economically meaningful result but also is a statistically necessary condition.

As shown in equations (25) and (26), employing panel data model to growth allows us to control not only for country-specific fixed effects but also for time-specific effects. The inclusion of country-specific fixed effects makes it possible to capture the other determinants of the country's steady state level of income that are not controlled for by the level of initial income and rates of saving and population growth. Allowing the time-specific effect is equally important since this term represents the world economic conditions namely that world economy as whole grows steadily in per capita terms, given the rate of world-wide technological progress and economic shocks common to all countries.

Assuming that the differences in the level of initial technology across countries, and hence country-specific effects are time invariant and correlated with the augmented neoclassical growth variables, Islam (1995) estimate the panel data model in equation (26) with a fixed effects (within group) estimator. To do so, he averaged annual data over the 1960-1985 period into the five-year time spans. It should be noted that the parameters λ^* and τ are treated as constant across time periods by Islam (1995), otherwise the country-specific effects, ξ_i would not be time invariant. Following the Islam (1995), many studies in the literature apply the augmented neoclassical growth model on panel data with country-specific fixed effects.[10] An outstanding result of these studies is that they find a higher rate of conditional convergence compared to single cross-sectional studies.[11] In addition, they generally conclude that other explanatory variables, especially human capital, either are insignificant or have unexpected signs.

A crucial feature of the fixed effects panel data models is that the coefficient estimates rely on only the variations in dependent variable and regressors within individuals (within-variation). In the context of growth empirics, the implications of this are twofold: First, some important infor-

---

[10] Examples include Caselli et al. (1996), Lee et al. (1997), Bond et al. (2001) amongst others.

[11] For instance, Islam (1995) concludes that the implied rate of convergence is $\lambda^* = 0.0375$ and this finding indicates that the half-life of convergence to steady state takes about 18.5 years. MRW report the same figures for very similar sample of countries over the same period as $\lambda^* = 0.0142$ and 48.8 years, respectively.

mation on the growth and cross-country growth differentials in the long run are missing from the panel data studies based on within-country variation since the variation across countries over the whole sample period (between-variation) does not play any role on the coefficient estimates of regression variables. Second, the explanatory variables should have some variation within countries. However, many growth variables are measured at less frequent time intervals, sometimes at only one point in time and do not change much over time or move on only one direction. Furthermore, some growth variables such as geographical characteristics or cultural attitudes are constant over time. In this case, the within-country variations will not be very informative.

It is also well-known fact in panel data econometrics that fixed effects estimates suffer from attenuation bias induced by measurement error.[12] This is particulary true if the explanatory variables more persistent than the measurement errors over time. Therefore, it is very likely that standard transformations like deviations from means or first-differencing exacerbate measurement error. Since most growth variables are time persistent there is more measurement error in panel growth model with fixed effects than single cross-country growth model. This may explain why fixed-effects estimates are smaller than those obtained from single cross-county growth regressions. In sum, panel growth model with fixed effects reduces omitted variable bias on the one hand, increases measurement error bias on the other hand. That is why care must be taken with the net bias while applying fixed effects panel models, as indicated by Hauk and Wacziarg (2009).

Another important problem is that fixed effects (or within group) estimates of dynamic panel growth model in equation (26) will be biased even if the error terms are serially uncorrelated, as pointed out by Nickell (1981). This "dynamic panel bias", also known as the Nickell bias, occurs due to the fixed effect (or within group) transformation. Since the fixed effect transformation is based on deviations from individual means, this transformation leads to a correlation between the transformed lagged dependent variable, $(y_{i,t-1} - \overline{y}_i)$, and the transformed error term, $(\mu_{i,t} - \overline{\mu}_i)$, that is the lagged

---

[12] See, for instance, Hsiao (1986) amongst others.

dependent variable is correlated with the mean of error term, $\overline{\mu}_i$ especially for panels with small T. It is obvious that the Nickel bias will not disappear in the context of panel growth models even if the number of countries goes to infinity due to the small number of time periods. Most panel studies in the empirical cross-country growth literature are based on 5- or 10-year intervals and given the available data starting from 1960, this makes panel growth models short. One promising way for overcoming this problem is first-differencing transformation of the dynamic model in equation (26) to wipe out the fixed effects, ξ_i as follows:

$$\Delta \log y_{i,t} = (1 + \gamma_1)\Delta \log y_{i,t-1} + \gamma \Delta X_{i,t} + \Delta \varphi_t + \Delta \mu_{i,t} \tag{27}$$

for $i = 1, .., N$ and $t = 3, ..., T$. However, as can be easily seen in the last equation, the term $\Delta \log y_{i,t-1} = (\log y_{i,t-1} - log y_{i,t-2})$ is correlated with the first-differenced error term, $\Delta \mu_{i,t} = (\mu_{it} - \mu_{i,t-1})$ even if $\mu_{i,t}$'s are serially uncorrelated since the term $\log y_{i,t-1}$ in the lagged dependent variable is correlated with the $\mu_{i,t-1}$ component of the first-differenced error term. Therefore, the coefficient estimates of first-differenced panel model by OLS will be again biased. As long as $\mu_{i,t}$'s are not serially correlated, the lagged value of endogenous variable, $\Delta \log y_{i,t-2}$, or simply $\log y_{i,t-2}$, fortunately, are uncorrelated with $\Delta \mu_{it}$. Obviously both variables are good instrument variables because they are clearly correlated with the endogenous variable as well. Therefore, one can obtain a consistent estimate of true parameter by applying two-stage least squares (2SLS) with these instrumental variables (Anderson and Hsiao (1981, 1982)).

Combining the basic first-differenced 2SLS estimator proposed by Anderson and Hsiao (1981, 1982) with the generalized methods of moments introduced by Hansen (1982), Holtz-Eakin et al. (1988) and Arellano and Bond (1991) develop first-differenced generalized method of moments (GMM) for dynamic panel models. Assuming that error terms are not serially correlated, that is $E[\mu_{i,t}\mu_{i,s}] = 0$ for $i \neq s$ and explanatory variables are weakly exogenous in the manner that $E[y_{i,t-1}\mu_{i,s}] = 0$ and $E[X_{i,t}\mu_{i,s}] = 0$ for $s > t$ (i.e. explanatory variables are uncorrelated with the future realisations of error term), this approach basically transforms the dynamic panel model

via first-differencing and then uses all available lagged level-values of variables as instruments for the endogenous variables in the transformed model. Differently from the first-differenced 2SLS estimator, the first-differenced GMM approach provides efficiency gains by exploiting additional moment conditions when $T > 3$. More compactly, this procedure uses the following moment conditions: $E[y_{i,t-s}\Delta\mu_{i,t}] = 0$ and $E[X_{i,t-s}\Delta\mu_{i,t}] = 0$, for $t = 3, ..., T$ and $s \geq 2$. It is apparent that the GMM method requires at least three periods of data for each country. When the number of time periods is greater than 3, additional instrumental variables become available and hence the model is over-identifying.[13]

The promising aspect of the first-differenced GMM procedure is dealing with the problem of endogeneity bias induced by omitted variables, simultaneity, and measurement error. Caselli, Esquivel and Lefort (1996) apply this procedure to the augmented neoclassical growth model in panel setting. Akin to Islam (1995), these authors conclude a considerably higher rate of convergence than that estimated by MRW.[14] The most outstanding finding is that the implied share of human capital is found to be negative and statistically significant. Caselli et al. (1996) interpret this finding as clear evidence against the validity of augmented neoclassical growth model.

The consistency of the first-differenced GMM estimator relies on the identifying condition that the lagged values of explanatory variables in level regression are valid instruments for the endogenous variables in first-differenced regression. For this purpose, Arellano and Bond (1991) propose two tests: first, a standard Sargan test of over-identifying restrictions to examine the validity of the moment conditions; and second, a serial correlation test to investigate the hypothesis of no serial correlation in the error terms, $\mu_{i,t}$. However, Blundell and Bond (1998) point out that if the explanatory

---

[13] More specifically for the third period, i.e., for $t = 3$ only y_{i1}, for $t = 4$ both y_{i1} and y_{i2}, and for period $t = T$ the vector $[y_{i1}, y_{i1}, ..., y_{i,T-2}]$ can be used as valid instruments for the lagged dependent variable in the first-differenced equation, $(\Delta \log y_{i,t-1})$. As seen, the number of instruments increases with T.

[14] These authors find the implied rate of convergence as approximately 8 percent, 7 percent and 10 percent in the unrestricted augmented neoclassical growth model, the restricted neoclassical growth model and the Barro type growth model, respectively.

variables in level regression are persistent over time, then past valued of these variables will be weak instruments for endogenous first-differenced variables. The reason is that in the case of persistent series, the past levels are less informative for future changes. A Monte Carlo study conducted by these authors shows that given the problem of weak instrument, the first-differenced GMM estimator is severely biased in dynamic panel models with small T. As mentioned above, panel growth models have small number of time periods and augmented neoclassical growth variables, especially level of output, are persistent over time. Therefore, estimating the augmented neo-classical growth model in panel form by the first-differenced GMM produces inconsistent results.

To mitigate the bias induced by the problem of weak instrument Arellano and Bover (1995) and Blundell and Bond (1998) suggest a system GMM estimator. In addition to instrumenting for endogenous first-differenced variables (in equation 27) using lagged values of variables in levels, the system GMM approach employs the past values of first-differenced variables as instruments for potential endogenous level variables (in equation 26). Therefore, this variant of GMM estimator is based on a system of two equations; the first-diffferenced equation with level instruments and the level equation with the first-differenced instruments. Under the assumption that the covariance between potential endogenous variables in level regression, that is $y_{i,t-1}$ and $X_{i,t}$ and country-specific fixed-effects, is constant over time, the available lagged first-differences of $y_{i,t-1}$ and $X_{i,t}$ can be used as valid instruments for these variables. More formally, if $E[y_{i,t+p}\xi_i] = E[y_{i,t+q}\xi_i]$ and $E[X_{i,t+p}\xi_i] = E[X_{i,t+q}\xi_i]$ for all p and q, then the moment conditions for the level regressions are $E[\Delta y_{i,t-s}(\xi_i + \mu_{i,t})] = 0$ and $E[\Delta X_{i,t-s}(\xi_i + \mu_{i,t})] = 0$, for $t = 3, ..., T$ and $s \geq 2$. Of course, the validity of these moment conditions requires the assumption of no serial correlation in $\mu_{i,t}$.[15]

---

[15] Indeed, the validity of these additional moment conditions relies on a stationary assumption about the initial conditions of explanatory variables in the level regression. This assumption implies that deviations of initial observations from their steady-state values are not correlated with fixed effects and hence past changes can be used as instruments for levels in untransformed model. Bond (2002) and Roodman (2009b)

These extra moment conditions (with the other standard conditions of GMM approach) make the system GMM more robust estimator than the first-differenced GMM in the presence of highly time persistent variables and short dynamic panels.[16] Addressing the problem of weak instrument, Bond et al. (2001) estimate the augmented neoclassical growth model in panel form by both the system and first-differenced GMM estimators and conclude that their parameter estimate of lagged dependent variable ($\log y_{i,t-1}$) is higher than the corresponding fixed effects estimate while the first-differenced GMM estimate is found to be less than the fixed effects estimate. In this regard, it is worth emphasising that a consistent estimator should lie in the range between the OLS and fixed effects estimators due to the fact that these two estimates are highly likely to be biased in opposite directions. This fact obviously provide a good consistency check on GMM estimators. That is, one can check the consistency of GMM estimates by comparing with OLS and fixed effects estimates (see, for instance, Hsiao (1986) and Bond (2002)). Therefore, Bond et al. (2001) asses these findings as evidence that given the high-degree of persistence in output, the first-differenced GMM estimates are severally biased and the system GMM estimates are more plausible and preferable. In this context, these authors conclude a slower rate of convergence than found by Caselli et al. (1996).

By using within-country variation, panel data methods with fixed effects allow us to multiply the number of observations and to gain degrees of freedom. This obviously help us to obtain more precise parameter estimates. Moreover, by controlling for country-specific fixed effects, these methods have undoubtedly improved the findings of cross-country growth literature in terms of robustness. The system GMM is particulary useful in this respect since dealing with the problem of weak instrument, this estimator alleviates the endogeneity bias stemming not only from time invariant omitted variables but also from simultaneity and measurement error. However, the system GMM

---

provide nice expositions of the initial conditions. See, also Bond et al. (2001) for the validity of the stationary assumption in the augmented neoclassical growth model.

