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Explaining the Negative Coefficient Associated with Human Capital in Augmented Solow Growth Regressions*

Jean-Louis ARCAND, Béatrice D'HOMBRES

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CERDI-CNRS, Université d'Auvergne
65, boulevard François Mitterrand - 63000 Clermont Ferrand -France
tel : +33-4-73177400 - fax : +33-4-73177428
email: B.Dhombres@u-clermont1.fr - arcandjl@alum.mit.edu
http: www.cerdi.org

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Abstract

In this paper we consider different explanations for why the coefficient associated with human capital is often negative in growth regressions once country-specific effects are controlled for whereas the coefficient in question is strongly positive in cross-sectional or panel results based on the pooling estimator. In turn, we explore: (i) additional sources of unobserved heterogeneity stemming from country-specific rates of labor-augmenting technological change, (ii) measurement error in the human capital series being used, and (iii) the lack of variability in the human capital series once the usual covariance transformations are implemented. Remaining unobserved country-specific heterogeneity and measurement error alone are shown to be inadequate explanations. The lack of variability in the human capital series is tackled using a new GMM-based estimator that combines the Hausman-Taylor (1981) approach, in which the impact of time-invariant covariates can be identified through use of covariance transformations of the variables themselves as instruments, with the orthogonality conditions of the Arellano-Bond (1991) estimator.

Keywords: Economic growth, human capital, measurement error, panel estimation.

Résumé

Pourquoi le coefficient associé au capital humain dans un modèle de Solow Augmenté est-il négatif ?

Cet article a pour objet d'étudier les différentes explications susceptibles de conduire dans une estimation de croissance à un coefficient associé à l'éducation tantôt négatif en effet fixe et tantôt positif en pooling. Ainsi, nous étudions successivement les biais liés (i) à la non prise en compte de l'hétérogénéité non observable dans le taux d'accumulation du progrès technologique, (ii) à l'erreur de mesure associée à la variable de capital humain traditionnellement utilisée, (iii) au manque de variabilité de la variable de capital humain une fois effectuées les transformations en effets fixes ou en différence première. Les biais causés par la non prise en compte des effets simultanés de l'erreur de mesure et du manque de variabilité sont contrecarrés par l'utilisation d'un nouvel estimateur de variables instrumentales qui combine à la fois l'approche de Hausman-Taylor (1981) et les conditions d'orthogonalités de l'estimateur de Arellano-Bond (1991).

Mots clés : croissance économique, capital humain, erreur de mesure, estimation en panel.

JEL: E13, C230, O400, O150.

1. INTRODUCTION

Since the seminal empirical contributions by Mankiw, Romer and Weil (1992, henceforth MRW) and Benhabib and Spiegel (1994), there has been a fundamental tension between cross-sectional and panel data results concerning the impact of education on the process of economic growth. Results based on cross-sectional data over 25 year time spans (or longer), such as those presented by MRW, indicate a strong positive effect of various measures of human capital on economic growth. In contrast, once country-specific fixed effects are controlled for, as in Benhabib and Spiegel (1994) or Islam (1995), the coefficient associated with human capital becomes either statistically indistinguishable from zero or negative and statistically significant at the usual levels of confidence.[1] Table 1 summarizes a number of recent empirical findings that follow this pattern, and underscores their worrisome nature. Given the high proportion of government expenditures devoted to education, the question that immediately arises, as it was cogently put by Pritchett (1997) is : Where has all the education gone ?[2]

The reason for including human capital in an empirical implementation of the Solow growth model –the point of departure for the contribution of MRW– was to reduce the point estimate of the coefficient associated with physical capital, held to be much too high in light of the mean value of labor's share in GDP across countries and across time periods.[3] In a restricted Solow growth regression estimated over the period 1960-1985, the point estimate of a , the share of capital in GDP, was found by MRW to be equal to 0.6.[4] Including human capital in the specification brought it down to the much more acceptable level of 0.31, with education's

[1] As Benhabib and Spiegel (1994, p. 154) put it, "the coefficient for human capital is insignificant and enters with the wrong sign…. whether we use the Kyriacou, Barro-Lee, or literacy data sets as proxies for the stock of human capital," while Islam (1995, p. 1153) states that "the coefficient on the human capital variable now appears…with the wrong sign….Whenever researchers have attempted to incorporate the temporal dimension of human capital variables into growth regressions, outcomes of either statistical insignificance or negative sign have surfaced."

[2] Pritchett uses one human capital stock and instruments using another in his specification. This method, known as the "indicator variable" approach, is well described in Wooldridge (2002).

[3] The issue of the "appropriate" value of capital's share has been considered by a number of authors. Hamilton and Monteagudo (1998) consider a vintage capital model that explains the lack of correspondence between the coefficient on capital in the estimation and the share of capital in GDP (see their references on p. 506). Gollin (2001) revises the estimates of labor's share of income (usually based on employee compensation) using data on self-employment and small enterprises, and shows that conventional estimates are likely to be severely biased for poor countries.

[4] MRW, 1992, Table I, p. 414; Islam, 1995, obtains 0.83, Table 1, p. 1141.

share coming in at 0.28.[5] As such, the augmented Solow specification on cross-sectional data can be said to have accomplished its mission.

With the increasing availability of internationally comparable panel data, however, it became difficult to justify estimating growth regressions on cross sections, given that the data, as well as the appropriate econometric techniques, allowed one to control for country-specific unobserved heterogeneity. As is well-known, failure to control for individual effects tends to bias point estimates upwards, when the individual effects in question are positively correlated with the variable whose marginal impact one is trying to estimate. As such, panel estimation through some sort of covariance transformation (such as fixed effects) provides one with an additional tool that can, *a priori*, bring down the point estimate of the coefficient associated with physical capital, and provide more robust estimates of the marginal impact of human capital on growth (presumably reducing, though not, hopefully, eliminating it).

The puzzle being tackled in this paper stems from the fact that, once country-specific fixed effects are controlled for, the baby has been thrown out along with the bath-water: the marginal impact of human capital on growth, within the admittedly limiting confines of the augmented Solow growth model, becomes negative.[6] A similar finding by Hamilton and Monteagudo (1998) leads them to the rather unpalatable conclusion that : "The suggestion that countries can significantly improve their growth by further investments in public education does not seem to be supported by the data."[7]

The purpose of this paper is, first, to understand why human capital's role vanishes once country-specific effects are controlled for and, second, to provide an empirical answer that restores human capital to the key positive role that is predicted by almost all growth theories. It is worth stressing that the reasoning, and the empirical results, presented in this paper apply to the augmented Solow model of economic growth. On the one hand, this approach is rather limiting, in that richer empirical specifications are possible if one considers more sophisticated theoretical underpinnings. On the other, the augmented Solow model provides a simple unifying framework within which to analyze the role of human capital: moreover, if

[5] MRW, 1992, Table II, p. 420.

[6] See, e.g., Islam, 1995, Table V, p. 1151, where the coefficient associated with human capital becomes negative and statistically significant for his NONOIL sample; it is statistically indistinguishable from zero in the INTER and OECD samples.

[7] Hamilton and Monteagudo (1998), p. 508.

human capital is not a significant determinant of growth even within the augmented Solow model, its purported positive role hinges on much more tentative and specific mechanisms (such as the capacity to adopt new technologies). In addition, despite the popularity of endogenous growth theories as theoretical constructs within which the determinants of growth can be understood, it is difficult to test them structurally: the Solow model can certainly not be criticized in this respect.[8]

The structure of this paper is as follows. In part 2, we set out the basic empirical specification of the augmented Solow model. In part 3 we consider the two simple covariance transformation habitually used to control for country-specific heterogeneity (the within and first-difference transformations) and discuss the upward biases that arise when these corrections are not implemented: this may be one reason for which the coefficient associated with human capital is large in the pooling and cross-sectional results. We also consider additional sources of country-specific heterogeneity that are not addressed by these procedures. Given the impact of controlling for country-specific effects on the coefficient associated with human capital, the main conclusion of this section is that some other source of negative bias is exacerbated by the usual covariance transformations such as the within or first-differencing procedures.

In part 4, we consider the classic errors in variables problem that may affect the education variable (and which is inevitable, given the method by which the Barro-Lee dataset was constructed), and show how this problem may bias the coefficient associated with human capital downwards. We discuss ways, suggested by Griliches and Hausman (1986), in which different covariance transformations may be combined to obtain, under certain conditions, consistent estimates of the parameters of interest, and why these conditions do not hold in the case under consideration. We also show, using results due to Dagenais (1994), how correcting for serial correlation in the pooling results provides additional evidence that the errors in variables problem affecting the education variable is severe, particularly once variables have been first-differenced. We then move on to instrumental variables estimation using the Arellano-Bond (1991a, 1991b) GMM estimator, which is often advocated as the

[8] For a critical review of the contribution of the endogenous growth literature to our understanding of economic growth, see Bardhan (1996). On the other hand, Klenow and Rodriguez-Clare (1997) stress the recent exaggerated use of the Neoclassical model in explaining differences in growth performance. Krueger and Lindahl (2001) provide a good discussion of the different manners in which human capital is entered into growth regressions.

best means of controlling for measurement error, and show that this approach does not solve the human capital puzzle, in that the usual tests of the overidentifying restrictions are rejected and, more pointedly, the coefficient associated with human capital remains either negative and statistically significant.

In part 5, our focus is on the low variance of the human capital variable, once the within or the first-difference transformations have been performed. We show that most of the variance in the Barro-Lee education variable stems from the initial level of education, and that the process that generates human capital can be approximated by constant, country-specific rates of growth of human capital. The impact of this dramatic fall in variance is that the effect of human capital on economic growth becomes almost impossible to identify, and that measurement error may become relatively large, in contrast to what obtains when country-specific effects are not controlled for. We then propose a new estimator based on the Hausman-Taylor (1981) approach, in which the impact of time-invariant covariates can be identified in panel data while controlling for individual effects through the use of covariance transformations of the variables themselves as instruments, which we combine with the orthogonality conditions of the Arellano-Bond (1991a, 1991b) estimator. We show that this new estimator solves the human capital puzzle, and yields point estimates of the coefficients on physical and human capital that are more consistent with *a priori* expectations than are those provided by other estimation methods. Part 6 concludes.

2. THE BASIC AUGMENTED-SOLOW EMPIRICAL SPECIFICATION

Let the production technology for country i at time t be given by the usual Cobb-Douglas functional form with labor-augmenting technological change

$$Y_{it} = K_{it}^{a} H_{it}^{j} (L_{it} A_{it})^{1-a-j} ,$$

where Y_{it} is GDP, K_{it} is the stock of physical capital, H_{it} is the stock of human capital, L_{it} is population, and A_{it} represents the level of technology (here, the productivity of labor). As is usual, we assume constant population growth $n = \dot{L}_{it} / L_{it}$, a constant depreciation rate d, and an exogenous rate of labor augmenting technological progress $g = \dot{A}_{it} / A_{it}$ (MRW, 1992, and Islam, 1995). Assuming neoclassical savings behavior (in both physical and human capital) yields the pair of dynamic factor accumulation equations

(1) $\dot{\hat{k}}_{it} = s_K \hat{k}_{it}^{a} \hat{h}_{it}^{j} - (n + g + d)\hat{k}_{it}$,

(2) $\dot{\hat{h}}_{it} = s_H \hat{k}_{it}^{a} \hat{h}_{it}^{j} - (n + g + d)\hat{h}_{it}$,

where $\hat{k}_{it} \equiv K_{it} / A_{it} L_{it}$, $\hat{h}_{it} \equiv H_{it} / A_{it} L_{it}$ represent variables expressed in terms of *efficiency units* of labor, and s_K and s_H represent the investment rates in physical and human capital, respectively.

Since s_H, the investment ratio in human capital, is not directly observable in the data, the usual practice in the empirical growth literature is to assume that one has an acceptable proxy for the steady-state level of human capital, and to work solely with the first of these equations.[9] Imposing the steady-state condition $\dot{\hat{k}}_{it} = 0$ yields the steady-state level of physical capital per efficiency unit of labor as

$$\hat{k}_{it}^{*} = \left(\frac{s_K}{n + g + d} \right)^{\frac{1}{1-a}} \hat{h}_{it}^{*\frac{j}{1-a}},$$

and therefore steady-state GDP *per capita* as

(3) $$y_{it}^{*} = \left(\frac{s_K}{n + g + d} \right)^{\frac{a}{1-a}} \hat{h}_{it}^{*\frac{j}{1-a}} A_{it},$$

where $\hat{h}_{it}^{*}$ represents the steady-state level of human capital per efficiency unit of labor. By a first-order Taylor expansion around the steady-state in terms of convergence from time $t - t$ to time t, by letting the investment ratio and the rate of population growth be functions of i and t, and by appending a disturbance term, one obtains the usual estimating equation:

(4) $$\begin{aligned} \Delta \ln y_{it} \equiv \ln y_{it} - \ln y_{it-t} &= -\left(1 - \exp\{-l\, t\}\right) \ln y_{it-t} \\ &+ \left(1 - \exp\{-l\, t\}\right) \left(\frac{a}{1-a} \left[\ln s_{Kit} - \ln(n_{it} + g + d) \right] + \frac{j}{1-a} \ln \hat{h}_{it}^{*} \right) \\ &+ g(t - \exp\{-l\, t\}(t - t)) + \left(1 - \exp\{-l\, t\}\right) \ln A_{i0} + m_i + h_t + e_{it}, \end{aligned}$$

where l is the annual rate of convergence towards the steady-state, t is the time that elapses between two time periods and $m_i + h_t + e_{it}$ is the composite disturbance term. In order to lighten notation, we shall rewrite the basic specification as

[9] A notable exception is Caselli, Esquivel and Lefort (1996), who assume that the enrollment ratio constitutes a proxy for s_H.

$$(5) \qquad \Delta \ln y_{it} = -g_0 \ln y_{it-t} + g_1 \left[\ln s_{Kit} - \ln(n_{it} + g + d) \right] + g_2 \ln \hat{h}^*_{it} + gt + g_0 g(t-t) + g_0 \ln A_{i0} + m_i + h_t + e_{it},$$

where $g_0 \equiv 1 - \exp\{-l\,t\}$, $g_1 \equiv (1 - \exp\{-l\,t\}) \dfrac{a}{1-a}$, $g_2 \equiv (1 - \exp\{-l\,t\}) \dfrac{j}{1-a}$.

This paper will focus on the sign of g_2, the coefficient associated with human capital in the augmented Solow model, as well as with the point estimate of j. The usual practice in the empirical growth literature is to replace $\hat{h}^*_{it}$ by h_{it}, the average number of years of schooling in the population above 15 years of age at the *end* of the period considered. In what follows, we approximate this by the Barro-Lee (1993, 1996) measure of human capital. The growth rate of GDP per capita (in constant domestic currency) comes from the World Bank, the initial level of GDP per capita comes from the Heston-Summers (1988) dataset, the source for the annual population growth rate and the investment rate in physical capital is the GDN.[10] Equation (5) constitutes the basic empirical specification that underlies all econometric studies of the augmented-Solow model, including the remainder of this paper.[11]

In order to estimate equation (5) using cross-sectional data as in MRW (1992), a strong identifying restriction needs to be imposed. Indeed, the only identifying restriction possible here is to assume that $g_0 \ln A_{i0} + m_i$ is identical across countries. Panel data allows one to relax this restriction, as noted by Islam (1995). This, and other identifying restrictions are the subject of the next section.

[10] Our dataset is available upon request.
[11] Our choice of dependent and explanatory variables (particularly in terms of the price indices used to evaluate the variables in question) is based on the motivations set out very clearly in Nuxoll (1994).

3. UNOBSERVED, COUNTRY-SPECIFIC HETEROGENEITY

Country-specific initial levels of technology

The principal contribution of Islam (1995) was to estimate equation (5) using country-specific effects thereby controlling for differences stemming from heterogeneity across countries in the initial value of $\ln A_{0i}$. This is because the within transformation sweeps out the term

(6) $\quad g_0 \ln A_{0i} + m_i$,

which would otherwise be included in the disturbance term, leading to biased estimates of the coefficients because of the correlation thereby induced between the explanatory variables and the error term.

In the absence of the within transformation, the bias in least squares estimation of the coefficient associated with human capital (g_2) in the basic growth regression is given by

(7) $$\text{plim}\hat{g}_{2OLS} = g_2 + \text{cov}\left[g_0 \ln A_{0i} + m_i, \hat{e}_{it}^h\right] \Big/ s_{e_h}^2 ,$$

where $s_{e_h}^2$ is the variance of the residual from the auxiliary regression of human capital on the other included regressors X_{it} (the initial value of GDP per capita, $\ln y_{it}$, the log of the investment ratio *minus* the population growth rate, and time dummies). That is $s_{e_h}^2 = \text{var}[\hat{e}_{it}^h]$ $= \text{var}[h_{it} - X_{it}\hat{w}_{OLS}]$, where $\hat{w}_{OLS}$ is the coefficient vector from the auxiliary regression.[12]

Since it is likely that the initial level of technology and the level of human capital are positively correlated (after purging the effect of the other covariates), it follows that $\text{cov}[g_0 \ln A_{0i} + m_i, \hat{e}_{it}^h] > 0$ and estimation of the growth regression by OLS should lead to an *upward* bias in the estimate of g_2. The within and first-difference procedures are the two main covariance transformations generally used to account for this bias, although both suffer from their respective limitations.

The equation being estimated through the within procedure is given by :

(8) $$\Delta \ln \tilde{y}_{it} = -g_0 \ln \tilde{y}_{it-t} + g_1\left[\ln \tilde{s}_{Kit} - \ln(\tilde{n}_{it} + g + d)\right] + g_2 \ln \tilde{h}_{it} + g_0 g(t - T^{-1}\textstyle\sum_{t=0}^{t=T} t) + \tilde{h}_t + \tilde{e}_{it},$$

where $\tilde{x}_{it} = x_{it} - x_{i\bullet} = x_{it} - T^{-1}\sum_{t=0}^{t=T} x_{it}$, represents variables expressed in terms of *deviations* with respect to their country-specific means ($x_{i\bullet}$ represents variables in terms of their country-specific means). Note that the entire term $g_0 g(t - T^{-1}\sum_{t=0}^{t=T} t) + \tilde{h}_t$ can be accounted for by time specific dummies.[13] The main weakness of the within transformation, as first noted by Anderson and Hsiao (1981), is that the resulting estimator will be inconsistent if some variables at time t are correlated with random shocks in any period $s \leq t$ (some elements of $x_{i\bullet}$ will then be correlated with the error term). We shall return to this problem later in the context of the issue of GMM estimation and autocorrelation.

An alternative means of eliminating the country specific effect is to first-difference the data. This yields the equation

$$
\begin{aligned}
(9)\qquad \Delta^2 \ln y_{it} &= \Delta \ln y_{it} - \Delta \ln y_{it-t} \\
&= -g_0 \Delta \ln y_{it-t} + g_1 \left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + g + d)\right] + g_0 g t + g_2 \Delta \ln h_{it} + \Delta h_t + \Delta e_{it},
\end{aligned}
$$

where $\Delta \ln x_{it} \equiv \ln x_{it} - \ln x_{it-t}$ and $\Delta^2 \ln x_{it} \equiv \Delta \ln x_{it} - \Delta \ln x_{it-t}$. This approach is similar to that used by Hamilton and Monteagudo (1998), who estimate over two ten-year periods (1960-70, 1975-85) using the MRW data, while allowing parameter estimates to vary by decade.[14] They then impose an increasingly stringent set of restrictions, ending up with a first-differenced form that imposes the theoretical constraints suggested by the augmented Solow model.[15] Note that first-differencing results *by construction* in correlation between $\ln y_{it-t} - \ln y_{it-2t}$ (the differenced lagged-dependent variable) and $e_{it} - e_{it-t}$ (the differenced error term), an issue that will be explicitly addressed below in the context of GMM estimation. For the moment, this source of bias in the first-differenced results will be ignored.

Estimation results corresponding to pooling (estimation by OLS in levels), the within procedure, and first-differencing are presented in columns (1), (2) and (3) of Table 2, and largely reproduce those obtained by other authors (see the summary provided by Table 1). In particular, we obtain a negative and statistically significant coefficient associated with human capital using the within procedure and a negative and statistically insignificant coefficient in

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[12] Griliches and Hausman, 1986, p.97, Hsiao, 1986, p. 64, equation (3.9.3).
[13] Alternatively, a second covariance transformation, in which variables are expressed as deviations with respect to time-specific means, will eliminate that portion of the disturbance term given by the previous expression.
[14] Hamilton and Monteagudo (1998), equation 14, p. 500.
[15] Hamilton and Monteagudo (1998), equation 15, p. 500, and equation 16, p. 502.

first-differences. In Figures 1 through 3, we present graphs of the type popularized by Robert Barro, in which the growth rate of GDP per capita, purged of the effects of all explanatory variables except the variable of interest (education), is plotted on the vertical axis, with education being plotted on the horizontal axis. The regression line also appears in the figure, and passes through the origin by construction: its slope is equal to the value of g_2 (the coefficient associated with human capital) estimated by each procedure.