[16] Bond (2002) and Roodman (2009a) nicely review the GMM approach for dynamic panel data model with a fixed effect and the small number of time periods and also present examples of these methods.

uses more instruments than the first-differenced GMM and this can cause test for over-identifying restrictions (such as the Sargan test or the Hansen tests) to be weak (Roodman (2009b)). This is particularly an important concern in the cross-country growth studies since they are based on small samples. Furthermore, the use of lagged values of endogenous variables as instruments is debatable in the literature due to the fact that the predetermined variables with respect to endogenous regressors do not guarantee that they are directly uncorrelated with growth and hence they are proper instruments. The most important reason is that many growth variables like school enrolment rate influence economic growth with a substantial time lag. Even if they are valid instruments, whether the instrumental estimate shows the effect of endogenous variable or of lagged value of that variable on economic growth remain unanswered. According to Mankiw (1995) the answer is generally neither. In this regard, one can suggest other predetermined variables except for the past values of endogenous variable as instruments, see, for instance, Bond et al. (2001). However, given the many growth theories and their proxies, it is very difficult to assume that a predetermined variable is uncorrelated with the omitted growth factors and hence error term in a growth regression. Put differently, finding a valid instrument for endogenous variables in cross-country growth regressions is almost impossible due to the open-endedness of growth theories as noted by Brock and Durlauf (2001). It may be worth reminding that if instrumental variable is not valid, the coefficient estimate will be again biased and in this case the OLS estimate would be more preferable as argued by Durlauf et al. (2005).

More to the point the panel growth models with fixed effects are conceptually flawed in two respects as Temple (1999a) and Wacziarg (2002) point out: First, treating the differences in technological efficiency across countries as country-specific fixed effects, panel data models on economic growth eliminate these effects despite the fact that explaining the fundamental causes of technological differences is one of the most important aims of empirical cross-country growth studies. In other words, as Hall and Jones (1997, p.174) state, "[I]t is the fixed effect itself that we are trying to explain." Therefore, in light of new growth theories extending the baseline cross-county growth regression with the inclusion of additional growth variables representing

unobserved level of technology is a more appealing way to examine the cross-country technological differences (we shall return to this issue later). Of course, one may claim that new growth theories and hence their proxies can be included in panel models. Yet, as mentioned above, most growth variables exhibit very little variation or remain constant through time such as variables related to institutional quality, geography, population heterogeneity, cultural affiliates.

Second, most panel studies analyse the growth over 5-year or 10-year time periods, as mentioned before. In this point, it is worth recalling that the baseline cross-country growth regression is derived from the log-linearization of output per worker around its steady-state solution in the neoclassical growth model. This implies that the time interval which growth and all right-hand-side variables averaged over, should be sufficiently long in order to reflect the long-run growth dynamics. However, it is very likely that panel studies with 5-year or 10-year averages employ the growth information in the short and medium run and clearly prone to business cycle effects.

Therefore, many researchers, for instance, Hall and Jones (1997), Pritchett (2000), and Wacziarg (2002) among others, do not find the use of panel data model with fixed effects as an appealing approach in order to investigate cross-country growth differences and growth causes. In our opinion, the panel growth regressions and the single cross-country growth regressions are actually complementary, rather than being alternatives to each other. Put differently, carrying out empirical research with both cross-sectional and panel data techniques and then comparing the findings are more consistent and illuminating strategy while analysing economic growth.[17]

The second criticism about MRW is that the secondary school enrolment rate is not an appropriate proxy for the investment rate in human capital. An important issue concerning school enrolment rate is that this variable is sometimes used as a proxy for level of human capital sometimes as a measure of change in human capital. It is however more appropriate to

---

[17] The study by Levine et al. (2000) is a good example in this respect. These authors investigate the impact of financial intermediary development on economic growth employing two econometric techniques: Both versions of GMM estimator and a single cross-sectional instrumental-variable estimator.

use school enrolment rate as a flow variable for human capital as indicated by Barro (1991) and Barro and Lee (1994b). Indeed, in the cross-country growth literature there are many studies (such as Barro (1991), Levine and Renelt (1992), Sala-i-Martin (1997b), Sala-i-Martin et al. (2004)) as well as Mankiw et al. (1992) that employ school enrolment rate as a proxy for accumulation of human capital and find that school enrolment rate is positively and significantly associated with economic growth. However, there are also other studies strongly criticising these findings. For instance Bils and Klenow (2000) argue that strong empirical relation between growth and school enrolment rate is spurious since it is more likely that both variables are correlated with other omitted factors such as openness to international trade or institutions. In addition, according to these authors there is the possibility that this relation reflects reverse causality. Similarly, Pritchett (2001) points out secondary school enrolment rate is an extremely poor proxy for growth in average years of schooling because school enrolment rates, especially those in developing countries, substantially increase over the time period in the cross-country growth analysis.

Due to these criticisms, there is a tendency in the literature about the schooling years per person published by Barro and Lee (1994a, 2000) as a more reliable measure for the level of human capital. However, some studies such as Benhabib and Spiegel (1994) and Pritchett (2001) employ average years of schooling as a measure of human capital stock and conclude that the relationship between change in years of schooling and growth of per capita income is insignificant and mostly negative. One possibility for this adverse relation is outlier effect. Temple (1999b) concludes a positive and significant relation between change in schooling year and growth when a number of extreme observations are omitted. Another possibility is that these studies are based on growth accounting framework rather than standard cross-country growth regression and hence their regression results may have suffered from omitted variable bias.

However, in spite of these possibilities, an important conclusion from these studies is that neither school enrolment rates nor average years of schooling are good proxies for human capital. The most important reason is that they do not directly measure cognitive skills of labour force since other factors

such as family background, health and nutrition have also a considerable effect on cognitive skills. Moreover, both variables do not measure the cross-country differences in the quality of education. As Wößmann (2003) argues that the impact of one year of schooling on human capital is not the same for all countries due to the differences in the quality of teachers, the educational infrastructure and the curriculum. In other words, depending on the quality of educational system, the effects of schooling on human capital and hence economic growth will be different across countries.[18] This leads some researchers to employ alternative variables measuring directly the quality of labour force such as teacher-student ratio or math and science test scores.[19] Unfortunately, cross-country comparable test scores are available for a small number of countries only. On the other hand, some authors (for example Temple (1999a), Benhabib and Spiegel (1994), Krueger and Lindahl (2001), Bils and Klenow (2000), Klenow and Rodríguez-Clare (1997), Hall and Jones (1999), Acemoglu (2009)) suggest measures of human capital based on returns to schooling or some measures based on the findings of other micro studies, specifically Mincerian approach to human capital.[20]

There is no doubt that the relation between growth and schooling (hence human capital) is a complex one. We expect a positive relation between these two due to the fact that education directly increases productive skills of labour force. In addition, schooling can stimulate economic growth through other channels such as reducing corruption, better conflict management, increasing health quality and so on. However, an increase in school attainment is necessary but not sufficient condition for accumulation of human capital. As

---

[18] Wößmann (2003) provides a nice survey of human capital measurement in the context of early cross-country growth studies. Emphasising the importance of both school quality and quantity, Hanushek and Woessmann (2008) review the role of cognitive skills on economic development.

[19] For instance, Hanushek and Kimko (2000) employing international math and science test scores from 31 countries conclude a significant and positive correlation between this variable and growth. Similarly, Jones and Schneider (2006) find that national average IQ test score is positively correlated with growth. Their finding is robust such that IQ test score passes a Bayesian model averaging test at 99.8 significance level.

[20] According to this approach, human capital is an exponential function of years of schooling.

pointed out by Pritchett (2001) institutional environment and demand for human capital are important factors. Yet, it is more likely that schooling significantly contributes to the level of human capital since it teaches how to learn and thus help to adapt and use new technological advances (Phelps (1995)). Therefore, variables measuring school attainment can still be used as a proxy for human capital, especially in the absence of better data.[21] MRW argue that if secondary school enrolment rate is proportional to saving rate for human capital (a reasonable assumption), then it can be used in the cross-country growth regressions. Of course problems such as data quality or measurement error associated with school enrolment rate are important. However, it may be worth reminding that all proxy variables in the cross-country growth literature are not free of these problems. As claimed by Mankiw (1995), many variables in the literature are crude proxies at best.

Thirdly, the assumption that the rate of technological progress is constant across countries is criticised. According to MRW, technology differs across countries due to the differences in initial level of technology, not differences in technological improvements. Put differently, they consider that technology is a public good freely and equally spreading over the world. Therefore, differences in growth are a result of differences in saving rates and population growth. However, as argued by Temple (1999a), there is no logical reason to expect that countries with initially different levels of technology experience the same rate of technological improvement. For instance, Bernard and Jones (1996) and Lee, Pesaran and Smith (1997) indicate that rates of technological progress vary across countries, even among industrial ones. Therefore, it seems difficult to explain growth miracles after the Second World War, such

---

[21] Cohen and Soto (2007) provided a new data set for average years of schooling over the period 1960-2000 as an alternative to schooling years published by Barro and Lee (2000). These authors replicate the previous studies which concluded negative and insignificant relation between growth and schooling and find that their new series is positively and significantly correlated with growth. Similarly, using more information and better methodology Barro and Lee (2010) have recently improved and updated their previous data set on education attainment for 146 countries from 1950 to 2010. Barro and Lee (2010) conclude that the new data set provides a more plausible proxy for the stock of human capital across countries compared to their previous one and the Cohen and Soto (2007) data set.

as Japan and South Korea, as purely a result of capital accumulation. On the other hand, one may conclude that this assumption is less unrealistic in the long run.[22] The reason is that innovations and technologies diffuse gradually across economies since countries try to access all technology available over the world. Diffusion of technology among countries may take a long time, yet eventually results in all countries experiencing the same rate of technological progress in the long run.[23]

Finally, some authors (for example Hall and Jones (1999), Frankel and Romer (1999), and Acemoglu et al. (2001)) suggest that the theoretical framework provided by MRW can be used for income-level regression instead of growth regression. More clearly, excluding the level of initial income as a right-hand-side variable from the baseline cross-country growth regression, these studies try to explain cross-county income differences. This approach is based on the assumption that initial-income levels were very similar across countries in the distant past and thus the current cross-country income differences have been a result of different growth performances over the very long run. Therefore, it may be possible to capture the long-run growth determinants from the cross-country income-level regression.

Even though this assumption seems reasonable since the primary objective of growth studies is to explain growth and ultimately income differences across countries, the disadvantages of income-level regressions are twofold. First, the theoretical foundations of income-level regression are not clear. As seen easily from the derivations of baseline cross-country growth regression described above, a cross-country income-level regression without the initial income as a right-hand-side variable is theoretically possible only if the

---

[22] See, for instance, Barro and Sala-i-Martin (1997), Hall and Jones (1997) and Eaton and Kortum (1996, 1999).

[23] Of course, the fact that the level of technology grows at the same rate across countries in the long run does not necessarily mean that one can assume a common rate of technological progress for any given sample. See Temple (1999a) and Aghion and Howitt (1999) for further discussion.

countries in the sample are in or around their steady states.[24] Therefore, the income-level approach explicitly requires the assumption that countries are randomly distributed in the vicinity of their steady states as Mankiw et al. (1992) points out. Second, the possible endogeneity problem between the dependent variable and regressors is more obvious in the income-level regression and finding good instruments in order to solve this problem is almost impossible as argued by Durlauf et al. (2009b).

Despite these problems, the large body of empirical cross-country growth literature consists of extended versions of the baseline specification in equation (23). A recent extension of this specification occurs through adding proxy variables suggested by the new growth theories as

$$
\varrho_i = \pi_0 + \pi_1 \log y_i(0) + \pi_2 \log(n_i + g + \delta) + \pi_3 \log s_{i,K} + \pi_4 \log s_{i,H} + \psi Z_i + v_i \tag{28}
$$

where Z_i is a vector of additional explanatory variables offered by new growth theories such as institutions, trade openness, geography, culture, political stability, etc., and ψ is a coefficient vector of these variables. The extended versions of the augmented neoclassical growth model in (28) can be rewritten in its generic form which is sometimes useful as follows

$$
\varrho_i = \gamma + \pi X_i + \psi Z_i + v_i \tag{29}
$$

where γ is constant term and X_i is a vector of explanatory variables suggested by the augmented neoclassical growth model, i.e. proximate determinants of growth and π is a vector of coefficient parameters of X variables.