Note that, despite what one might think in terms of what appear to be outliers (in Figures 2, 3 and 4), the unbounded nature of the influence function associated with the within and first-difference estimators does not lie behind the negative g_2 coefficient. For example, when one re-estimates the equation in first-differences by least absolute deviations (LAD), rather than by least squares, a method that is robust to leptokurtic (i.e., "fat tailed") disturbance terms, and which is often used when one wishes to obtain results that are robust to outliers, the estimated value of g_2 goes from $\hat{g}_{2OLS} = -0.0125$ with an associated t-statistic of -1.629, to $\hat{g}_{2dLAD} = -0.0188$ with an associated t-statistic of -3.415 (the same result obtains, qualitatively, when one estimates by LAD after the within transformation). Controlling for influential observations therefore simply reinforces the puzzling negative coefficient associated with human capital.[16]

These results highlight the main issue tackled by this paper, namely the instability of the sign of the coefficient associated with human capital, which ranges from being positive and statistically significant (pooling results), to being negative and statistically significant (within).

At this point, it is worthwhile explicitly stating those hypotheses under which the within and first-differenced results will be unbiased, as well as alternative, weaker, hypotheses that will be considered at greater length in what follows.

ASSUMPTION 1 (exogeneity): $E[\ln h_{it}' e_{is}] = E[\ln(n_{it} + g + d)' e_{is}] = E[\ln s_{Kit}' e_{is}] = 0, \ \forall \ s, t$.

[16] Temple (1999b) is able to obtain a positive coefficient on human capital on the Benhabib and Spiegel (1994) dataset, using OLS on first-differenced data, following use of least trimmed squares which allows him to eliminate 14 outliers. This specification does not, however, correspond to the augmented Solow model and involves only 64 observations (our first-differenced results involve 635 observations).

ASSUMPTION 2 (predeterminedness) : $E[\ln y_{it}' e_{is}] = E[\ln h_{it}' e_{is}] = E[\ln(n_{it} + g + d)' e_{is}] = E[\ln s_{Kit}' e_{is}] = 0, \forall \; s > t$.

ASSUMPTION 3 (correlated effects) : $E[\ln h_{it}' (g_0 \ln A_{i0} + m_i)]$, $E[\ln(n_{it} + g + d)'(g_0 \ln A_{i0} + m_i)]$, $E[\ln s_{Kit}' (g_0 \ln A_{i0} + m_i)] \neq 0$.

Both the within and first-differencing procedures are explicitly designed to deal with ASSUMPTION 3 (correlated effects), and the within procedure will yield unbiased estimates when ASSUMPTION 1 (exogeneity) holds. On the other hand, the within procedure will be biased when ASSUMPTION 1 (exogeneity) is not satisfied, while first-differencing induces correlation between the differenced lagged dependent variable and the differenced error term, as previously noted, even when ASSUMPTION 1 is satisfied. ASSUMPTION 2 (predeterminedness) is crucial in allowing one to overcome this particular hurdle using instrumental variable or GMM estimation. This issue will be addressed in section 4.

Country-specific rates of labor-augmenting technological change

A potential source of bias not accounted for by Islam (1995) is constituted by country-specific rates of technological progress.[17] Consider the basic growth regression, which may now be expressed as:

$$\begin{aligned}\Delta \ln y_{it} = & -g_0 \ln y_{it-t} + g_1 [\ln s_{Kit} - \ln(n_{it} + g_i + d)] + g_2 \ln h_{it} \\ & + g_i t + g_0 g_i (t - t) + g_0 \ln A_{i0} + m_i + h_t + e_{it},\end{aligned} \tag{10}$$

where the difference with equation (9) is that g has been replaced with the *country-specific* growth rate of labor productivity g_i. In order to assess the magnitude of the bias induced by failure to control for differences in g_i, consider a first-order Taylor expansion around $n_{it} + d$, which allows one to write $\ln(n_{it} + g_i + d) = \ln(n_{it} + d) + (n_{it} + d)^{-1} g_i$. It follows that the basic growth regression can be rewritten as:

$$\begin{aligned}\Delta \ln y_{it} = & -g_0 \ln y_{it-t} + g_1 [\ln s_{Kit} - \ln(n_{it} + d)] + g_2 \ln h_{it} \\ & - g_1 (n_{it} + d)^{-1} g_i + g_i t + g_0 g_i (t - t) + g_0 \ln A_{i0} + m_i + h_t + e_{it}.\end{aligned}$$

Neither the within procedure nor first-differencing eliminates this source of bias. In the case of the within procedure, the term

$$J_{it} = g_0 g_i \left(t - T^{-1} \sum_{t=0}^{t=T} t \right) - g_1 g_i \left((n_{it} + d)^{-1} - T^{-1} \sum_{t=0}^{t=T} (n_{it} + d)^{-1} \right)$$

remains, leading to a bias given by

(11) $$\text{plim}\hat{g}_{2w} = g_2 + \text{cov}[J_{it}, e_{it}^{\tilde{h}}] \big/ s^2_{e_{\tilde{h}}} ,$$

where $s^2_{e_{\tilde{h}}} = \text{var}[e_{it}^{\tilde{h}}] = \text{var}[\ln \tilde{h}_{it} - \tilde{X}_{it}\hat{w}_w]$ is the variance of the residual from the auxiliary regression of human capital on the other regressors using the within procedure. Similarly, the equation to be estimated by least squares after first-differencing is now given by

(12) $$\begin{aligned} \Delta^2 \ln y_{it} = -g_0 \Delta \ln y_{it-t} + g_1 \left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + d) \right] + g_2 \Delta \ln h_{it} \\ - g_1 g_i \Delta (n_{it} + d)^{-1} + g_0 t\, g_i + \Delta h_t + \Delta e_{it} , \end{aligned}$$

with the bias being given by

(13) $$\text{plim}\hat{g}_{2d} = g_2 + \text{cov}\left[g_i \left(g_0 t - g_1 \Delta (n_{it} + d)^{-1} \right), e_{it}^{\Delta h} \right] \big/ s^2_{e_{\Delta h}} ,$$

where $s^2_{e_{\Delta h}} = \text{var}[e_{it}^{\Delta h}] = \text{var}[\Delta \ln h_{it} - \Delta X_{it}\hat{w}_d]$ is the variance of the residual from the corresponding auxiliary regression. Since it is likely that the level of human capital is positively correlated with the country-specific rate of technological progress, failure to account for this problem is likely to bias estimates of the impact of human capital on growth *upwards*.[18]

The solution to this problem is to move to *second-difference*s, which will eliminate $g_0 t\, g_i$ from equation (12), and to assume multiplicative country-specific fixed effects to account for the remaining source of heterogeneity ($g_1 g_i \Delta^2 (n_{it} + d)^{-1}$) since the equation to be estimated by least squares is now given by:

(14) $$\begin{aligned} \Delta^3 \ln y_{it} = -g_0 \Delta^2 \ln y_{it-t} + g_1 \left[\Delta^2 \ln s_{Kit} - \Delta^2 \ln(n_{it} + d) \right] + g_2 \Delta^2 \ln h_{it} \\ - g_1 g_i \Delta^2 (n_{it} + d)^{-1} + \Delta^2 h_t + \Delta^2 e_{it} . \end{aligned}$$

Note that, if second-differencing alone is performed, the bias will be equal to

$$\text{plim}\hat{g}_{2d} = g_2 + \text{cov}\left[-g_1 \Delta (n_{it} + d)^{-1} g_i, e_{it}^{\Delta h} \right] \big/ s^2_{e_{\Delta h}} .$$

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[17] This issue is considered explicitly by Lee, Pesaran and Smith (1998) who consider a stochastic version of the Solow growth model. It is also worth emphasizing that the assumption of country-specific rates of technological change is linked to the debate concerning s -convergence.

[18] More precisely, and as with the bias stemming from uncontrolled for differences in the initial level of technology, we assume that the residual from the auxiliary regression is, like human capital itself, positively correlated here with the country-specific rate of technological change.

Estimates of the parameters of the growth regression in second-differences and in second-differences with multiplicative country-specific effects are presented in columns (6) and (7) of Table 2. Figure 4 presents a Barro-type graph corresponding to the second-differenced results.

Note that there is some evidence that the specification in terms of labor-augmenting technological change employed in the basic MRW specification is itself misplaced. Boskin and Lau (2000) find, for the G7 countries, that "technical progress is simultaneously purely tangible capital and human capital augmenting, that is, generalized Solow-neutral…. Technical progress has been capital, not labor, saving." On the other hand, this should not present particular problems in the context of empirical implementations of the augmented Solow model since different forms of technological progress cannot be identified.[19]

It is also worth noting that other sources of unobserved heterogeneity can readily be found in the augmented Solow model. The most obvious stems from the linearization around the steady-state used to move from equation (3) (the steady-state level of GDP per capita) to equation (4) (the basic growth regression). This is because, while it is customary to write the annual rate of convergence towards the steady as a constant $l = (n + g + d)(1 - a - j)$, one should really be writing $l_{it} = (n_{it} + g + d)(1 - a - j)$. The speed of convergence should therefore vary over time. It should also vary across countries.

The first problem is considered implicitly by Hamilton and Monteagudo (1998), who allow for coefficients that vary over the two time periods of their estimations.[20] It is also dealt with partially by Rappaport (1999), who explicitly considers variations over time in the speed of convergence, although his empirical specification is chosen (rightly, in his case) for its tractability rather than its faithfulness to the theoretical construct of the Solow model. The second problem (country-specific rates of convergence) is implicitly tackled in Durlauf, Kourtellos and Minkin (2001) in that their non-parametric approach allows all coefficients to

[19] In the basic augmented Solow specification, if we change the production function so that it is specified in terms of Solow-neutral technological change, $Y_{it}=A_{it}K_{it}^{a}H_{it}^{j}(L_{it})^{1-a-j}$, with all other assumptions remaining the same, the country-specific term in the growth regression becomes $[(1+j)/(1-a)]\ln A_{i0} + m_i$. The within procedure or first-differencing will therefore eliminate this source of bias. The same discussion goes for country-specific rates of technological change in the second-differencing procedure. Note, however, that the magnitude of the bias stemming from the failure to account for country-specific effects will be changed by dint of the fact that the country-specific term is now multiplied by $(1+j)/(1-a)$.

[20] Hamilton and Monteagudo (1998), equation 9, p. 498 in theoretical terms, equation 14, p. 500 for the empirical results.

vary over countries, as a function of the initial level of GDP per capita. However, as they do not seek to impose the restrictions implied by the Cobb-Douglas functional form, they do not furnish one with estimates of country-specific heterogeneity in the rate of convergence. It is interesting to note, in terms of the human capital puzzle, that their estimate of g_2 is positive for values of log GDP per capita lying roughly between 6.3 ($544) and 7.5 ($1,808), and is negative otherwise.[21]

Simple covariance transformations
and the coefficient associated with human capital: lessons learned

The upshot of these three simple covariance transformations, and the likely direction of bias induced by the failure to control for unobserved country-specific heterogeneity in pooling regressions or cross-sectional studies, is that there is probably significant positive bias introduced by failure to control for differences in A_{i0} and g_i. The fact that the coefficient associated with human capital goes from being positive to being negative (as well as the fact that the point estimate of a is significantly reduced –similar expressions for the bias in the coefficient associated with physical capital hold) is evidence enough of that. However, given that the estimates of j are either negative and statistically significant, or statistically indistinguishable from zero, there must be other sources of bias, not controlled for by the within, first-differencing, or second-differencing procedures, which bias estimates of j *downwards*. Moreover, these potential sources of bias may be exacerbated by the procedures in question. The natural candidate is of course measurement error in the human capital variable.

4. MEASUREMENT ERROR

As with most authors, we use the measure of the stock of human capital (average number of years of schooling in a given population) constructed by Barro and Lee (1993, 1996). This variable was generated partly by using census information on school attainment. Unfortunately, available census data only give information for a subset corresponding to 40

[21] Durlauf, Kourtellos and Minkin (2001), Figure 1, p. 934. An additional source of bias in the standard tests of the augmented Solow model involves the imposed functional form. Duffy and Papageorgiou (2000) show that a CES functional form is preferred over the usual Cobb-Douglas specification, although they use a human capital adjusted measure of the labor input (i.e. education does not enter as a separate input or, more precisely, its coefficient is restricted to being the same as that associated with labor) and do not consider the augmented Solow

percent of time periods. Barro and Lee were therefore obliged to infer missing data from enrollment ratios (as well as from adult illiteracy rates which allows one to construct a good proxy of the no-schooling category). As noted by Krueger and Lindahl (2001), and many other authors, "errors in measurement are inevitable because the enrollment ratios are of doubtful quality in many countries...errors cumulate over time, the errors will be positively correlated over time."[22] For the time being, the serial correlation aspect of the Barro-Lee human capital variable, as well as the impact of any serial correlation that there may be in the associated measurement error will be ignored: our focus, in this section, will be on the classical measurement error problem.[23]

Assume that one observes an error-ridden measure of human capital h'_{it} given by the true value of human capital h_{it} plus an error term :

ASSUMPTION 4 (classical measurement error): $\ln h'_{it} = \ln h_{it} + u_{it}$, where u_{it} is distributed i.i.d. with mean zero and variance s_u^2.

ASSUMPTION 4 (classical measurement error) implies that the bias in the coefficient associated with human capital is given by

(15) $$\text{plim}\,\hat{g}_{2w} = g_2 + \text{cov}[J_{it}, e_{it}^{\tilde{h}}] \big/ s^2_{e_{\tilde{h}}} - \left[(T-1) g_2 s_u^2 \big/ T\,(s^2_{e_{\tilde{h}}} + s_u^2)\right],$$

in the case of the within estimator, and by

(16) $$\text{plim}\,\hat{g}_{2d} = g_2 + \text{cov}\left[g_i\left(g_0 t - g_1 \Delta(n_{it} + d)^{-1}\right), e_{it}^{\Delta h}\right] \big/ s^2_{e_{\Delta h}} - \left[2 g_2 s_u^2 \big/ (s^2_{e_{\Delta h}} + s_u^2)\right]$$

in the case of the first-difference estimator (there is simply an extra term in each equation with respect to the expressions given in equations (11) and (13)). In the case of second-differences with multiplicative country-specific effects, the bias should be equal to

(17) $$\text{plim}\,\hat{g}_{22d} = g_2 - 4 g_2 s_u^2 \big/ (s^2_{e_{\Delta^2 h}} + s_u^2),$$

where $e_{\Delta^2 h} = \text{var}[e_{it}^{\Delta^2 h}] = \text{var}[\Delta^2 \ln h_{it} - \Delta^2 X_{it} \hat{w}_{22d}]$. These three expressions are standard examples of *attenuation bias* stemming from an errors in variables problem. Computing the

model *per se* since their focus is on an aggregate production function.

[22] Nehru, Swanson and Dubey (1995) provide an alternative measure of the human capital stock that is sometimes used in empirical studies of the augmented Solow model (see, e.g. Temple, 1999a).

[23] Temple (1999b) considers the robustness of the MRW cross-sectional results to classical measurement error, using the Klepper and Leamer (1984) reverse regression technique as well as classical method of moments estimators (Carroll, Ruppert and Stefanski, 1995). He does not, however, consider the robustness of the panel data literature. He finds that estimates of j lie between 0.15 and 0.38 (p. 371).

attenuation bias due to measurement error is much more complicated in the case where several variables are affected. Nelson (1995) shows that the *vector* of OLS parameters is also asymptotically biased towards zero. While this does explain why the coefficient associated with human capital might be biased downwards, it implies that, far from being overestimated, the coefficient associated with physical capital may be *underestimated* (the opposite of what is usually believed).

Note that it may be the case that the two sources of bias (upward from the failure to control for unobserved country-specific heterogeneity, downward for measurement error) cancel each other out in the pooling results. A similar argument could be made for the remaining unobserved heterogeneity stemming from g_i and measurement error on human capital in the within and first-difference estimations; the fact that the coefficient associated with human capital is negative would suggest that the downward bias from measurement error overwhelms the upward bias from g_i in these estimations. Simply controlling for unobserved heterogeneity stemming from uncontrolled for differences in A_{0i} and m_i by the within procedure or first-differencing leaves the negative measurement error bias intact (moreover, it *worsens* it with respect to the corresponding expression for the pooling estimator in that the denominator falls, since $s^2_{e_{\Delta h}} < s^2_{e_h}$ —more on this fall in variance in section 5). This might be conjectured to be a reason why the pooling results yield a reasonable, that is positive, estimate of j whereas correcting for unobserved heterogeneity in A_{0i} and m_i yields a negative j .

Within versus first-differences:
estimating the magnitude of the bias due to measurement error

Can anything be said concerning the magnitude of the bias in the estimates of g_2 stemming from classical measurement error using the simple covariance transformations that have been the subject of the paper up until now? As is well-known (Griliches and Hausman, 1986), different covariance transformations that control for the country-specific fixed effect can be combined in order to obtain consistent estimators for g_2 and s^2_u. In particular, when one combines the first-difference and within estimators, one obtains:[24]

[24] Hsiao, 1986, p. 65, equations (3.9.8) and (3.9.9); similarly, there are $T/2-1=3$ other estimators, using other "long" differences, that allow one to deduce the magnitude of the bias.

(18) $$\hat{g}_2 = \left[\frac{2\hat{g}_{2w}}{s^2_{e_{\Delta h}}} - \frac{(T-1)\hat{g}_{2d}}{Ts^2_{e_{\tilde{h}}}}\right]\left[\frac{2}{s^2_{e_{\Delta h}}} - \frac{(T-1)}{Ts^2_{e_{\tilde{h}}}}\right]^{-1}, \ \hat{s}^2_u = \left(\frac{\hat{g}_2 - \hat{g}_{2d}}{\hat{g}_2}\right)\frac{s^2_{e_{\Delta h}}}{2}.$$

Computing the empirical counterparts to equation (18) on the basis of the results presented in columns 2 and 3 of Table 2 yields $\hat{g}_2 =$-0.2247 and $\hat{s}^2_u =$ 0.006. Combining the two covariance transformations therefore still leads us to a negative point estimate for $\hat{g}_2$, which runs counter to common sense. Part of the answer to this additional puzzle must surely lie in the relative magnitudes of the within and first-difference coefficients: it is usually expected that the bias is greater in the within than in the first-difference results, although here (if the true coefficient is positive) the opposite obtains. This means that one or more of the maintained assumptions needed to implement the Griliches and Hausman approach must be violated. The problem is that it is impossible to say at this stage which one it is.

The issue of the potential for sign-reversal induced by the two covariance transformations brings this question into sharper focus. If one ignores the bias stemming from unobserved country-specific heterogeneity in the within results, classical measurement error *per se* cannot explain a reversal of the sign of the coefficient since, from equation (15), one can deduce that $\text{sign}[\text{plim}\hat{g}_{2w}] = \text{sign}[g_2(Ts^2_{e_{\tilde{h}}} + s^2_u)/T(s^2_{e_{\tilde{h}}} + s^2_u)] = \text{sign}[g_2]$. In the case of the first-difference estimator, on the other hand (and again ignoring the bias stemming from failure to account for country-specific g_i), the formula given in equation (16) implies that it suffices that $s^2_{e_{\Delta h}} < s^2_u$ for sign reversal to obtain. It follows that, while classical measurement error can explain a statistically insignificant coefficient associated with human capital in the within results, it cannot explain a statistically significant negative coefficient, if one accepts the basic hypothesis that the true coefficient is indeed positive. On the other hand, classical measurement error can account for the sign reversal that appears in the first-difference results, since the first-difference transformation will result (usually) in a large reduction in the variance of the human capital variable. This last issue will be explored at much greater length in section 5.

A further indication of the presence of measurement error:
the impact of correcting for serial correlation in the first-differenced results

As was first noted by Grether and Maddala (1973), and more recently by Dagenais (1994), the combination of serially correlated errors in the equation's disturbance term (e_{it} in equation

(5)) and measurement error in one of the variables (human capital) can lead to extremely puzzling results when corrections for serial correlation are carried out. Assume that the disturbance term in the growth regression follows a first-order autoregressive process: $e_{it} = r_e e_{it-1} + x_{it}$, where x_{it} is white noise.