Whether recent extended versions of MRW attempt to explain differences in initial level of technology or to allow differences in the rate of technological

---

[24] Taking the logarithm of the steady state value of output per unit of effective labour expressed in equation (18) and rearranging it, produce the following level regression:

$$
\log \frac{Y_i(t)^*}{L_i(t)^*} = a + gt - \frac{\alpha + \beta}{1 - \alpha - \beta} \log(n_i + g + \delta) + \frac{\alpha}{1 - \alpha - \beta} \log s_{i,K} + \frac{\beta}{1 - \alpha - \beta} \log s_{i,H} + \varepsilon_i
$$

where $\log(Y_i(t)^*/L_i(t)^*)$ is the logarithm of the steady-state level of income per worker, and the other variables are as before.

progress across countries is, however, unclear, as argued by Temple (1999a). Put differently, whether Z_i determines the steady state level of income or long-run growth rate is not defined. The only difference between the cross-country growth specification by MRW and its recent extensions is that the term $g + \eta a + \eta \varepsilon_i$ in equation (22) is replaced by the term $g + \eta a + \psi Z_i + \eta \varepsilon_i$ in equation (28). This would lead one to interpret the introduction of ψZ_i to relate to differences in the level of initial technology, $A_i(0)$. The reason is that extended versions of MRW ignore the fact that the terms g and $\log(n_i + g + \delta)$ should be replaced with the terms g_i and $\log(n_i + g_i + \delta)$, respectively if the new growth theories allow some degree of heterogeneity across countries in the rate of technological progress. Of course, allowing new growth theories to affect the rate of technological progress is not easy since this makes the cross-country growth regression nonlinear via the terms $g_i(Z_i)$ and $\log(n_i + g_i(Z_i) + \delta)$.[25]

It is, therefore, more appropriate to accept that the extensions of the MRW specification occur by replacing the initial level of technology with potential growth variables. Recall that two key assumptions behind the MRW approach: first, the rate of technological progress is constant and equal across countries; and second, the initial differences in the level of technology, as a part of the error term are uncorrelated with right-hand-side variables. Even if the common technological progress assumption is defendable, at least in the long run, it is almost untenable to assume that initial technological differences, $A_i(0)$ are distributed independently from the any regressors in equation (23) and hence OLS estimates of that equation suffer from the omitted variables bias, as pointed out earlier. Yet, in light of new growth theories replacing the term $A_i(0)$ with the potential growth variables obviously alleviates this bias. Therefore, given the problems of panel data methods discussed above, extending the MRW specification with the inclusion of new growth theories is a more appealing way not only to analyse the causes of growth differences but also to deal with omitted variable bias.

---

[25] Rodrìguez (2007) recently attempts to fill this gap and empirically analyses the nonlinearities in the growth process.

On the other hand, in spite of these facts, one can claim that Z_i has an effect on the long-run growth rate. The reason is that many cross-country growth works cover 20 or 30 years and some Z_i variables enter the regression as period averages. Therefore, it may not be reasonable to assume that countries experience the same rate of technological progress over the sample period. As suggested by Durlauf, Johnson and Temple (2005), whether Z_i affects the income level or growth rate in the long run depends on the researcher's prior beliefs.

However, even if it is plausible to assume that the interpretation of Z_i depends on the researcher's beliefs, another important problem related to Z_i remains. As mentioned earlier, while the X_i variables are generally constant in empirical cross country studies, there is no consensus about the Z_i variables in the literature. Therefore selecting Z_i variables is problematic and the selection differs from one study to another and thus raising the model uncertainty problem in cross-country growth regressions. We turn to this next.

3 Model Uncertainty and Cross-Country Growth Regressions

It is obvious that one of the most fundamental and controversial problem with cross-country growth regressions is model uncertainty and this issue has been acknowledged by many authors since the important work by Levine and Renelt (1992).[26] Indeed, model uncertainty is a crucial problem for any kind of empirical work in economics. However, the degree and solution to this problem become more severe and difficult in the context of cross-country growth regression since, as pointed out by Brock and Durlauf (2001, p.234), growth theories are fundamentally open-ended in the sense that "[t]he idea that the validity of one causal theory of growth does not imply the falsity of another." Thus new growth theories suggest a wide range of different explanations for cross-country growth differences such as

---

[26] See, for instance, Mankiw (1995), Sala-i-Martin (1997b,a), Temple (1999a, 2000), Brock and Durlauf (2001).

quality of institutions, openness to international trade, political stability, resource curse, population heterogeneity, the role of geography and so on. For instance, a survey by Durlauf, Johnson and Temple (2005) concludes that 145 different proxies have been found to be statistically significant in at least one study. This implies that identification of explanatory variables is a very important task and thus the bias induced by variable selection and the other misspecification issues in a particular cross-country regression is immense.

However, it is impossible to simply run a cross-country growth regression including all variables suggested by new growth theories due to the large number of growth variables and the limited number of countries in the world. Furthermore, the number of countries in a particular cross-country growth regression is considerably less than the actual number of countries because of data availability.[27] Of course, in the empirical cross-country growth literature, there is no study attempting to employ all possible variables. Rather, many studies chose a subset of explanatory variables and then report a selected model with the results of diagnostic test to provide robust evidence for one or more of the variables of interest. However, during the last decade this approach has been criticised since the results of these studies are very sensitive to included and/or excluded variables. The main difficulty in these studies is that several different models may all provide reasonable representations of the data, but lead to very different conclusions about what causes economic growth. Under these conditions, presenting results of a single preferred model can often be misleading.

Brock, Durlauf and West (2003, p.268) characterise the model uncertainty in a more general context. These authors suggest that "[i]t is useful in specifying a model space to consider several distinct levels of model uncertainty and build up the space sequentially." They then highlight three basic aspects of model uncertainty: First and most importantly, "theory uncertainty" stems from disagreements over alternative theories used to ex-

---

[27] As noted by Sala-i-Martin (2001), empirical cross-country growth works are subject to small sample econometrics. Therefore, the econometric problems discussed in cross-country growth empirics are common to other applied studies with small samples.

plain the same phenomenon. Of course, this disagreement is closely related to the absence of strong empirical evidence that would be conclusive for ranking alternative theories; The second is "specification uncertainty". Many empirical proxies for a particular variable give rise to this kind of uncertainty. Therefore, specification uncertainty is sometimes referred to as "proxy uncertainty". However, specification uncertainty encompasses the possible nonlinearities and lag length of variables as well as proxy uncertainty; The third is "heterogeneity uncertainty" stemming from the heterogeneity among different observations. For example, in the growth context, the effect of a particular theory and/or variable on Kenya will undoubtedly be different from that on the United Kingdom. This is why one needs to clarify whether there is heterogeneity in the growth process among the countries or regions being considered. Different specifications of heterogeneity among countries and regions produce different models and raise model uncertainty.

In short, theory, specification and heterogeneity uncertainties related to the model selection process produce different models.[28] Therefore, specifying the model space is the first step in handling the model uncertainty problem. However, the specification of the model space is generally based on the researcher's judgment. For example, whilst one researcher may interpret model uncertainty as proxy uncertainty, another may emphasise only heterogeneity uncertainty in the context of cross-country growth study.

Levine and Renelt (1992) is the first study to take into account model uncertainty in the empirical cross-country growth literature. Employing a variant of Leamer's extreme bounds analysis (Leamer (1983), Leamer and Leonard(1983)), these authors test the robustness of coefficient estimates for a large number of policy indicators as other explanatory variables alter. To illustrate the basic mechanism of a modified version of extreme bounds analysis (EBA hereafter) employed by Levine and Renelt (1992), consider the generic representation of cross-country growth regression expressed in

---

[28] Cross-country growth regression is a very good case for all levels of model uncertainty. However, it is worth recalling that other applied works in economics are not free from model uncertainty as defined here.

equation (29) in the following form

$$\varrho_i = \gamma + \pi X_i + \delta p_i + \psi Z_i + v_i \tag{30}$$

where X is the vector of variables always included in the regressions,[29] Z is a subset of variables chosen from a pool of over 50 variables suggested by previous growth studies and p is the variable of interest.

In order to carry out an EBA test, Levine and Renelt (1992) firstly run the benchmark regression including only X variables and the variable of interest, p. In the second step, the authors compute the regression results for all possible linear combinations of one to three variables from the pool of variables and determine the highest and lowest values for the coefficient estimate of variable of interest, $\hat{\delta}$, and its the corresponding standard error, $\hat{\sigma_\delta}$. Levine and Renelt (1992) identify the upper extreme bound as the highest value of $\hat{\delta}$ plus two times its standard error and define the lower extreme bound as the lowest value of $\hat{\delta}$ minus two times its standard error over all possible models for the variable of interest and then conclude the EBA test such that the variable of interest, p, is robust if its coefficient is significant and has the same sign at the extreme bounds ($\hat{\delta} \pm 2\hat{\sigma_\delta}$). If the coefficient of variable of interest does not remain significant and/or changes its sign, then EBA test indicates that this variable is fragile.

In a nutshell, Levine and Renelt (1992) investigate the robustness of the relationship between growth and a variable of interest according to the stability of the sign and statistical significance of the estimated coefficient over all possible models. Using more than 50 variables over the 1960-1989 period, Levine and Renelt (1992) find that only the initial level of income and the share of investment in GDP are robustly correlated with growth. In other words, except for these two, they conclude that all variables are fragile.[30]

---

[29] These variables are the initial level of real GDP per capita in 1960, the investment share of GDP, the initial secondary school enrolment rate, and the average annual rate of population growth.

[30] In addition, Levine and Renelt (1992) carry out the same analysis for the investment rate and conclude that only trade ratio is robustly and positively associated with investment.

Sala-i-Martin (1997b,a) criticises Levine and Renelt (1992) and argues that the EBA test is too extreme as they conclude a variable is fragile if the coefficient estimate loses its statistical significance and/or changes its sign even in one regression. Sala-i-Martin (1997b,a) suggests that one should consider the whole distribution of $\hat{\delta}$, and assign a level of confidence for the robustness test instead of labelling a variable as robust or fragile according to extreme bounds. In order to compute the cumulative distribution function of $\hat{\delta}$, he calculates the weighted averages of all estimates of δ and its corresponding standard error for each model as follows

$$\hat{\delta} = \sum_{i=1}^{M} \omega_i \hat{\delta}_i \tag{31}$$

$$\hat{\sigma_\delta} = \sum_{i=1}^{M} \omega_i \hat{\sigma}_{\delta,i} \tag{32}$$

where $\hat{\delta}$ and $\hat{\sigma_\delta}$ are the weighted averages of the coefficient of variable of interest and of its standard error over all possible models, respectively. The weights, ω_i are the critical point of the analysis and calculated as a proportion of the integrated likelihoods of each model as follows

$$\omega_i = \frac{\ell_{\delta i}}{\sum_{m}^{M} \ell_m} \tag{33}$$

where ℓ_m is the likelihood of each of the M models.[31]

Sala-i-Martin (1997b,a) argues that if 95 percent of cumulative distribution function of $\hat{\delta}$ lies on each side of zero, then that variable can be considered robust. Put differently, a variable is robust if its statistical significance and sign hold over 95 percent of all possible models. Unlike Levine

---

[31] Notice that $\sum_{m}^{M} \omega_i = 1$. As can be seen, the weighting scheme gives higher weights to the regressions or models which are more likely to be the true model.

and Renelt (1992), Sala-i-Martin (1997b) concludes that 21 of 59 variables are robustly correlated with growth.[32]

Even though Levine and Renelt (1992) and Sala-i-Martin (1997b,a) provide useful information concerning the model uncertainty problem in the cross-country growth literature, the econometric methods in these studies are subject to important drawbacks:[33] One problem with EBA is that extreme bounds depend on the selection of doubtful variables. In other words, different selections yield different extreme bounds. Generally, most of EBA applications classify the variables as fixed and doubtful variables and this classification is sometimes arbitrary, even though it is reasonable and defendable in the study by Levine and Renelt(1992). Secondly, extreme bound levels can come from models which are unreasonable in some ways or even clearly poor. For instance McAleer (1994) criticises Levine and Renelt (1992) since they present summary statistics of extreme bounds without diagnostic tests and also ignoring functional form misspecification.[34] Thirdly and perhaps most importantly, if one of the doubtful variables is important in explaining the dependent variable, then fragile results are inevitably obtained. More clearly, while testing for the sensitivity of a particular variable of interest over all possible models, that key variable will be sometimes omitted. Models excluding key varible(s) certainly affect the sign and statistical significance of $\hat{\delta}$. Therefore, it is possible to conclude that EBA is useful but not efficient and so overstates model uncertainty. On the other hand one may argue that Sala-i-Martin (1997b,a) version of EBA is more reasonable than Levine and Renelt (1992), but statistical properties of

---

[32] In his subsequent work, Sala-i-Martin (1997a) introduced the average investment rate between 1960 and 1990 as an additional fixed regressor and concludes that 17 of 59 variables are robustly correlated with growth. The reason for including average investment rate in the later study is to highlight the channels through which the variable of interest affects growth, namely via effects on the level of efficiency.