If human capital were the only variable in the regression, and if it and the measurement error are *not* serially correlated (ASSUMPTION 4, classical measurement error), the bias in $\hat{g}_2$ induced when one corrects for serial correlation in the presence of measurement error (ignoring unobserved country-specific heterogeneity) is exactly the same as given above (for example, equation (17)). On the other hand, if one assumes that human capital is serially correlated, with

(19) $h_{it} = r_h h_{it-1} + z_{it}$,

where z_{it} is white noise, the expression for bias becomes:[25]

(20) $$\text{plim}\hat{g}_2 = \frac{g_2 s_h^2 (1 + r_e^{*2} - 2 r_h r_e^*)}{s_h^2 (1 + r_e^{*2} - 2 r_h r_e^*) + s_u^2 (1 + r_e^{*2})},$$

where $$r_e^* = \frac{r_e s_e^2 (s_h^2 + s_u^2)^2 + g_2^2 (s_u^2)^2 r_h s_h^2}{(s_u^2 + s_h^2)[s_e^2 (s_h^2 + s_u^2) + g_2^2 s_u^2 s_h^2]}.$$

It should be apparent from equation (20) that bias which induces sign reversal is a possibility, if one corrects for serial correlation (it suffices for the numerator to be negative and the denominator to be positive, which is entirely possible). Moreover, Dagenais shows that the bias induced by correcting for serial correlation is increasing in the ratio of the variance s_u^2 of the measurement error to the variance s_h^2 of the true variable. When one re-estimates the pooling regression (column (1) in Table 2) while correcting for first-order serial correlation, the parameter estimates change very little.[26] In light of the previous comments, this may be taken as indication that the variance of the measurement error is relatively small with respect to the variance of the education variable *in levels*.

On the other hand, when one re-estimates the regression in first-differences while correcting for first-order serial correlation (in the first-differenced residuals), the change in the point

[25] See Dagenais (1994), equations (10)-(12), p. 155, for the general case in which the measurement error is itself serially correlated.
[26] Not presented but available upon request.

estimates is impressive.[27] In particular, the coefficient associated with human capital more than doubles (in absolute value), and becomes statistically significant at the usual levels of confidence. Results are presented in column (4) of Table 2. What can be inferred from this last finding ? Assume that the disturbance term of the growth regression in first-differences follows a first-order autoregressive process: $\Delta e_{it} = r_{\Delta e} \Delta e_{it-1} + x_{it}$, where x_{it} is white noise. Then an expression similar to equation (20) obtains where we substitute $s^2_{\Delta h}$, $r^{*2}_{\Delta e}$, $r_{\Delta h}$, and $s^2_{\Delta u}$ for their counterparts in levels. The implication is that the variance of the measurement error is relatively large with respect to the variance of the education variable, when both are expressed *in first differences*. Of course, while this result does indicate that measurement error is a potentially serious problem, we are still left with the puzzle of why sign-reversal obtains in the *absence* of correcting for serial correlation.

Instrumental variables estimation

The traditional cure for an errors in variables problem is, of course, estimation by instrumental variables. Concomitantly, we now return to the issue of the correlation, induced by first-differencing, between the first-differenced disturbance term and the first-differenced lagged dependent variable, that was mentioned earlier. Again, the standard cure, first advocated by Anderson and Hsiao (1981), involves instrumental variables estimation.

Recall, from equation (9), that first-differencing induces correlation between $\Delta \ln y_{it-t} = \ln y_{it-t} - \ln y_{it-2t}$ and $\Delta e_{it} = e_{it} - e_{it-t}$, since $\ln y_{it-t}$ is correlated with e_{it-t}. We now make the following identifying assumption:

ASSUMPTION 5 (no autocorrelation in the error term): $E[e_{it} e_{is}] = 0,\ s < t$.

In the absence of serial correlation in e_{it}, and under ASSUMPTION 2 (all right-hand-side variables are predetermined) a valid instrument for $\Delta \ln y_{it-t}$ is given by $\ln y_{it-2t}$. This is because $\ln y_{it-2t}$ is orthogonal to $\Delta e_{it} = e_{it} - e_{it-t}$ (if e_{it} were autocorrelated, this would no

[27] We present evidence below in the context of Arellano-Bond GMM estimation that the residuals of the growth regression in first-differences are indeed serially correlated of order one, although this serial correlation is negative.

longer be the case because one could write $e_{it-t} = r_e e_{it-2t} + x_{it-t}$, with x_{it-t} white noise and $\ln y_{it-2t}$ would no longer be orthogonal to $\Delta e_{it} = r_e(e_{it-t} - e_{it-2t}) + x_{it} - x_{it-t}$). Moreover, given ASSUMPTION 5, $\ln y_{it-3t}$ is also a valid instrument for $\Delta \ln y_{it-t}$, as is any $\ln y_{it-nt}, n \geq 2$. This is expressed by the following orthogonality condition:

ASSUMPTION 6 (orthogonality condition on lagged dependent variable):

$$E[\ln y_{it-nt}{}' \Delta q_{it}] = 0, n \geq 2 \text{, where } \Delta q_{it} = \Delta h_t + \Delta e_{it} = \Delta^2 \ln y_{it} + g_0 \Delta \ln y_{it-t}$$
$$-g_1\left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + g + d)\right] - g_2 \Delta \ln h_{it} - g_0 g t \ .$$

In terms of the other explanatory variables, we pose the following additional orthogonality conditions, which simply formalize ASSUMPTION 2 (predeterminedness) in GMM terminology :

ASSUMPTION 7 (orthogonality conditions on explanatory variables): $E[\ln h'_{it-nt}{}' \Delta q_{it}]$

$$= E[\ln(n_{it-nt} + g + d)' \Delta q_{it}] = E[\ln s_{Kit-nt}{}' \Delta q_{it}] = 0, n \geq 2 \ .$$

Note that using the human capital variable lagged two periods and more as instruments will be valid only when ASSUMPTION 4 and ASSUMPTION 5 *both* hold, that is when there is no autocorrelation in the disturbance term in the growth regression and well as no autocorrelation in the measurement error affecting human capital. Autocorrelation in e_{it} renders the explanatory variables lagged two periods inadmissible as instruments for the same reasons as for $\ln y_{it-2t}$. On the other hand, autocorrelation in the measurement error, which one may write as $\ln h'_{it} = \ln h_{it} + u_{it}$, where $u_{it} = r_u u_{it-t} + u_{it}$, with u_{it} white noise, implies that $u_{it-2t} = r_u^{-1} u_{it-t} - r_u^{-1} u_{it-t}$. Since ASSUMPTION 7, for the specific case of the human capital variable, may be written as $E[(\ln h_{it-2t} + u_{it-2t})'(\Delta h_t + e_{it} - e_{it-t})] = 0$, substitution implies that

$$E[\underbrace{(\ln h_{it-2t} + r_u^{-1} u_{it-t} - r_u^{-1} u_{it-t})}_{h'_{it-2t}}{}' (\Delta h_t + e_{it} - e_{it-t})] \neq 0 \ ,$$

since u_{it-t} is correlated with e_{it-t}. Autocorrelation in the measurement error therefore results in a violation of the orthogonality condition given by ASSUMPTION 7.

Current econometric technique combines the instruments defined by ASSUMPTIONS 6 and 7 in an optimal manner through the use of the generalized method of moments (GMM) estimator. The key to understanding the GMM approach, pioneered by Arellano-Bond (1991a, 1991b), is to note that the number of lags that may be used as instruments depends upon the time dimension of the panel. In the case at hand, $T = 8$. Formally speaking, we set up the problem as a set of 6 growth regressions in first-differences because: (i) the first time period is lost through first-differencing $(T-1)$ and (ii) two additional time periods are lost because the minimal set of instruments is constituted by the explanatory variables lagged two periods, although we retrieve the period lost through first-differencing in terms of instruments $(T-1-2+1=6)$. These six equations are estimated as a system, imposing the restrictions that the coefficients are equal across equations. In our notation, the system of equations is as follows, where we indicate the set of valid instruments for each equation in parentheses:

$$
\begin{cases}
\Delta^2 \ln y_{it} = g_0 gt - g_0 \Delta \ln y_{it-t} + g_1 \left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + g + d) \right] + g_2 \Delta \ln h_{it} + \Delta q_{it} \\
\qquad (\text{instruments} = \ln y_{it-nt}, \ln x_{it-nt},\ n = 2, \ldots, 7) \\
\qquad \vdots \qquad\qquad\qquad\qquad \vdots \\
\Delta^2 \ln y_{it-4t} = g_0 gt - g_0 \Delta \ln y_{it-5t} + g_1 \left[\Delta \ln s_{Kit-4t} - \Delta \ln(n_{it-4t} + g + d) \right] + g_2 \Delta \ln h_{it-4t} + \Delta q_{it-4t} \\
\qquad (\text{instruments} = \ln y_{it-7t}, \ln x_{it-7t}, \ln y_{it-6t}, \ln x_{it-6t}) \\
\Delta^2 \ln y_{it-5t} = g_0 gt - g_0 \Delta \ln y_{it-6t} + g_1 \left[\Delta \ln s_{Kit-5t} - \Delta \ln(n_{it-5t} + g + d) \right] + g_2 \Delta \ln h_{it-5t} + \Delta q_{it-5t} \\
\qquad (\text{instruments} = \ln y_{it-7t}, \ln x_{it-7t})
\end{cases}
$$

This means that for those observations where $\Delta \ln y_{it-5t}$ is regressed on $\Delta \ln y_{it-6t}$ and $\ln x_{it-5t}$, $\ln y_{it-7t}$ and the matrix of explanatory variables $\ln x_{it-7t}$ are the admissible instruments, whereas for those observations where $\Delta \ln y_{it-4t}$ is regressed on $\Delta \ln y_{it-5t}$ and $\ln x_{it-4t}$, $\ln y_{it-7t}$ and $\ln y_{it-6t}$ are both admissible, as are $\ln x_{it-6t}$ and $\ln x_{it-7t}$, and so on as one moves forward in time.

A well-known example of the application of this estimator to the augmented Solow model is the paper by Caselli, Esquivel and Lefort (1996), who find, estimating over the 1960-1985 time period with $t = 5$ and $T = 5$: (i) substantially higher rates of convergence than was previously found using conventional panel techniques ($\hat{l} \approx 0.10$), (ii) an implied capital share that is much more in line with conventional wisdom than those obtained using simple cross-sections ($\hat{a} \approx 0.49$) and, unfortunately, (iii) a negative and statistically significant coefficient associated with the human capital variable ($\hat{j} \approx -0.25$).[28] On the basis of this last finding, Caselli, Esquivel and Lefort (1996) reject the augmented Solow model outright.

Caselli, Esquivel and Lefort (1996) are careful to test for first-order serial correlation in the disturbance term in the growth equation which, in the presence of measurement error in the human capital variable, is equal to $g_2 u_{it} + e_{it}$. The absence of first-order serial correlation in the disturbance term of the growth equation in levels is implied, in the growth equation expressed in first-differences, by : (i) the *presence* of negative first-order serial correlation and (ii) the *absence* of second-order serial correlation:[29] they cannot reject the null hypothesis that ASSUMPTIONS 4 and 5 hold. This last statement follows because the absence of serial correlation in the composite disturbance term $g_2 u_{it} + e_{it}$ implies its absence in both of its components.[30]

As a further test for the presence of autocorrelation in the measurement error, Caselli, Esquivel and Lefort (1996) re-estimate their specification while dropping the most recent instruments. They show that the results are not very different according to whether they use the restricted or unrestricted matrix of instruments.[31]

In the first column of Table 2, we present results corresponding to application of the Arellano-Bond estimator to our data. Our results are similar to those of Caselli, Esquivel and Lefort (1996), in that our estimate of j is negative and highly significant. Moreover, the situation is even worse in that the point estimate is twice that found by Caselli, Esquivel and Lefort. As with their specification, the Sargan test of the overidentifying restrictions strongly rejects the specification, with a p-value coming in at the 3 percent level. Manifestly, the Arellano-Bond estimator does *not* provide one with a solution to the human capital puzzle. As we shall see

[28] Caselli, Esquivel and Lefort, 1996, Table 3, p. 376.

[29] Arellano and Bond, 1991a, pp. 281-2.

[30] Note that some authors reject the use of lagged right-hand-side variables altogether as instruments, even in the absence of serial correlation concerns. For example, Rappaport (2000) notes that "the potential for a reverse causal link from the current income level to any of the "stock" conditioning variables (i.e., right-hand-side variables constrained to a finite time derivative) " should be of great concern in any instrumental variable procedure based on the Arellano-Bond approach. As he puts it: "To the extent that an included right-hand-side stock variable is a normal good, its level will increase with income; *education* and public capital seem obvious examples. The persistence of stock variables along with optimization by forward-looking agents rule out using lagged values as instruments" (Rappaport, 2000, p. 13).

[31] A further development on the methodology implemented by Caselli, Esquivel and Lefort (1996) is provided by Bond, Hoeffler and Temple (2001), who use the system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach combines equations in levels with those in first-differences,

below, part of the problem lies in the low variability of the human capital variable once first-differencing is performed, with an additional source of difficulty probably stemming from the weakness of the instruments used in the standard GMM procedure. It is this "weak instrument" problem that the new estimator introduced in the next section is designed to overcome.

5. LOW VARIABILITY IN THE HUMAN CAPITAL VARIABLE

There are two additional standard reasons that could explain the *lack of significance* of the human capital variable (though not sign-reversal *per se*) once country-specific effects have been accounted for through a covariance transformation such as first-differencing. The first involves multicollinearity induced by the covariance transformation. The second involves a reduction in the *variance* of the human capital variable following the covariance transformation. This is because the least squares estimate of the variance of $\hat{g}_{2w}$ is given by $\mathrm{var}[\hat{g}_{2w}] = s_{\tilde{e}}^2 / s_{\tilde{h}}^2 (1 - R_{\tilde{h}}^2)$, where $R_{\tilde{h}}^2$ is the R-squared of the auxiliary regression of human capital on the other explanatory variables and $s_{\tilde{h}}^2$ is the variance of the human capital variable after the covariance transformation.

The term $(1 - R_{\tilde{h}}^2)^{-1}$, which is known as the variance inflation factor (VIF), is a measure of the collinearity that exists between human capital and the other included regressors.[32] If the degree of collinearity is high, $\mathrm{var}[\hat{g}_{2w}]$ will be large, *ceteris paribus*. Similarly, if the covariance transformation results in a dramatic fall in $s_{\tilde{h}}^2$ with respect to s_h^2 (its counterpart in levels), then again, $\mathrm{var}[\hat{g}_{2w}]$ will be large when compared with $\mathrm{var}[\hat{g}_{2OLS}]$.[33] If we consider the pooling and the within results, the VIFs are almost identical in that the R^2 of the auxiliary regressions come in at 0.6676 for the pooling regression and 0.6675 for the within regression. It is therefore not an increase in collinearity stemming from the within transformation that is driving the human capital puzzle.

where the variables in the equations in levels are instrumented using twice lagged first-differenced variables.

[32] We include the VIF for the human capital variable for all estimations presented in Table 2, as well as the variance of the residuals of the auxiliary regression of human capital on the other explanatory variables.

[33] When we speak of a reduction in $s_{\tilde{h}}^2$, we mean of course, a reduction with respect to $s_{\tilde{e}}^2$.

On the other hand, the within transformation does result in a substantial reduction in the variance of the human capital variable, which goes from $s_h^2 = 0.6935$ in levels to $s_{\tilde{h}}^2 = 0.1321$ after the within transformation. Removing country-specific means therefore does result in a substantial loss in the variance that could be the cause of insignificant coefficients associated with the human capital variable. The situation is even worse when one carries out first-differencing, with $s_{\Delta h}^2 = 0.0230$. This dramatic fall in variance is illustrated in Figure 5, where we plot different kernel density estimates of the human capital variable following various transformations (all variables have had their unconditional mean subtracted, which explains why all the kernels are centered on zero): it is obvious that the within and first-difference transformations correspond to substantial mean-preserving decreases in the "spread" (in the sense of Rothschild and Stiglitz) of the distribution of $\ln h_{it}$, with respect to the situation in levels (graphically, the estimated distributions become much more concentrated around zero). As one would expect from the respective variances reported above, this decrease in the spread is much more noticeable for the first-difference transformation than for the within transformation.

In order to counter this problem, Mairesse (1990, p. 92, 1993, p. 435) suggests carrying out a "between" estimation *after* performing the first-difference transformation. The first step eliminates the country-specific effect, while the second should ensure that variables expressed in first-differences recover sufficient variance for their effect to be identifiable. In terms of the problem at hand, this approach will be worthwhile only if the second transformation allows one to recoup a sufficient amount of variance: this is not the case, since the variance of the education variable after the second transformation falls once again, to $s_{b\Delta h}^2 = 0.0060$. Results corresponding to the between regression on first-differences are presented in column 5 of Table 2. Once again, the procedure in question does not solve the human capital puzzle.

The growth process of human capital

The preceding findings in terms of the variances associated with various covariance transformations of the human capital variable naturally leads one to investigate its statistical properties more closely. Recall that the within transformation purges the human capital variable of its country-specific mean over the period. All that remains are within-country changes in human capital, and if that rate of growth is roughly constant (the variable is in logs), the within transformation will have removed inter-country differences due to differences in the initial level of education, leaving only relatively small differences in the between-period growth rate of human capital. The same is true of the first-difference transformation. In order to illustrate this point formally, consider the following exponential growth process for human capital: $h_{it} = h_{i0}\exp\{a_i t\}$ which implies that

(21) $\ln h_{it} = \ln h_{i0} + a_i t$,

where h_{i0} is the (country-specific) initial level of human capital, and a_i is its (country-specific) growth rate. If we consider the first-difference transformation, equation (9) may then be re-expressed as :

(22) $\Delta^2 \ln y_{it} = -g_0 \Delta \ln y_{it-t} + g_1\left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + g + d)\right] + g_0 gt + g_2 a_i t + \Delta h_t + \Delta e_{it}$.

What is clear in equation (22) is that *the entire effect of human capital in the regression will be identified through the variations in* a_i.[34] How great can one expect the fall in variance of the human capital variable to be when one moves from estimation in levels to estimation in first-differences, when human capital follows the process defined by (21)? Let $\mathrm{var}[a_i] = s_a^2$, and $\mathrm{var}[\ln h_{i0}] = s_{h_0}^2$. Then it can be shown that the variance of the logarithm of human capital in a pooling regression over T periods is given by:

$$s_{h_t}^2 = (T-1)s_{h_0}^2 + t^2 s_a^2 \sum_{n=1}^{n=T-1} n^2 .$$[35]

Now consider a regression in first-differences. The variance of the first-difference of the logarithm of human capital, where the equation is estimated over $T-1$ periods, is given by:

$$s_{\Delta h_t}^2 = (T-1)t^2 s_a^2 .$$

The ratio of the variances of log human capital in levels and log human capital in first-differences is therefore given by:

(23) $$\frac{s_{h_t}^2}{s_{\Delta h_t}^2} = \frac{s_{h_0}^2}{t^2 s_a^2} + \frac{1}{T-1}\sum_{n=1}^{n=T-2} n^2 + T - 1 .$$[36]

[34] Note that, if this were indeed the true process generating human capital, the effect of the latter would not be identifiable at all in the equation estimated in second-differences ? this is indeed what happens, in the sense that the standard error associated with human capital becomes extremely large when one moves to second-differences; see the results presented in Table 2, column 6.

[35] See APPENDIX 1 for the derivation.

[36] It is interesting to note that this expression provides part of the explanation for why the coefficients (and especially their standard errors) vary as the time frame (2 twenty-year periods, 4 ten-year periods, etc.) over which growth regressions in first differences are estimated changes.

Here $t = 5$ and $T = 8$ which implies that $s^2_{h_t} / s^2_{\Delta h_t} = 20 + (s^2_{h_0} / 25 s^2_a)$. Thus, if human capital follows the process given by (21), one expects the variance that is performing the function of identification to fall by a factor of *at least* 20. This is indeed what happens when one performs the first-difference transformation: the resulting ratio of variances is approximately equal to 30 (here $\text{var}[\ln h_{i1960}] = s^2_{h_0} = 1.013$).

How good an approximation of the behavior of the human capital variable is the process described by equation (21)? In order to assess its empirical validity, we simply performed the regression suggested by (21), thereby estimating country-specific, time-invariant growth rates of human capital. For the regression in question $\overline{R}^2 = 0.8519$, and the resulting estimate of s^2_a is equal to 0.00029 (the F-test associated with the null-hypothesis that the estimated $\hat{a}_i$ are equal across countries, and thus that $s^2_a = 0$, is rejected with a p-value below 0.001). If we constrain the growth rates to be equal ($a_i = a_j = a$ and thus $s^2_a = 0$), the mean rate of growth of human capital is equal to 0.024 per five-year period. The results are represented graphically in Figure 6, where we plot the actual value of $\ln h_{it}$ against the value predicted by (21): as should be obvious from the Figure, the fit is extremely good.