[33] EBA is heavily criticised by McAleer et al. (1985) and Hendry and Mizon (1990).

[34] Therefore, Granger and Uhlig (1990) propose *reasonable EBA* such that extreme bounds may come from models having R^2 values very close to maximum achievable value of R^2 over the model space. If this is done, then models with relatively low goodness-of-fit will be eliminated. Similarly, Temple (2000) suggests reporting a table listing models with the results of diagnostic tests instead of presenting only upper and lower extreme bounds.

this approach, especially the weighting scheme of models, are unclear since they are not based on a formal statistical theory (as Barro and Sala-i-Martin (2004) point out).

In summary, both versions of EBA fail to provide satisfactory solutions to the problem of identifying the true determinants of growth. Two approaches recently appeared in the literature.

The general-to-specific modelling (GETS henceforth) approach[35] is based on the idea that the true model can be characterised by a sufficiently rich regression. This means that a regression including all possible regressors has all the information about the dependent variable. However, the information presented by the *general regression* can be represented by a parsimonious regression called the *specific regression*. Of course, this specific regression must have some desirable properties such that it must be well defined, it should encompass every other parsimonious regression and so on. In short, the GETS approach starts with the general model and then searches for a specific model comparing all possible models in the model space according to some statistical criteria. Bleaney and Nishiyama (2002), Hoover and Perez (2004), and Hendry and Krolzig (2004) apply this approach to cross-country growth regressions.

The paper by Bleaney and Nishiyama (2002) is, in essence, based on the encompassing test among three non-nested models for cross-country growth regressions suggested by Sachs and Warner (1997), Barro (1997) and Easterly and Levine (1997). Even though these three models have some common explanatory variables, Bleaney and Nishiyama (2002) conclude that none of them dominates each other according to non-nested hypothesis testing procedures. This means that a model encompassing these three models fits the data better. Therefore, they combine the explanatory variables of the three models and eliminate them according to the GETS approach to derive a specific model which passes a battery of statistical tests successfully. According to Bleaney and Nishiyama (2002), this model cannot be improved by adding or omitting any variable, and can be used as a benchmark model in order to test new growth theories.

---

[35] It is sometimes referred to as London School of Economics (LSE) methodology.

Hoover and Perez (2004) and Hendry and Krolzig (2004) apply the GETS methodology directly to the data set employed by Sala-i-Martin (1997b,a) after some adjustment.[36] In both studies, a linear model including the number of revaluations and coups, the ratio of equipment investment, fraction of confucians, fraction of open years according to the Sachs and Warner (1995) criteria and fraction of protestants as explanatory variables of growth is estimated.[37] An interesting point concerning the results of these two studies is that the R^2 values of the regressions are found to be 0.42 and 0.44, respectively. This implies that the selected models explain less than 50 percent of the cross-country growth differentials. In addition, theoretically important variables, such as initial income level and variables relating to human capital, are not included in the final model.

One important criticism of the GETS methodology is that there can be several simplification paths from the general model and there is no guarantee that a particular simplification path leads to the true model. That is why the GETS approach is sometimes referred as "sophisticated data mining", as Hendry (1995) points out. However, Hoover and Perez (2004) and Hendry and Krolzig (2004) argue that the GETS approach employed in their papers is based on multiple-path searching program in order to handle this objection. In other words, both studies implement the GETS approach by employing the automated search algorithm first suggested by Hoover and Perez (1999) and then improved by Krolzig and Hendry (2001) in order to take into account competing models derived from different search paths and to select one on the basis of encompassing tests. In particular, the *PcGets* algorithm developed by Hendry and Krolzig (2005) is effective in reducing searching costs when the initial model is more general than needed.

The selection process of the specific model is based on six stages: First, assuming the true model is nested in a sufficiently rich model, a general

---

[36] The original data set used by Sala-i-Martin (1997b,a) contains 64 variables (including the dependent variable) for 138 countries. After a number of variables and countries are dropped from the data set in order to provide a complete data matrix, the resulting data set includes 126 countries and 61 variables and the dependent variable.

[37] Hendry and Krolzig (2004) also apply the GETS methodology on the data set used by Fernández et al. (2001).

unrestricted model (GUM) is formulated. In the second and third stages, a set of mis-specification tests and selection criteria are applied for final selection between mutually encompassing congruent models and then the GUM is estimated to check the congruence of the specification. Therefore, after the second and third stages, the GUM is reformulated as a baseline general model for the next steps. Fourth, a pre-search reduction process is carried out. In other words, the highly insignificant variables are eliminated using a less stringent significance level in order to simplify large dimensional problems. Thus, this stage is optional, not necessary. The fifth and main stage consists of multiple-path reduction searches. In this stage, many possible reduction paths are undertaken from each feasible initial deletion and each reduction is diagnostically evaluated for the congruence of the final model. That is, after a particular reduction path, if all diagnostic tests are successfully passed and all remaining variables are statistically significant, then that model is considered as a terminal specification. Next another reduction path is searched and hence another terminal model is selected and so on. After all possible paths are investigated and all terminal models are determined, encompassing tests are carried out for each union of terminal models to find an undominated encompassing contender. The union of surviving terminal models which is referred to as the smaller GUM is employed for a new multiple-path reduction search. The search process continues until a unique model, called the specific model, emerges. In the sixth and final stage, the significance of every variable in the final model is evaluated in two overlapping sub-samples for reliability of the specific model.[38]

The second approach is Bayesian model averaging (BMA hereafter) which was developed by, *inter alia*, Madigan and Raftery (1994), Hoeting (1994),

---

[38] While applying the *PcGets* algorithm, one can set any selection criteria for the significance levels, from strong to weak. The program also provides two basic strategies for these, namely liberal and conservative strategies. Both strategies are based on the critical values depending on sample size and for large samples on the number of possible explanatory variables. If there are many potentially irrelevant variables and few relevant variables, the conservative strategy is suggested. Conversely, for few irrelevant and many relevant variables, liberal strategy is better (Granger and Hendry (2005)).

Chatfield (1995), Draper (1995), Raftery et al. (1997).[39] The basic idea of BMA is to incorporate the model uncertainty into statistical inference such that the true model is considered as an unobservable random variable. In order to show this more formally suppose that the data for a random variable Y are generated by a particular model in the model space which encompasses all possible models. That is, assume that there are k possible different models and model space can be defined such that $\mathcal{M} = \{M_1, \ldots, M_k\}$, where $\mathcal{M}$ denotes the model space and M_j is one of its typical element as follows

$$M_j = \{p(\theta_j, y); \ \theta_j \in \Omega\} \tag{34}$$

where θ_j is the vector of unknown population parameters in some parameter space Ω, y is a vector of sample observations for Y and $p(\theta_j, y)$ is the joint density function for θ given y in j^{th} model, M_j. In this context, the likelihood function for model M_j is expressed by $\ell_j(\theta_j | y, M_j)$

In this setting, as pointed out by Wasserman (2000), model averaging refers to the procedure of estimating the quantity of interest under each possible model and then averaging those estimates according to the probabilities assigned to each model. Therefore, BMA accounts for model uncertainty by integrating the posterior probabilities of every possible model given the data such that:

$$p(\theta | y) = \sum_{j=1}^{k} p(\theta_j | y, M_j) p(M_j | y) \tag{35}$$

where $p(M_j | y)$ is the posterior probability of model M_j conditional on the data.

As can be seen in the last equation, the BMA estimate of parameter vector θ is the weighted average of all possible posterior probabilities of θ conditional on data and each possible model, with weights equal to posterior probabilities of each possible model. The obvious feature of BMA expressed in equation (35) is that model uncertainty is incorporated into subsequent

---

[39] The basic paradigm for BMA was presented by Leamer (1978). See Hoeting et al. (1999) for the historical development of BMA.

inference by considering the model as a random variable as well as θ and Y.[40] This implies that, in order to obtain a BMA estimate of θ, we first need to specify prior probabilities for each model, $p(M_j)$, indicating how likely it is the true model given the model space, and then for each model we need to assign priors to the parameters in that model, $p(\theta_j|M_j)$. In the light of these explanations, using the Bayes's rule, the posterior probability of model M_j can be expressed as

$$p(M_j|y) = \frac{p(y|M_j)p(M_j)}{\sum_{h=1}^{k} p(y|M_h)p(M_h)} \tag{36}$$

where

$$P(y|M_j) = \int \ell_j(\theta_j|y, M_j)p(\theta_j|M_j)d\theta_j \tag{37}$$

is the integrated likelihood of model M_j. This shows how the observed data support the assigned prior probability that M_j is the true model while assuming that one model in the model space is true. In this setting, the posterior inclusion probabilities of variable, Z can be calculated as follows:

$$\mu_Z \equiv \sum_{j=1}^{k} I(Z|M_j)p(M_j|y) \tag{38}$$

where

$$I(Z|M_j) = 0 \quad if \quad Z \notin M_j$$
$$= 1 \quad if \quad Z \in M_j$$

The verbal explanation of expression (38) is that the posterior inclusion probability for variable Z, denoted by μ_Z, is equal to the sum of posterior

---

[40] In the Bayesian context, an unknown population parameter is considered as a random variable such that an unknown population parameter is assigned with a subjective probability distribution which summarises our knowledge about that parameter. This property is another departure from the classical context since in the classical framework the unknown population parameter is treated as constant and hence a probability distribution can not assign to that parameter.

probabilities of all models including that variable. Therefore, μ_Z is interpreted as the probability of variable Z being included in true growth model and hence variables with high posterior inclusion probabilities are considered as robust growth determinants. Using the equations (36) and (37) one can also obtain Bayes factor for model M_j against the model M_h as:

$$B_{jh} = \frac{p(M_j|y)p(M_h)}{p(M_h|y)p(M_j)} = \frac{\int \ell_j(\theta_j|y, M_j)p(\theta_j|M_j)d\theta_j}{\int \ell_h(\theta_h|y, M_h)p(\theta_h|M_h)d\theta_h} \quad (39)$$

The Bayes factor for model M_j versus model M_h shows the probability that model M_j is true vis-a-vis model M_h. For instance if $B_{jh} = 5$, then model M_j is five times likely than model M_h, given the data. Therefore, we can compare the possible models using the Bayes factors for these models. However the main objective of BMA is to provide a better average value of parameters of interest, not to provide the "best" model.

Even though BMA is a coherent way in order to tackle model uncertainty, implementation of this procedure in the context of linear regression is not easy. There are two important difficulties which a researcher must overcome.[41] First, one needs to assign appropriate priors to models and their parameters, namely coefficients of regressors and variance for error term. Especially, specifying plausible priors over the models is a challenging task. The most common approach in the model averaging literature in which model uncertainty mostly considered as variable uncertainty is assigning uniform prior to each possible model. This approach is however problematic in the context of cross-country growth regression because it is very difficult to assume that the probability that one regressor appears in a growth model is independent from the absence or presence of other regressors, as indicated by Brock et al. (2003). The reason is that some regressors, such as alternative proxies for a particular growth theory are quite similar, while some regressors are quite disparate, such as proxy variables belonging to different growth theories.[42] That is why theories represented by a larger number of variables

---

[41] Indeed, these difficulties are the main reasons for why BMA was not popular until recently.

[42] This problem is very similar to red bus/blue bus problem in discrete choice theory while determining the probability of an individual's choice of a red bus over the taxi.

take higher weights than those measured by a smaller number of proxies. In order to overcome these difficulties, Brock et al. (2003) suggest a tree structure according to different layers of model uncertainty for prior model probability whereas Sala-i-Martin, Doppelhofer and Miller (2004) propose model priors by selecting a prior expected model size.[43] Similarly, there is no consensus about the priors on model parameters. For instance, while Brock and Durlauf (2001) and Sala-i-Martin et al. (2004) apply diffuse priors, Fernández et al. (2001) employ Zelner's g-prior structure for the coefficients of explanatory variables in each model. Detailed discussions of prior structures over the models and their parameters in BMA applications can be found in Ley and Steel (2009), Moral-Benito (2011b) and Eicher et al. (2011).

The second difficulty arising in the implementation of BMA is related to computation of posteriors. When the potential regressors and so the number of possible models are enormous (as in the case of cross-country growth regression), then computation of posterior probabilities of parameters of interest is very difficult, and in some cases practically infeasible. In this regard, most applications of BMA use a subset of model space as a reliable approximation to model space instead of searching all possible models. The most common approach, developed by Madigan and York (1995), is known as Markov chain Monte Carlo model composition (MC^3 henceforth) technique. The MC^3 method employs a Markov chain that moves through the model space and visits the only models with high posterior probabilities. An alternative approach is Occam's window which produces a reduced set of models for calculation of model averaging (see Madigan and Raftery (1994) and Hoeting (1994)).

Fernández et al. (2001), Brock and Durlauf (2001), Brock et al. (2003), Sala-i-Martin et al. (2004), Masanjala and Papageorgiou (2008), Ulaşan (2008), Eris (2010) are examples of the applications of BMA in the cross-

---

Undoubtedly, this probability is affected by the possibility of choosing a blue bus since blue bus is a quite substitute for red bus. See Brock et al. (2003) for a detailed discussion.

[43] These authors choose a prior expected model size as $\bar{q} = 7$ in the context of existing cross-country growth studies, where q is the number of explanatory variables in a possible model.

country growth context.[44] It may be worth summarising the findings of Fernández et al. (2001) and Sala-i-Martin et al. (2004) since these two are the most prominent studies amongst others. Sala-i-Martin et al. (2004) conclude that 18 of 67 potential growth variables have higher posterior inclusion probabilities with respect to corresponding priors. Among these, the only five variables, namely dummy for East Asia, primary school enrolment rate in 1960, the average price of investment goods, initial level of income per capita and the share of a country's land area in tropics have a posterior inclusion provability above 50 percent. There are four growth variables, population density in coastal areas, the malaria prevalence index, initial level of life expectancy and fraction of Confucians, have relatively higher posterior inclusion probabilities. Fernández et al. (2001) find four variables with a posterior inclusion probability above 90 percent. These are initial level of income per capita, fraction of Confucians, initial level of life expectancy and machinery-equipment investment. In addition, the posterior inclusion probabilities of sub-Saharan Africa dummy, fraction of muslims, rule of law and fraction of open years based on Sachs and Warner (1995) are found to be higher than 50 percent.

In this regard, we want to emphasise two points about BMA applications in the growth empirics literature: first, most studies determine the cutoff level for the posterior inclusion probabilities according to the attached priors. In other words, in order to decide the statistically robust association between a possible variable and economic growth, the criterion that the posterior inclusion probability of that variable should be equal to or above its prior inclusion probability is considered as a sufficient condition. Although this simple rule of thumb seems plausible, a formal treatment of hypothesis testing in Bayesian context is a more appealing way to determine robust growth determinants. Ulaşan (2008), Mirestean and Tsangarides (2009), and Eris (2010) are few examples attempting to interpreting the posterior findings in the framework of Bayesian hypothesis testing.[45]

---

[44] The approach in Sala-i-Martin (1997b,a) is close in spirit to that of BMA.

[45] Different from classical approach, in the Bayesian context hypothesis tests are based on the comparison of two hypothesis, denoted by H_0 and H_1. The posterior probability of each hypothesis shows how much H_0 and H_1 being correct, given data. In this setting,

The second point which we emphasise is that findings of BMA studies are very sensitive to choice of data source for real income per capita as Ciccone and Jarociński (2010) recently show. These authors conclude that minor changes in measurement of income level, such as the revisions of Penn World Table (PWT) income data or the differences between PWT and the World Bank World Development Indicators (WDI) have substantial impact on the posterior findings. The reason is that BMA approach gives much weight to the sum of squared errors while assigning posterior inclusion probabilities of models and hence small variations in R^2 lead to large differences in posterior inclusion probabilities. Ciccone and Jarociński (2010) replicate the BMA analysis of Sala-i-Martin et al. (2004) by using two recent revisions of PWT, namely PWT version 6.1 and PWT version 6.2 as well as the original data set PWT version 6.0 over the 1960-1996 period and find 23 robust growth determinants according to PWT 6.1 and/or PWT 6.2. The empirical analysis based on PWT 6.0 data yields only 19 variables as robust growth correlates. More importantly, the findings indicate that there are considerable disagreements about the robust growth variables amongst the three versions of PWT data. Some of these variables are considered as prominent growth determinants in the literature, such as fraction of open years, price of investment goods, the index of malaria prevalence, initial

---

the posterior odds ratio in favour of H_0 relative to H_1 calculated by

$$K_{01} = \frac{p(H_0|y)}{p(H_1|y)}$$

where y denotes the sampled data as before. As seen, the aim of hypothesis testing in the Bayesian context is to provide the statistical evidence in favour of one hypothesis with respect to another. However, the most common measure for hypothesis testing is Bayes factors (see Kass and Raftery (1995) and Wasserman (2000)) and defined as follows:

$$B_{01} = \frac{p(H_0|y)}{p(H_1|y)} \div \frac{p(H_0)}{p(H_1)}$$

The Bayes factors show how much the data have changed our prior odds in favour of hypothesis H_0 against hypothesis H_1. In the growth context, one can define the hypothesis H_0 as a particular growth variable being included in the true growth model and the hypothesis H_1 as that variable being excluded in the true growth model.

life expectancy and so on. Ciccone and Jarociński (2010) also examine the sensitivity of BMA results to choosing PWT and WDI for income data over the sample period of 1975-1996 and conclude that posterior inclusion probabilities are considerably different when using WDI instead of PWT income data.[46]

Finally, it is worth noting that most of the recent BMA applications in the literature adapt this methodology to panel data models in order to address the problem of model uncertainty in the presence of endogeneity. These studies generally use lagged or initial values of endogenous variables as instruments. For instance, Durlauf et al. (2008) apply BMA to an unbalanced panel in the context of two-stage least squares. Mirestean and Tsangarides (2009) propose a limited information BMA (LIBMA) approach developed by Chen et al. (2009) and based on the system GMM estimation. Combining a likelihood function of a dynamic panel growth model with BMA framework, Moral-Benito (2011a) employs an approach, called as Bayesian Averaging of Maximum Likelihood Estimates (BAMLE) for simultaneously tackling omitting country fixed-effects and model uncertainty. Extending the Durlauf et al. (2008) approach, Eicher et al. (2012) suggest an instrumental variable BMA (IVBMA) method. Extension of BMA framework to a panel setting is certainly a fruiful research era in order to deal with both model uncertainty and different forms of endogenity as noted by Durlauf et al. (2009b) and Moral-Benito (2011b). However, as discussed in the previous section, we have the same reservations about the panel growth models and predetermined variables as proper instruments for this line of research.

Although we consider BMA as the most promising approach to address the issue of model uncertainty, we do not purport that we have a negative

---

[46] Indeed, the sensitivity of empirical findings to choose of data source for income per capita and growth rate is an important, but generally ignored problem in the cross-country growth literature as Hanousek et al. (2008) point out. Although, the vast majority of the literature based on the PWT data, Hanousek et al. (2008) compare three widely-used data sources, namely IMF's International Finance Statistics (IFS), PWT and WDI, and show that results of several recent studies depend on the used data source for growth rate. According to these authors, using own-country data (like IFS) for growth rate and PPP-adjusted cross-country comparable data (such as PWT or WDI) for income level is a more appropriate strategy while running cross-country growth regressions.

view about the GETS approach. Obviously, both approaches are valuable statistical techniques for tackling model uncertainty and have their own advantages and disadvantages.[47] There is no doubt that the GETS approach is particularly useful if one needs a specific model for some purpose, e.g. forecasting.[48] On the other hand, an important advantage of BMA is that it provides a better framework for policy evaluation as discussed in the next section.

4   Model Uncertainty and Policy Evaluation in Cross-Country Growth Regression

Undoubtedly, the most important aim of cross-country growth studies is to explain growth differences across countries and to suggest policy implications which may be effective in promoting growth. Brock and Durlauf (2001, p. 230) argue that "[I]n emprical macroeconomics, efforts to explain cross-country differences in growth behavior since World War II become a predominant area of research. The implications of this work for policymakers are immense...[I]n turn, the academic community has used this new empirical work as the basis for strong policy recommendations." However, as indicated by Brock and Durlauf (2001), Brock et al. (2003), Easterly (2005) and Rodrik (2005) this literature largely fails with respect to the perspective of policy evaluation. While Rodrik (2005) points out the endogeneity problem between the policy variable and economic growth, Easterly (2005)

---

[47] There is a vast statistical literature debating classical versus Bayesian approaches on model uncertainty and model selection problem. See, for instance, Chatfield (1995), Hoover and Perez (1999), Pötscher (1991), Granger and Hendry (2005), Hansen (2005). It is obvious that the solution of the matter is beyond the scope of this paper. Yet, we just remind that classical econometric model selection methods such as the GETS approach suffer from four conceptual errors namely parametric vision, the assumption of true data generating process, evaluation based on fit, ignoring the effect of model uncertainty on subsequent statistical inference as noted by Chatfield (1995) and Hansen (2005).

[48] Another advantage of the GETS approach is that it is labour saving as noted by Hendry and Krolzig (2005). For instance, according to Hendry and Krolzig (2004), implementation of GETS approach to Sala-i-Martin (1997b,a)'s data set by *PcGets* takes approximately two hours, including stacking the data.

argues that the strong effects of policies obtained from cross-country growth regressions are mainly a result of extreme observations. Brock and Durlauf (2001) and Brock et al. (2003) emphasise the difficulty of macroeconomic policy evaluation in the presence of model uncertainty.

According to Brock and Durlauf (2001) and Brock et al. (2003), policy analysis can be carried out on the basis of two factors, namely the policy maker's preferences and a conditional distribution of the outcome of interest given the policy and available information. The authors argue that standard practice in the cross-country growth literature is uninformative from the perspective of policy evaluation since it fails to appropriately define the policy maker's preferences and ignores model uncertainty. Hence, Brock and Durlauf (2001) and Brock et al. (2003) propose that cross-country growth work for policy recommendations requires an explicit decision-theoretic formulation. Using the findings of modern statistical decision theory,[49] these authors integrate model uncertainty into policy analysis.[50] In this section, we briefly summarise the implications of model uncertainty for policy evaluation in the context of cross-country growth regressions.

Recall the generic representation of cross-country growth regression expressed in equation (30). The key question in the context of policy evaluation is how a policy maker can use the cross-country growth regressions in order to formulate policy recommendations for enhancing the growth in country i.[51] Suppose that variable p in equation (30) represents a policy

---

[49] Wald (1950), Brainard (1967), Chamberlain (2000), Sims (1980, 2002), Berger (1985), Manski (2000), Heckman (2001) are few examples.

[50] Although Brock and Durlauf (2001) and Brock et al. (2003) focus mainly on the cross-country empirical growth work, the framework developed by these authors are explicitly subject to other macroeconomic empirical analysis in formulating policy recommendations in the presence of model uncertainty. For a more general context concerning the issue, see Brock and Durlauf (2006) and Brock et al. (2007). In terms of policy analysis, a related direction of the literature is carried by Hansen and Sargent (2001) that emphasise the robust control theory to analyse macroeconomic policy under the model uncertainty.

[51] As noted by Eriş (2005), the term "policy maker" is used in a broader sense in the manner that he or she may be an economist suggesting a government to implement a particular policy, say openness to international trade, using some cross-country growth regression.

variable of interest which can be controlled by the policy maker. The standard answer to this question in the growth literature is to make policy suggestions according to the hypothesis tests for the coefficient corresponding with the policy variable of interest. More precisely, a policy maker recommends a change in the magnitude of the policy variable p for stimulating growth in country i according to the statistical significance of δ, typically assessed at 5 percent level, using a single model and a given data set. Obviously, this policy evaluation is conditional on the model employed by policy maker as well as data set.