Note that the preceding argument is a powerful explanation for the *imprecision* of the estimates of the coefficient associated with human capital, after the first-difference transformation. It does not, however, explain a negative and statistically significant coefficient. In order to do so, measurement error must again be invoked. If the measurement error takes a form such that its magnitude is relatively important, relative to that of the transformed human capital variable, then (i) the process generating the human capital variable, (ii) measurement error and (iii) the first-difference transformation which results in a dramatic fall in the variance of the human capital variable may explain the negative coefficient associated with human capital.

Suppose that there is measurement error in the country-specific *growth rate* of human capital. We pose this as follows:

$$\ln h'_{it} = \ln h_{i0} + (a_i + q_{it})t, \text{ where } q_{it} \text{ is i.i.d.} \sim N(0, s^2_q).$$

Under this assumption, the equation in first-differences is given by

$$(24)\quad \Delta^2 \ln y_{it} = -g_0 \Delta \ln y_{it-t} + g_1 \left[\Delta \ln s_{Kit} - \Delta \ln(n_{it} + g + d) \right] + g_0 gt + g_2 t a_i + g_2 t q_{it} + \Delta h_t + \Delta e_{it}.$$

Ignoring problems stemming from uncontrolled-for heterogeneity in the growth rate of labor productivity (g_i), the bias resulting from the measurement error on the growth rate of human capital is then given by:

$$\text{plim}\hat{g}_{2d} = g_2 - \left[2g_2 t s_q^2 \big/ (s^2_{e_{\Delta h}} + s_q^2) \right],$$

where (as in equation (13)), $s^2_{e_{\Delta h}}$ is the variance of the residuals from the auxiliary regression of $\Delta \ln h_{it}$ on the other explanatory variables, expressed in first-differences). The key issue is that s_q^2 may be of the same order of magnitude as $s^2_{\Delta h_t}$ (or more precisely, $s^2_{e_{\Delta h}}$): it will nevertheless be extremely small (by a factor of 30, as shown in equation (23)) with respect to $s^2_{h_t}$. The point being made here is that the instrumental variables method that one is looking for must simultaneously deal with the measurement error problem (and, therefore, orthogonalize, $\Delta \ln h'$ with respect to the error term), and inject enough "between" variance (i.e., cross-country variance) for the impact of human capital to be precisely identified after the first-difference transformation, which deals with ASSUMPTION 3 (correlated effects) but leaves very little variance in the transformed variable. Given that external instruments are unavailable, the next logical step is to consider instrumental variable estimators that use covariance transformations themselves as instruments, first proposed by Hausman and Taylor (1981), and developed further by Amemiya and McCurdy (1986), Breusch, Mizon and Schmidt (1989) and Cornwell, Schmidt and Wyhowski (1992), although this approach will have to be modified in order to take the orthogonality conditions given by ASSUMPTIONS 6 and 7 into account.

Hausman-Taylor estimation

To the best of our knowledge, no use of the Hausman-Taylor (1981) estimator has been made in the empirical growth literature, and this is surprising.[37] Although Judson (1995) does mention their paper, she confines her estimations to the within, variance components (random

[37] In related work, we (2002) have found that the impact on economic growth of many time-invariant variables identified in the empirical literature using pooling regressions is dramatically altered once country-specific effects are controlled-for using the Hausman-Taylor approach. The basic point being made is that it is empirically dubious to present results concerning time-invariant variables when an appropriate and well-established (since 1981) empirical technique does exists which simultaneously controls for unobserved

effects), and GLS estimators. Hausman and Taylor (1981) provide consistent and efficient estimators for the coefficients associated with time-invariant variables when these variables are correlated with unobserved heterogeneity, when we have no external exogenous instruments, and when ASSUMPTION 1 (exogeneity) is satisfied. The principle of this method consists in using the transformations in terms of deviations with respect to their country-specific means of the exogenous explanatory variables and their country-specific means as instruments.

Consider a growth equation in which $X = [X_{1it}; X_{2it}]$ are the time-varying explanatory variables and $Z = [Z_{1it}; Z_{2it}]$ are the time-invariant explanatory variables. X_{1it} and Z_{1it} are assumed to be doubly exogenous, in that they are uncorrelated with the disturbance term e_{it} and the unobserved country-specific effects $g_0 \ln A_{0i} + m_i$ (i.e., ASSUMPTION 1 (exogeneity) holds but there are no correlated effects). We express the lack of correlation between X_{1it} and Z_{1it} with $g_0 \ln A_{0i} + m_i$ by posing:

ASSUMPTION 8 (orthogonality of X_{1it} and Z_{1it} with the individual effect):

$$E[Z_{1i}'(g_0 \ln A_{0i} + m_i)] = 0 \text{ and } E[X_{1it}'(g_0 \ln A_{0i} + m_i)] = 0 .$$

The X_{2it} and Z_{2it} variables, on the other hand, are singly exogenous in that they are assumed by Hausman and Taylor to be correlated with $g_0 \ln A_{0i} + m_i$ but uncorrelated with e_{it} (ASSUMPTIONS 1 and 3 hold for them). The set of instruments proposed by Hausman-Taylor (1981) is :

(25) $A_{HT} = [Q_v X_{it}; P_v X_{1it}; Z_{1i}]$,

where P_v and Q_v are the idempotent matrices that perform the between and within transformations, respectively; under ASSUMPTION 1 (exogeneity) $Q_v X_{it}$ is a legitimate set of instruments since $E[(Q_v X_{it})' e_{it}] = 0$ (alternatively, one may specify the set of instruments as $A_{HT} = [Q_v X_{it}; P_v X_{1it}; P_v Z_{1i}]$). These results have been extended by Amemiya and McCurdy (1986) and Breusch, Mizon and Schmidt (1989) (henceforth, AM and BMS) who suggest the wider set of instruments given by :

heterogeneity and allows one to identify the impact of time invariant covariates.

(26) $A_{AM} = [Q_v X_{it}; X_{it}^*; P_v Z_{1i}]$, $A_{BMS} = [Q_v X_{it}; X_{it}^*; Q_v X_{2it}^*; P_v Z_{1i}]$,

where X_{it}^* and X_{2it}^* are defined as in Amemiya-McCurdy (1986). The Amemiya-McCurdy instrument set assumes that the doubly exogenous variables are uncorrelated with the country-specific effect, *at each* t. The Breusch-Mizon-Schmidt instrument set assumes that $E[X'_{2it}(g_0 \ln A_{0i} + m_i)]$ is the same, $\forall\ t$. Notice, that the HT, AM and BMS instrument sets are all admissible only if ASSUMPTION 1 (exogeneity) holds. This is because that portion of the country-specific means given by $x_{it} + x_{it-t}$ will be correlated with e_{it} under ASSUMPTIONS 6 and 7. This suggests using the remaining portion $(\sum_{j=0}^{j=t-2t} x_{ij})$ as instruments that will satisfy the predeterminedness assumptions that one is willing to impose in the context of GMM estimation.

A new instrumental variables estimator

Assume that the right-hand-side variables satisfy ASSUMPTION 2 (predeterminedness), as well as the corresponding orthogonality conditions given by ASSUMPTIONS 6 and 7.[38] Consider the following projection matrix P_{T-j}, which transforms time-varying variables into their individual *conditional* means from time 1 to time $t - j$; that is :

(27) $P_{T-j}{}' X_{it} = (t-j)^{-1} \sum_{t=1}^{t=t-j} X_{it} \equiv X_{i\bullet(t-j)}$.

For example, if $T = 4$ and we want to consider individual means of a variable, conditional on the mean being computed from time $t-1$ backwards (i.e., $j = 1$), one obtains for X_{i4}:

$$X_{i\bullet 3} = \left(X_{i3} + X_{i2} + X_{i1}\right)/3 .$$

One can think of P_{T-j} as being the product of two matrices, $P_{T-j} = P_A S_{T-j}$, where P_A is a conventional idempotent matrix (of dimension $[(T-j)N] \times [(T-j)N]$) that transforms a $(T-j)N \times 1$ vector of variables into its individual means, and S_{T-j} is a $[(T-j)N] \times TN$ matrix that deletes the most recent j observations from each individual. If we premultiply a time-invariant variable by P_{T-j}, we simply obtain a $(T-j)N \times 1$ vector of the $T-j$ earliest elements of the variable itself, where the most recent j observations for each individual will

[38] Note that we have no time-invariant variables (be they correlated or not with the country-specific effect) in our growth regressions, although our proposed instrument set can readily be expanded, as with the HT, AM and BMS instrument sets, to accommodate them.

have been deleted. In what follows, most of the discussion will be phrased in terms of the case where $j = 1$.

The reason for doing this transformation, rather than the usual Hausman-Taylor (henceforth HT) one is that, despite the absence of exogeneity, and thanks to ASSUMPTIONS 5, 6, 7 and 8: $E[X_{1i\bullet(t-1)}{}' l_i] = 0$ (trivially, by ASSUMPTION 8), and $E[X_{1i\bullet(t-1)}{}' e_{it}] = 0$ (by ASSUMPTIONS 5, 6 and 7). The combination of these two conditions implies that we can use $X_{1i\bullet(t-1)}$ as instruments for Z_{2i}, and the same necessary condition for identification as in HT holds. If there are no time-invariant variables in the regression, as is the case in the context of the augmented Solow growth regressions considered here, $X_{1i\bullet(t-1)}$ is not needed as an instrument for the non-existent Z_{2i}. The second result is essential when time-invariant variables *are* present in that it ensures that $X_{1i\bullet(t-1)}$ is a valid instrument since it will be orthogonal to the *composite* error term $l_i + e_{it}$. On the other hand, a useful property of the two results is that they imply that $X_{1i\bullet(t-1)}$ will be a valid instrument for X_{2it}. If we had some X_{3it} variables which we knew to be orthogonal to e_{it} ($E[X_{3it}{}' e_{is}] = 0, \forall\ t, s$), then we could add the conventional HT instruments given by $X_{3i\bullet}$ to $X_{1i\bullet(t-1)}$ so as to obtain a broader instrument set for Z_{2i}.

Now consider our twist on the "within" transformation :

(28) $\tilde{X}_{it-1(t-1)} \equiv X_{it-1} - X_{i\bullet(t-1)}$.