The first problem with this kind of policy analysis in the context of cross-country growth regressions is that it neglects theory, specification and heterogeneity uncertainties. Secondly, even if model uncertainty can be eliminated, policy analysis based on statistical significance is problematic from the perspective of policy maker's preferences. In order to explain these problems more clearly, following the notation of Brock and Durlauf (2001) we define the policy maker's preferences in terms of utility (or objective) function as

$$V(\varrho_i, O_i) \tag{40}$$

where ϱ_i is growth rate of GDP per capita in country i, as previously defined, and O_i indicates the set of characteristics in country i affecting policy maker's utility. In the context of policy maker's utility function, implementing or suggesting a policy change which is effective for enhancing growth depends on comparisons of policy maker's utilities in alternative settings. More clearly, if the policy maker believes that a particular policy variable has some effect in increasing growth, then he faces two options: either implementing or not implementing a policy change. Therefore, denoting the level of policy variable by p, policy maker's decision set will be $A = \{0, dp_i\}$, where dp_i represents the policy change and for simplicity it is assumed to be positive. The objective of empirical work is to develop a decision rule which is conditional on observable data D. Since the cross-country growth regression in equation (30) is linear, the effect of a marginal change in p is δ. Therefore, the growth rate in country i will be $\varrho_i + \delta dp_i$ in the case of a policy change while it is ϱ_i in the absence of policy implementation. Policy evaluation requires

comparison of expected utilities of policy maker with and without policy change

$$E(V(\varrho_i + \delta dp_i, O_i)|D) - E(V(\varrho_i, O_i)|D) \tag{41}$$

where E represents the expected value operator. The conventional wisdom in the empirical cross-country growth literature is to compute this comparison selecting one model as if it is true model and applying a statistical significance test. A statistically insignificant coefficient is taken to mean that a particular policy is not important for economic growth while the statistical significance is used as strong evidence that the policy is important for economic growth. This kind of decision rule is implicitly assumed that the policy maker's utility function is defined by

$$E(V(\varrho_i + \delta dp_i, O_i)|D) - E(V(\varrho_i, O_i)|D) = [\widehat{\delta}(dp_i) - 2\hat{\sigma}_\delta(dp_i)] \geq 0 \tag{42}$$

where $\widehat{\delta}$ and $\hat{\sigma}_\delta$ denote the OLS coefficient estimate of policy variable p and its corresponding standard error, respectively. Obviously both are conditional on a particular model. Then one would suggest policy implementation in the form of dp_i if the t-statistic in OLS regression is equal or greater than 2 (2 is selected according to typical assessment of statistical significance level at 5 percent).

Policy analysis based on significance level is, however, troublesome in many ways even if the model used in OLS regression is true as argued by Brock and Durlauf (2001), Durlauf (2002) and Brock, Durlauf and West (2003). We emphasise two important problems: First, the policy maker evaluates a particular policy only using the mean and variance of the policy variable. However, the whole probability distribution of δ might be important for policy analysis. For instance, a policy maker may be more sensitive to negative growth rates than positive ones or the effect of growth on poverty can be asymmetric and a typical policy maker tries to act in socially acceptable way. Second, even if the policy maker takes into account only the mean and variance of policy variable of interest, policy analysis based on statistical significance considers the effect of policy change on the component of growth rather than the effect of the policy change on growth per se. In other words,

a statistically significant coefficient of estimate shows the marginal effect of the policy variable on growth and does not provide a clear answer to whether policy change should be implemented.

The message of these criticisms is that one should define more appropriate utility functions and assess a policy change under alternative policy scenarios.[52] Obviously, this policy evaluation will be based on a particular model only if policy maker is certain that the model at hand is true. Yet, since he is not certain about the true model, this adds another uncertainty to the uncertainty over parameter δ. In the case of model uncertainty, the policy maker will not want to evaluate a policy change according to a particular model. Instead, he or she will want to make expected utility comparison expressed in equation (41), conditioning on data. This means that comparison of expected utilities for a given policy should be based on the assumption that the true model is not known. Since calculation of expected utility information expressed in equation (41) contains all information for policy evaluation, in the absence of information about the true model, this expression explicitly requires accounting for model uncertainty since expected utilities are conditional on only data not on possible models. Therefore, this requires us to modify the expected utility comparison

---

[52] Brock and Durlauf (2001) and Brock et al. (2003) explore policy implications of cross-country growth analysis employing some alternative utility functions such as risk neutrality, ambiguity aversion and so on. According to these authors, the utility functions that they examine are not particularly compelling, but they are useful to illustrate in order to interpret growth regressions for policy analysis in the presence of model uncertainty. For instance, these authors indicate that EBA employed by Levine and Renelt (1992) corresponds to an extreme risk aversion utility for policy maker. More compactly, according to EBA a policy change is implemented only if

$$E(V(\varrho_i + \delta dp_i, O_i)|D) - E(V(\varrho_i, O_i)|D) > 0$$

for every model in the model space. See Eriş (2005) for a nice treatise showing what kinds of decision rules arise under the considerations of different assumptions for the policy maker's utility functions and policy robustness preference parameters accounting model uncertainty.

equation as

$$E(V(\varrho_i + \delta dp_i, O_i)|D) - E(V(\varrho_i, O_i)|D) =$$
$$\sum_k P(M_k|D)E(V(\varrho_i + \delta dp_i, O_i)|D, M_k) - \sum_k P(M_k|D)E(V(\varrho_i, O_i)|D, M_k)$$

(43)

where $P(M_k|D)$ is the probability that model M_k is the true causal relationship between the growth rate and explanatory variables for given data, D. Therefore, the last equation explicitly accounts model uncertainty and as mentioned before, the aim of any policy relevant empirical work is to compute these expected utilities.

As can be seen, equation (43) illustrates that the expected utility comparison depends on the weighted averages of the coefficient of the policy variable, and expected utility calculations are independent of a particular model. Rather, the true model as an unobservable random variable is integrated to this calculation. Hence, the second important message is that identifying (a) particular model(s) according to some model selection criteria does not have any intrinsic value from the perspective of policy evaluation in the presence of model uncertainty. In contrast, the standard practice in the literature evaluates a policy change according to a particular model and sometimes compares the coefficient estimates with those obtained from modified specifications of that model in order to provide robustness of data analysis. This kind of policy analysis not only does ignore model uncertainty but also does not provide a clear information for policy evaluation. For instance, if the estimated coefficient of a policy variable is large in one regression while small in another, drawing a conclusion concerning the policy variable of interest is unclear. However, the calculation in equation (43) clearly removes this kind of concerns since each possible model is integrated into the calculation. This methodology, known as "model averaging" in the statistics literature, is a coherent way not only in order to handle model uncertainty but also for policy evaluation.

5   Conclusion

In this paper, we reviewed the recent cross-country growth literature aiming to explain growth differences across countries using regression analysis and other statistical methods. Even though this literature was mainly inspired by endogenous growth theories, the neoclassical growth model, especially its augmented version by Mankiw et al. (1992) is still the workhorse for cross-country growth empirics. For instance Mankiw (1995) argues that "[I]f the goal is to explain why standard of living is higher today than a century ago, then neoclassical model is not very illuminating. . . [A] more challenging goal is to explain the *variation* in economic growth that we observe in different countries in different times (p. 280). . . [E]ndogenous growth models provide a plausible description of worldwide advances in knowledge. The neoclassical growth model takes world wide technological advances as given and provides a plausible description of international differences (p. 308)."

The most outstanding feature of the recent empirical cross-country growth literature is that a large number of factors have been suggested as fundamental growth determinants. Together with the small sample property, this leads to an important problem, model uncertainty: Which factors are more fundamental in explaining growth dynamics and hence growth differences are still the subject of academic research. Recent attempts based on general-to-specific modeling or model averaging are promising but have their own limits.

Closely related to model uncertainty, and indeed the ultimate goal of the literature is policy evaluation. In spite of the fact that model uncertainty has been recognised since the important work by Levine and Renelt (1992), it is very surprising that cross-country growth studies have been used for policy analysis without paying attention to model uncertainty. It is obvious that any policy recommendation derived from a particular cross-country growth regression is troublesome since in the presence of model uncertainty it is conditional on the selected model.

Although we emphasise model uncertainty in this overview, other econometric problems, especially, measurement error, outliers, parameter heterogeneity and nonlinearities in growth process are equally important in this

literature. Due to these problems, cross-country growth empirics can be considered as a mix of economic theory and statistics and it might be more reasonable to refer to it as "growth econometrics" as Durlauf et al. (2005) point out.

In conclusion, given the challenging econometric problems, the results of cross-country growth studies have been controversial in terms of robustness. The implications of this are threefold: First, it is more plausible to accept cross-country growth studies as a wider picture of growth process. This means that combining findings of this literature with detailed case studies is a worthwhile task. Second, it may be more useful to shift research agenda towards more practical or pragmatic issues rather than the international growth differences as suggested by Pritchett (2000). Third, introducing new statistical tools and better proxy variables will make cross-country growth studies more informative.

References

Acemoglu, D. (2009). *Introduction to Modern Economic Growth.* Princeton and Oxford: Princeton University Press.

Acemoglu, D., Johnson, S., and Robinson, J. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation. *American Economic Review*, 91(5): 1369–1401. URL http://ideas.repec.org/a/aea/aecrev/v91y2001i5p1369-1401.html.

Aghion, P., and Howitt, P. (1999). *Endogenous Growth Theory.* Cambridge, USA and London, UK: MIT Press.

Anderson, T., and Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. *Journal of the American Statistical Association*, 76(375): 598–606. URL http://www.jstor.org/stable/2287517.

Anderson, T., and Hsiao, C. (1982). Formulation and Estimation of Dynamic Models Using Panel Data. *Journal of Econometrics*, 18(1): 47–82. URL http://ideas.repec.org/a/eee/econom/v18y1982i1p47-82.html.

Arellano, M., and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58(2): 277–297. URL http://ideas.repec.org/a/bla/restud/v58y1991i2p277-97.html.

Arellano, M., and Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-components Models. *Journal of Econometrics*, 68(1): 29–51. URL http://ideas.repec.org/a/eee/econom/v68y1995i1p29-51.html.

Barro, R. (1997). *Determinants of Economic Growth: A Cross-Country Empirical Study.* Cambridge: MIT Press.

Barro, R., and Lee, J. (1994a). Data Set for a Panel of 138 Countries. Discussion paper. URL http://www.nber.org/pub/barro.lee/.

Barro, R., and Lee, J.-W. (1994b). Sources of Economic Growth. *Carnegie-Rochester Conference Series on Public Policy*, 40(3): 1–46. URL http://ideas.repec.org/a/eee/crcspp/v40y1994ip1-46.html.

Barro, R., and Lee, J.-W. (2000). International Data on Educational Attainment: Updates and Implications. Working Paper 42, Center for International Development at Harvard University. URL http://www.cid.harvard.edu/ciddata/ciddata.html.

Barro, R., and Lee, J.-W. (2010). A New Data Set of Educational Attainment in the World, 1950-2010. Working Paper 15902, National Bureau of Economic Research, Cambridge, MA. URL http://www.nber.org/papers/w15902.

Barro, R., and Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2): 223–251. URL http://ideas.repec.org/a/ucp/jpolec/v100y1992i2p223-51.html.

Barro, R., and Sala-i-Martin, X. (1997). Technological Diffusion, Convergence, and Growth. *Journal of Economic Growth*, 2(1): 1–26. URL http://ideas.repec.org/a/kap/jecgro/v2y1997i1p1-26.html.

Barro, R., and Sala-i-Martin, X. (2004). *Economic Growth*. Cambridge, USA and London, UK: MIT Press.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *Quarterly Journal of Economics*, 106(2): 407–443. URL http://ideas.repec.org/a/tpr/qjecon/v106y1991i2p407-43.html.

Benhabib, J., and Spiegel, M. (1994). The Role of Human Capital in Economic Development Evidence from Aggregate Cross-Country Data. *Journal of Monetary Economics*, 34(2): 143–173. URL http://ideas.repec.org/a/eee/moneco/v34y1994i2p143-173.html.

Berger, J. (1985). *Statistical Decision Theory and Bayesian analysis*. New York: Springer-Verlag, 2nd edition.

Bernard, A., and Jones, C. (1996). Technology and Convergence. *Economic Journal*, 106(437): 1037–1044. URL http://ideas.repec.org/a/ecj/econjl/v106y1996i437p1037-44.html.

Bils, M., and Klenow, P. (2000). Does Schooling Cause Growth? *American Economic Review*, 90(5): 1160–1183. URL http://ideas.repec.org/a/aea/aecrev/v90y2000i5p1160-1183.html.

Bleaney, M., and Nishiyama, A. (2002). Explaining Growth: A Contest Between Models. *Journal of Economic Growth*, 7(1): 43–56. URL http://ideas.repec.org/a/kap/jecgro/v7y2002i1p43-56.html.

Blundell, R., and Bond, S. (1998). Initial conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, 87(1): 115–143. URL http://ideas.repec.org/a/eee/econom/v87y1998i1p115-143.html.

Bond, S. (2002). Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice. *Portuguese Economic Journal*, 1(2): 141–162. URL http://eco.unex.es/jramajo/dynpanel.pdf.

Bond, S., Hoeffler, A., and Temple, J. (2001). GMM Estimation of Empirical Growth Models. CEPR Discussion Paper 3048, Centre for Economic Policy Research, London. URL http://ideas.repec.org/p/cpr/ceprdp/3048.html. Available at http://www.cepr.org/pubs/dps/DP3048.asp.

Brainard, W. C. (1967). Uncertainty and the Effectiveness of Policy. *American Economic Review*, (2): 411–425. URL http://www.jstor.org/stable/1821642.

Brock, W., and Durlauf, S. (2001). Growth Empirics and Reality. *World Bank Economic Review*, 15(2): 229–272. URL http://www.jstor.org/stable/3990263.

Brock, W., and Durlauf, S. (2006). Macroeconomics and Model Uncertainty. In D. Colander (Ed.), *Post-Walrasian Macroeconomics: Beyond the Dynamic Stochastic General Equilibrium*, pages 116–134. New York: Cambridge University Press.

Brock, W. A., Durlauf, S. N., and West, K. D. (2003). Policy Evaluation in Uncertain Economic Environments (with discussion). *Brookings Papers on Economic Activity*, 2003(1): 235–321. URL http://ideas.repec.org/a/bin/bpeajo/v34y2003i2003-1p235-322.html.

Brock, W. A., Durlauf, S. N., and West, K. D. (2007). Model Uncertainty and Policy Evaluation: Some Theory and Empirics. *Journal of Econometrics*, 136(2): 629–664. URL http://ideas.repec.org/a/eee/econom/v136y2007i2p629-664.html.

Caselli, F., Esquivel, G., and Lefort, F. (1996). Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics. *Journal of Economic Growth*, 1(3): 363–389. URL http://ideas.repec.org/a/kap/jecgro/v1y1996i3p363-89.html.

Chamberlain, G. (2000). Econometrics and Decision Theory. *Journal of Econometrics*, 95(2): 255–283. URL http://ideas.repec.org/a/eee/econom/v95y2000i2p255-283.html.

Chatfield, C. (1995). Model Uncertainty, Data Mining and Statistical Inference. *Journal of the Royal Statistical Society, Series A (Statistics in Society)*, 158(3): 419–466. URL http://www.jstor.org/stable/2983440.

Chen, H., Mirestean, A., and Tsangarides, C. (2009). Limited Information Bayesian Model Averaging for Dynamic Panels with Short Time Periods. Working Paper 09/74, International Monetary Fund, Washington, D.C. URL http://ideas.repec.org/p/imf/imfwpa/09-74.html.

Ciccone, A., and Jarociński, M. (2010). Determinants of Economic Growth: Will Data Tell? *American Economic Journal: Macroeconomics*, 2(4): 222–246. URL http://ideas.repec.org/a/aea/aejmac/v2y2010i4p222-46.html.

Cohen, D., and Soto, M. (2007). Growth and Human Capital: Good data, Good results. *Journal of Economic Growth*, 12(1): 51–76. URL http://ideas.repec.org/a/kap/jecgro/v12y2007i1p51-76.html.

Draper, D. (1995). Assessment and Propagation of Model Uncertainty. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1): 45–97. URL http://www.jstor.org/stable/2346087.

Durlauf, S. (1996). Controversy on the Convergence and Divergence of Growth Rates. *Economic Journal*, 106(437): 1016–1018. URL http://www.jstor.org/stable/10.2307/2235374.

Durlauf, S. (2002). Policy Evaluation and Empirical Growth Resarch. In N. Loayza, and R. Soto (Eds.), *Economic Growth: Sources, Trends, and Cycles*, pages 163–190. Santiago, Chile: Central Bank of Chile. URL http://ideas.repec.org/h/chb/bcchsb/v06c06pp163-190.html.

Durlauf, S., and Johnson, P. (1995). Multiple Regimes and Cross-country Growth Behaviour. *Journal of Applied Econometrics*, 10(4): 365–384. URL http://ideas.repec.org/a/jae/japmet/v10y1995i4p365-84.html.

Durlauf, S., Johnson, P., and Temple, J. (2005). Growth Econometrics. In P. Aghion, and S. N. Durlauf (Eds.), *Handbook of Economic Growth*, volume 1A, chapter 8, pages 555–677. Amsterdam: North-Holland. URL http://ideas.repec.org/h/eee/grochp/1-08.html.

Durlauf, S., Johnson, P., and Temple, J. (2009a). The Econometrics of Convergence. In T. C. Mills, and K. Patterson (Eds.), *Palgrave Handbook of Econometrics*, volume 2: Applied Econometrics, chapter 23, pages 1087–1118. London: Palgrave Macmillan.

Durlauf, S., Johnson, P., and Temple, J. (2009b). The Methods of Growth Econometrics. In T. C. Mills, and K. Patterson (Eds.), *Palgrave Handbook of Econometrics*, volume 2: Applied Econometrics, chapter 24, pages 1119–1179. London: Palgrave Macmillan.

Durlauf, S. N., Kourtellos, A., and Tan, C. (2008). Are Any Growth Theories Robust? *Economic Journal*, 118(527): 329–346. URL http://ideas.repec.org/a/ecj/econjl/v118y2008i527p329-346.html.

Easterly, W. (2005). National Polices and Economic Growth: A Reappraisal. In P. Aghion, and S. N. Durlauf (Eds.), *Handbook of Economic Growth*, volume 1A, chapter 15, pages 1015–1059. Amsterdam: North-Holland. URL http://ideas.repec.org/h/eee/grochp/1-15.html.

Easterly, W., and Levine, R. (1997). Africa's Growth Tragedy: Policies and Ethnic Divisions. *Quarterly Journal of Economics*, 112(4): 1203–1250. URL http://ideas.repec.org/a/tpr/qjecon/v112y1997i4p1203-50.html.

Eaton, J., and Kortum, S. (1996). Trade in ideas Patenting and productivity in the OECD. *Journal of International Economics*, 40(3-4): 251–278. URL http://ideas.repec.org/a/eee/inecon/v40y1996i3-4p251-278.html.

Eaton, J., and Kortum, S. (1999). International Technology Diffusion: Theory and Measurement. *International Economic Review*, 40(3): 537–570. URL http://www.jstor.org/stable/10.2307/2648766.

Eicher, T., A.Lenkoski, and Raftery, A. (2012). Bayesian Model Averaging and Endogeneity Under Model Uncertainty: An Application to Development Determinants. *Econometric Reviews*, Forthcoming.

Eicher, T., Papageorgiou, C., and Raftery, A. (2011). Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants. *Journal of Applied Econometrics*, 26(1): 30–55. URL http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.186.776.

Eriş, M. (2005). *Essays on Economic Growth and Cross-Country Growth Empirics*. Ph.D. thesis, University of Wisconsin at Madison. URL http://gradworks.umi.com/31/86/3186296.html.

Eris, M. (2010). Population Heterogeneity and Growth. *Economic Modelling*, 27(5): 1211–1222. URL http://dx.doi.org/10.1016/j.econmod.2010.02.010.

Fernández, C., Ley, E., and Steel, M. (2001). Model Uncertainty in Cross-Country Growth Regressions. *Journal of Applied Econometrics*, 16(5): 563–576. URL http://ideas.repec.org/a/jae/japmet/v16y2001i5p563-576.html.

Frankel, J., and Romer, D. (1999). Does Trade Cause Growth? *American Economic Review*, 89(3): 379–399. URL http://ideas.repec.org/a/aea/aecrev/v89y1999i3p379-399.html.

Galor, O. (1996). Convergence? Inferences from Theoretical Models. *Economic Journal*, 437(106): 1056–1069. URL http://ideas.repec.org/a/ecj/econjl/v106y1996i437p1056-69.html.

Granger, C., and Hendry, D. (2005). A Dialogue Concerning A New Instrument for Econometric Modelling. *Econometric Theory*, 21(1): 278–297. URL http://ideas.repec.org/a/cup/etheor/v21y2005i01p278-297_05.html.

Granger, C. J., and Uhlig, H. (1990). Reasonable Extreme-Bounds Analysis. *Journal of Econometrics*, 44(1-2): 159–170. URL http://ideas.repec.org/a/eee/econom/v44y1990i1-2p159-170.html.

Hall, R., and Jones, C. (1997). Levels of Economic Activity across Countries. *American Economic Review Papers and Proceedings*, 87(2): 173–177. URL http://ideas.repec.org/a/aea/aecrev/v87y1997i2p173-77.html.

Hall, R., and Jones, C. (1999). Why Do Some Countries Produce So Much More Output Per Worker Than Others? *Quarterly Journal of Economics*, 114(1): 83–116. URL http://ideas.repec.org/a/tpr/qjecon/v114y1999i1p83-116.html.

Hanousek, J., Hajkova, D., and Filer, R. (2008). A Rise by Any Other Name? Sensitivity of Growth Regressions to Data Source. *Journal of Macroeconomics*, 30(3): 1188–1206. URL http://ideas.repec.org/a/eee/jmacro/v30y2008i3p1188-1206.html.

Hansen, B. (2005). Challenges for Econometric Model Selection. *Econometric Theory*, 21(1): 60–68. URL http://ideas.repec.org/a/cup/etheor/v21y2005i01p60-68_05.html.

Hansen, L. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50(4): 1029–1054. URL http://ideas.repec.org/a/ecm/emetrp/v50y1982i4p1029-54.html.

Hansen, L., and Sargent, T. (2001). Robust Control and Model Uncertainty. URL http://homepages.nyu.edu/~ts43/.

Hanushek, E., and Kimko, D. (2000). Schooling, Labor-Force Quality, and the Growth of Nations. *American Economic Review*, 90(5): 1184–1208. URL http://ideas.repec.org/a/aea/aecrev/v90y2000i5p1184-1208.html.

Hanushek, E. A., and Woessmann, L. (2008). The Role of Cognitive Skills in Economic Development. *Journal of Economic Literature*, 46(3): 607–668. URL http://www.aeaweb.org/articles.php?doi=10.1257/jel.46.3.607.

Hauk, W., and Wacziarg, R. (2009). A Monte Carlo Study of Growth Regressions. *Journal of Economic Growth*, 14(2): 103–147. URL http://ideas.repec.org/a/kap/jecgro/v14y2009i2p103-147.html.

Heckman, J. (2001). Micro Data, Heterogeneity, and the Evaluation of Public Policy: Nobel Lecture. *Journal of Political Economy*, 109(4): 673–748. URL http://ideas.repec.org/a/ucp/jpolec/v109y2001i4p673-748.html.

Hendry, D. (1995). *Dynamic Econometrics*. Oxford: Oxford University Press.

Hendry, D., and Krolzig, H.-M. (2004). We Ran One Regression. *Oxford Bulletin of Economics and Statistics*, 66(5): 799–810. URL http://ideas.repec.org/a/bla/obuest/v66y2004i5p799-810.html.

Hendry, D., and Krolzig, H.-M. (2005). The Properties of Automatic GETS Modelling. *Economic Journal*, 115(502): C32–C61. URL http://ideas.repec.org/a/ecj/econjl/v115y2005i502pc32-c61.html.

Hendry, D., and Mizon, G. (1990). Procrustean Econometrics: Or Stretching and Squeezing Data. In C. W. J. Granger (Ed.), *Modelling Economic Series*, pages 121–136. Oxford: Clarendon Press.

Hoeting, J. (1994). *Accounting for Model Uncertainty in Linear Regression*. Ph.D. thesis, University of Washington.

Hoeting, J., Madigan, D., Raftery, A., and Volinsky, C. (1999). Bayesian Model Averaging: A Tutorial. *Statistical Science*, 14(4): 382–417. URL http://www.jstor.org/stable/2676803.

Holtz-Eakin, D., Newey, W., and Rosen, H. (1988). Estimating Vector Autoregressions with Panel Data. *Econometrica*, 56(6): 1371–1395. URL http://ideas.repec.org/a/ecm/emetrp/v56y1988i6p1371-95.html.

Hoover, K., and Perez, S. (1999). Data Mining Reconsidered: Encompassing and the General-to-Specific Approach to Specification Search. *Econometrics Journal*, 2(2): 167–191. URL http://ideas.repec.org/a/ect/emjrnl/v2y1999i2p167-191.html.

Hoover, K., and Perez, S. (2004). Truth and Robustness in Cross-country Growth Regressions. *Oxford Bulletin of Economics and Statistics*, 66(5): 765–798. URL http://ideas.repec.org/a/bla/obuest/v66y2004i5p765-798.html.

Hsiao, C. (1986). *Analysis of Panel Data*. Cambridge: Cambridge University Press, first edition.

Islam, N. (1995). Growth Empirics: A Panel Data Approach. *Quarterly Journal of Economics*, 110(4): 1127–1170. URL http://ideas.repec.org/a/tpr/qjecon/v110y1995i4p1127-70.html.

Islam, N. (2003). What Have We Learnt from the Convergence Debate? *Journal of Economic Surveys*, 17(3): 309–362. URL http://ideas.repec.org/a/bla/jecsur/v17y2003i3p309-362.html.

Jones, G., and Schneider, W. (2006). Intelligence, Human Capital, and Economic Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *Journal of Economic Growth*, 11(1): 71–93. URL http://ideas.repec.org/a/kap/jecgro/v11y2006i1p71-93.html.

Kass, R., and Raftery, A. (1995). Bayes Factors. *Journal of the American Statistical Association*, 90(430): 773–795. URL http://www.jstor.org/stable/2291091.

Klenow, P., and Rodríguez-Clare, A. (1997). The Neoclassical Revival in Growth Economics: Has It Gone Too Far? In B. S. Bernanke, and J. Rotemberg (Eds.), *NBER Macroeconomics Annual 1997*, pages 73–103. MIT Press. URL http://ideas.repec.org/h/nbr/nberch/11037.html.

Kormendi, R., and Meguire, P. (1985). Macroeconomic Determinants of Growth: Cross-Country Evidence. *Journal of Monetary Economics*, 16(2): 141–163. URL http://ideas.repec.org/a/eee/moneco/v16y1985i2p141-163.html.

Krolzig, H.-M., and Hendry, D. (2001). Computer Automation of General-to-Specific Model Selection Procedures. *Journal of Economic Dynamics and Control*, 25(6-7): 831–866. URL http://ideas.repec.org/a/eee/dyncon/v25y2001i6-7p831-866.html.

Krueger, A. B., and Lindahl, M. (2001). Education for Growth: Why and For Whom? *Journal of Economic Literature*, 39(4): 1101–1136. URL http://ideas.repec.org/a/aea/jeclit/v39y2001i4p1101-1136.html.

Leamer, E. (1978). *Specifaction Searches: Ad Hoc Inference with Nonexperimental Data.* New York: Wiley.

Leamer, E. (1983). Let's Take the Con Out of Econometrics. *American Economic Review*, 73(1): 31–43. URL http://ideas.repec.org/a/aea/aecrev/v73y1983i1p31-43.html.

Leamer, E., and Leonard, H. (1983). Reporting the Fragility of Regression Estimates. *Review of Economics and Statistics*, 65(2): 306–317. URL http://ideas.repec.org/a/tpr/restat/v65y1983i2p306-17.html.

Lee, K., Pesaran, M., and Smith, R. (1997). Growth and Convergence in a Multi-Country Empirical Stochastic Solow Model. *Journal of Applied Econometrics*, 12(4): 357–392. URL http://ideas.repec.org/a/jae/japmet/v12y1997i4p357-92.html.

Levine, R., Loayza, N., and Beck, T. (2000). Financial Intermediation and Growth: Causality and Causes. *Journal of Monetary Economics*, 46(1): 31–77. URL http://ideas.repec.org/a/eee/moneco/v46y2000i1p31-77.html.

Levine, R., and Renelt, D. (1992). A Sensivity Analysis of Cross-Country Growth Regressions. *American Economic Review*, 82(4): 942–963. URL http://ideas.repec.org/a/aea/aecrev/v82y1992i4p942-63.html.

Ley, E., and Steel, M. (2009). On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regression. *Journal of Applied Econometrics*, 24(4): 651–674. URL http://ideas.repec.org/a/jae/japmet/v24y2009i4p651-674.html.

Lucas, R. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22(1): 3–42. URL http://ideas.repec.org/a/eee/moneco/v22y1988i1p3-42.html.

Madigan, D., and Raftery, A. E. (1994). Model Selection and Accounting for Model Uncertainty in Graphical Models Using Occam's Window. *Journal of the American Statistical Association*, 89(428): 1535–1546. URL http://www.jstor.org/stable/2291017.

Madigan, D., and York, J. (1995). Bayesian Graphical Models for Discrete Data. *International Statistical Review*, 63(2): 215–232. URL http://www.jstor.org/stable/10.2307/1403615.

Mankiw, G. (1995). The Growth of Nations. *Brookings Papers on Economic Activity*, 1995(1): 275–326. URL http://ideas.repec.org/a/bin/bpeajo/v26y1995i1995-1p275-326.html.

Mankiw, G., Romer, D., and Weil, D. (1992). A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics*, 107(2): 407–437. URL http://ideas.repec.org/a/tpr/qjecon/v107y1992i2p407-37.html.

Manski, C. (2000). Identification problems and decisions under ambiguity: Empirical analysis of treatment response and normative analysis

of treatment choice. *Journal of Econometrics*, 95(2): 415–442. URL http://ideas.repec.org/a/eee/econom/v95y2000i2p415-442.html.

Masanjala, W., and Papageorgiou, C. (2008). Rough and Lonely Road to Prosperity: A reexamination of the sources of growth in Africa using Bayesian Model Averaging. *Journal of Applied Econometrics*, 23(5): 671–682. URL http://ideas.repec.org/a/jae/japmet/v23y2008i5p671-682.html.

McAleer, M. (1994). Sherlock Holmes and the Search for Truth: A Diagnostic Tale. *Journal of Economic Surveys*, 8(4): 317–370. URL http://ideas.repec.org/a/bla/jecsur/v8y1994i4p317-70.html.

McAleer, M., Pagan, A., and Volker, P. (1985). What Will Take the Con Out of Econometrics? *American Economic Review*, 75(3): 293–307. URL http://ideas.repec.org/a/aea/aecrev/v75y1985i3p293-307.html.

Mirestean, A., and Tsangarides, C. (2009). Growth Determinants Revisited. Working Paper 09/268, International Monetary Fund, Washington, D.C. URL http://www.imf.org/external/pubs/cat/longres.aspx?sk=23426.0.

Moral-Benito, E. (2011a). Determinants of Economic Growth: A Bayesian Panel Data Approach. *Review of Economics and Statistics*, Forthcoming.

Moral-Benito, E. (2011b). Model Averaging in Economics. Available at http://www.moralbenito.com/papers/maecon.pdf.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49(6): 1417–1426. URL http://ideas.repec.org/a/ecm/emetrp/v49y1981i6p1417-26.html.

Phelps, E. (1995). The Growth of Nations: Comment. *Brookings Papers on Economic Activity*, 1995(1): 311–313. Discussion of Mankiw paper with the same title.

Pritchett, L. (2000). Understanding Patterns of Economic Growth: Searching for Hills among Plateaus, Mountains, and Plains. *The World Bank Economic Review*, 14(2): 221–250. URL http://wber.oxfordjournals.org/content/14/2/221.abstract.

Pritchett, L. (2001). Where Has All the Education Gone? *The World Bank Economic Review*, 15(3): 367–391. URL http://wber.oxfordjournals.org/content/15/3/367.full.pdf.

Pötscher, B. (1991). Effects of Model Selection on Inference. *Econometric Theory*, 7(2): 163–185. URL http://ideas.repec.org/a/cup/etheor/v7y1991i02p163-185_00.html.

Quah, D. (1996). Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *Economic Journal*, 106(437): 1045–1055. URL http://ideas.repec.org/a/ecj/econjl/v106y1996i437p1045-55.html.

Raftery, A., Madigan, D., and Hoeting, J. (1997). Bayesian Model Averaging for Linear Regression Models. *Journal of the American Statistical Association*, 92(437): 179–191. URL http://www.jstor.org/stable/2291462.

Rodrìguez, F. (2007). Cleaning Up the Kitchen Sink: Growth Empirics When the World Is Not Simple. Available at the author's web page.

Rodrik, D. (2005). Why We Learn Nothing from Regressing Economic Growth on Policies. Available at the author's web page .

Romer, P. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, 94(5): 1002–1037.

Roodman, D. (2009a). How to Do Xtabond2: An Introduction to Difference and System GMM in Stata. *Stata Journal*, 9(1): 86–136.

Roodman, D. (2009b). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics*, 71(1): 135–158.

Sachs, J., and Warner, A. (1995). Economic Reform and the Process of Global Integration. *Brookings Papers on Economic Activity*, 1: 1–118. URL http://ideas.repec.org/a/bin/bpeajo/v26y1995i1995-1p1-118.html.

Sachs, J., and Warner, A. (1997). Sources of Slow Growth in African Economies. *Journal of African Economies*, 6(3): 335–376. URL http://jae.oxfordjournals.org/content/6/3/335.abstract.

Sala-i-Martin, X. (1996). The Classical Approach to Convergence Analysis. *Economic Journal*, 106(437): 1019–1036. URL http://ideas.repec.org/a/ecj/econjl/v106y1996i437p1019-36.html.

Sala-i-Martin, X. (1997a). I Just Run Four Million Regressions. Working paper 6252, National Bureau of Economic Research, Cambridge, MA. URL http://ideas.repec.org/p/nbr/nberwo/6252.html.

Sala-i-Martin, X. (1997b). I Just Run Two Million Regressions. *American Economic Review*, 87(2): 178–183. URL http://ideas.repec.org/a/aea/aecrev/v87y1997i2p178-83.html.

Sala-i-Martin, X. (2001). Comment on "Growth Empirics and Reality," by William A. Brock and Steven N. Durlauf. *World Bank Economic Review*, 15(2): 277–282. URL http://www.jstor.org/stable/10.2307/3990265. Discussion of Brock and Durlauf paper with the same title.

Sala-i-Martin, X., Doppelhofer, G., and Miller, R. (2004). Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach. *American Economic Review*, 94(4): 813–835. URL http://ideas.repec.org/a/aea/aecrev/v94y2004i4p813-835.html.

Sims, C. (1980). Macroeconomics and Reality. *Econometrica*, 48(1): 1–.48. URL http://ideas.repec.org/a/ecm/emetrp/v48y1980i1p1-48.html.

Sims, C. (2002). The Role of Models and Probabilities in the Monetary Policy Process. *Brookings Papers on Economic Activity*, 2002(2): 1–62. URL http://ideas.repec.org/a/bin/bpeajo/v33y2002i2002-2p1-62.html.

Solow, R. (1956). A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics*, 70(1): 65–94. URL http://www.jstor.org/stable/1884513.

Solow, R. (2007). The Last 50 Years in Growth Theory and the Next 10. *Oxford Review of Economic Policy*, 23(1): 3–14. URL http://oxrep.oxfordjournals.org/content/23/1/3.abstract.

Summers, R., and Heston, A. (1988). A New Data Set of International Comparisons of Real Product and Price Levels Estimates for 130 Countries, 1950-1985. *Review of Income and Wealth*, 34(1): 1–25. URL http://ideas.repec.org/a/bla/revinw/v34y1988i1p1-25.html.

Summers, R., and Heston, A. (1991). The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988. *Quarterly Journal of Economics*, 106(2): 327–368. URL http://ideas.repec.org/a/tpr/qjecon/v106y1991i2p327-68.html.

Swan, T. (1956). Economic Growth and Capital Accumulation. *Economic Record*, 32: 334–361. DOI http://onlinelibrary.wiley.com/doi/10.1111/j.1475-4932.1956.tb00434.x/abstract.

Temple, J. (1999a). The New Growth Evidence. *Journal of Economic Literature*, 37(1): 112–156. URL http://www.jstor.org/stable/2564727.

Temple, J. (1999b). A Positive Effect of Human Capital on Growth. *Economics Letters*, 65(1): 131–134. DOI http://ideas.repec.org/a/eee/ecolet/v65y1999i1p131-134.html.

Temple, J. (2000). Growth Regressons and What the Textbooks Don't Tell You. *Bulletin of Economic Research*, 52(3): 181–205. URL http://www.efm.bris.ac.uk/ecjrwt/abstracts/growreg.htm.

Ulaşan, B. (2008). *Trade Openness and Economic Growth: A Cross-Country Empirical Investigation*. Ph.D. thesis, University of Nottingham.

Wacziarg, R. (2002). Review of Easterly's "The Elusive Quest for Growth". *Journal of Economic Literature*, 40(3): 907–918. URL http://ideas.repec.org/a/aea/jeclit/v40y2002i3p907-918.html.

Wald, A. (1950). *Statistical Decision Functions*. New York: Wiley.

Wasserman, L. (2000). Bayesian Model Selection and Model Averaging. *Journal of Mathematical Psychology*, 44(1): 92–107. URL http://www.sciencedirect.com/science/article/pii/S0022249699912786.

Wößmann, L. (2003). Specifying Human Capital. *Journal of Economic Surveys*, 17(3): 239–270. URL http://ideas.repec.org/a/bla/jecsur/v17y2003i3p239-270.html.

Please note:

You are most sincerely encouraged to participate in the open assessment of this article. You can do so by either recommending the article or by posting your comments.

Please go to:

The Editor