One can think of this as premultiplying the variables by the "anihilator matrix" $Q_{T-1} = (\mathbf{I}_{(T-1)N} - P_{T-1})S_{T-1}$, where $\mathbf{I}_{(T-1)N}$ is the identity matrix of dimension $(T-1)N \times (T-1)N$. Q_{T-1} transforms a variable, after deleting the observation at time t for each individual, into deviations of the variable lagged one period, with respect to its individual mean, measured from $t-1$ backwards. (Of course, if we premultiply a time-invariant Z_i vector by Q_{T-1}, we simply get a $T-1$ dimensional vector of zeroes.) For example, for $T = 4$, one obtains, starting from X_{i4}:

$$\tilde{X}'_{i3(3)} = \left[X_{i3} - X_{i\bullet3} \quad X_{i\,2} - X_{i\bullet3} \quad X_{i\,1} - X_{i\bullet3} \right].$$

This second transformation of variables yields the following properties: $E[\tilde{X}_{1it-1(t-1)}{}' l_i] = 0$, (trivially, by ASSUMPTION 8); $E[\tilde{X}_{1it-1(t-1)}{}' e_{it}] = 0$ (by ASSUMPTIONS 5, 6 and 7); $E[\tilde{X}_{2it-1(t-1)}{}' l_i] = 0$ (X_{2it} has been purged of its component that is correlated with l_i); $E[\tilde{X}_{2it-1(t-1)}{}' e_{it}] = 0$ (by ASSUMPTIONS 5, 6 and 7).

The preceding discussion suggests the following instrument set as an alternative to HT, when exogeneity does not hold, but conditions by ASSUMPTIONS 5, 6, 7 and 8 do, in the context of an augmented Solow growth regression :

(29) $\left[\tilde{X}_{1it-1(t-1)} \quad \tilde{X}_{2it-1(t-1)} \quad X_{1i\bullet(t-1)}\right]$.

APPENDIX 2 provides additional developments geared towards expanding this instrument set, as well as some remarks concerning the future potential for extensive hypothesis testing.

Results

In column 2 of Table 3, we present results corresponding to application of the conventional Hausman-Taylor instrument set. More explicitly, our assumptions are that (i) all variables, except for the 7 time period dummies, are correlated with the country-specific effects, (ii) the education variable is correlated with the time-varying component of the disturbance term because of a classical measurement error problem and (iii) the two other explanatory variables are not. Formally, this means that the HT instrument set being used is given by

(30) $[Q_v \ln y_{it-t} \quad Q_v[\ln s_{Kit} - \ln(n_{it} + g + d)] \quad Q_v X_{1it} \quad P_v X_{1it}]$,

where X_{1it} is constituted by the time period dummies. In essence, this is the conventional HT instrument set given in equation (25), modified for the absence of time-invariant covariates (Z_{1i} vanishes), and where one of the elements of $Q_v X_{it}$ has been dropped as an instrument because it is believed to be correlated with the time-varying component of the error term because of a classical measurement error problem.[39]

In comparison with the results presented in Table 2, as well as those corresponding to the Arellano-Bond estimator (column 1 of Table 3), the results are encouraging. First, the point estimate of a is equal to 0.509, which is extremely close to that which is obtained in the

[39] The degrees of overidentification is therefore equal to 7 +1 (time dummies + constant) - 1 (dropped element of $Q_v X_{it}$) = 7.

within results (Table 2, column 2). Second, and more importantly, the point estimate of j is equal to 0.490, and is statistically significant at the 6 percent level. Interestingly, and in line with what one would expect if time-invariant, country-specific measurement error that is *negatively* correlated with the schooling variable (*not* the classical measurement error dealt with in part 4) were present, the point estimate of j is substantially greater than in the pooling results, by a factor of 3. The estimated rate of annual convergence (l) is in line (roughly 0.5 percent per year) with the results stemming from the pooling estimation, and is much smaller than that which obtains using the within estimator. Unfortunately, the test of the overidentifying restrictions yields a p-value of 0.008 leading one, at any level of confidence, to reject. It is probable that the assumption that $Q_v \ln y_{it-t}$ and $Q_v[\ln s_{Kit} - \ln(n_{it} + g + d)]$ are admissible HT instruments is untenable, because of a contemporaneous correlation with the time-varying portion of the disturbance term.[40]

In column 3 of Table 3, we present results corresponding to a simple version of our new instrument set, in which instruments are limited to the deviations of the variables with respect to the conditional country-specific means only for the initial period (1960). More explicitly, the instrument set being used is

$$(31) \qquad [\tilde{X}_{2it-1(t-1)}],$$

since we assume that *no* X_{1it} variables (those uncorrelated with the country-specific effects) obtain in the equation (therefore, $\tilde{X}_{1it-1(t-1)}$ and $X_{1i\bullet(t-1)}$ drop out from the instrument set given in equation (29)). This specification is overidentified with 3 degrees of freedom,[41] and yields a point estimate of a equal to 0.65, roughly halfway between the pooling and within results, and larger, by 0.15, than the conventional HT results. As with the conventional Hausman-Taylor estimates, the point estimate of j is slightly below 0.50 (with an associated p-value of 9 percent), while the convergence rate falls even further, to 0.33 percent per year.

[40] When one relaxes this assumptions, and allows for only the time dummies in deviations and country-specific means to constitute the HT instruments, the overidentifying restrictions continue to be rejected. This should not be surprizing, by dint of the fact that these variables have extremely weak explanatory power in the corresponding instrumenting equations.

[41] Given that deviations with respect to conditional means are used as instruments, we are left with only 5 five-year periods for estimation purposes, since variables expressed as deviations with respect to conditional means must be lagged at least two periods, and conditional means must span at least two periods to be meaningful. This implies that there are 8 parameters to be estimated: 5 period-specific constants, and the three parameters presented in the Tables. In the results presented in column 3 of Table 3, there are 11 instruments, constituted by 10 deviations with respect to conditional means plus the constant. This yields 3 degrees of freedom for the test of the overidentifying restrictions. A similar computation yields the 11 degrees of freedom for the results

Unfortunately, in terms of the validity of our choice of instruments, the specification fails the test of the overidentifying restrictions: the p-value associated with the test is equal to 0.05 which, at conventional levels of confidence, would lead one to reject.

In column 4 we extend the instrument set to include deviations of variables over the last *two* time periods (1965 and 1960) with respect to their country-specific conditional means. The results are striking. First, the point estimate for j comes in at 0.98, and is significant at the 1 percent level of confidence. This seems *too* large, but it cannot be denied that human capital is thereby restored to its position of prominence as an important determinant of economic growth. The point estimate of a falls back to the value found with the conventional HT estimator, and is equal to 0.50; the annual rate of convergence also moves back towards the conventional HT level, and is equal to 0.64 percent per year, surprizingly close to the number obtained using the pooling estimator. Finally, and this provides us with some confidence in the relative robustness of our results, the instrument set is not rejected by the test of the overidentifying restrictions, with the p-value of the associated test statistic (with degrees of freedom equal to 11) being equal to 0.60: this is the first instance presented in Table 3 where an instrumental variables-based estimator is not rejected by a test of the corresponding overidentifying restrictions. It is also in sharp contrast to what happens when the Arellano-Bond estimator was used.

6. CONCLUDING REMARKS

In this paper, we have attempted to explain why, once conventional panel estimation techniques such as the within procedure or first-differencing are performed, the coefficient associated with human capital, which is positive and statistically significant in cross-sectional or pooling regressions, becomes either statistically indistinguishable from zero or negative and statistically significant. After reviewing the forms of bias that are likely to arise in the augmented Solow model, we showed that the crucial issue revolves around the lack of variability in the education variable once country-specific heterogeneity is accounted for, and how standard covariance transformations result in the measurement error that affects human capital becoming the dominant source of identifying variance. We have proposed an estimator, based on the Hausman-Taylor (1981) approach, which allows one to identify the

presented in column 4, since here there are 18 deviations with respect to conditional means.

impact of time invariant variables while controlling for individual effects, which we combined with the orthogonality restrictions that appear to be reasonable in the context of cross-country panel data. A first application of this new estimator revealed that it may allow one to solve the negative human capital coefficient puzzle, although further testing would be desirable.

The contributions of this paper to the literature on economic growth are, we believe, two-fold. First, we have shown, sometimes (and unfortunanely) rather laboriously, that a clear understanding of the underlying data-generating process is essential for one to be able to choose the right empirical instrument. The Barro-Lee human capital variable is an extremely useful creation which does, however, bring with it important problems, that have led to an econometric puzzle that has baffled growth-specialists in recent years.

Second, from the methodological perspective, we have shown that the Hausman-Taylor approach can be fruitfully applied to the empirics of economic growth. Concomitantly, we have shown that it is a viable alternative, when modified to take into account the milder identifying assumptions recently popularized by the GMM literature, to the Arellano-Bond approach which is sometimes, especially in parsimonious specifications such as the augmented Solow model, plagued by a problem of weak instruments. Further investigations will involve exploring the broader instrument sets made possible by our approach, as well as developing a battery of hypothesis tests that will provide further checks on the validity of the identifying assumptions.

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APPENDIX 1

The variance of human capital in a pooling regression over T periods when $h_{it} = h_{i0}\exp\{a_i t\}$ is given by :

$$
\begin{aligned}
s^2_{h_t} &= \sum_{t=0}^{t=T-1} \mathrm{var}[\ln h_{it}] = \sum_{t=0}^{t=T-1} \mathrm{var}[\ln h_{i0} + a_i t] = (T-1)\mathrm{var}[\ln h_{i0}] + \sum_{t=0}^{t=T-1} \mathrm{var}[a_i t] \\
&= (T-1)s^2_{h_0} + \mathrm{var}[a_i 0] + \mathrm{var}[a_i t] + \mathrm{var}[a_i 2t] + \ldots + \mathrm{var}[a_i (T-2)t] + \mathrm{var}[a_i (T-1)t] \\
&= (T-1)s^2_{h_0} + t^2 s^2_a + 4t^2 s^2_a + \ldots + (T-2)^2 t^2 s^2_a + (T-1)^2 t^2 s^2_a \\
&= (T-1)s^2_{h_0} + t^2 s^2_a \sum_{n=1}^{n=T-2} n^2 + (T-1)^2 t^2 s^2_a \\
&= (T-1)s^2_{h_0} + t^2 s^2_a \sum_{n=1}^{n=T-1} n^2 .
\end{aligned}
$$

In first-differences over $T-1$ periods, the corresponding expression is obtained as :

$$
s^2_{\Delta h_t} = \sum_{t=0}^{t=T-1} \mathrm{var}[\ln h_{it} - \ln h_{it-1}] = \sum_{t=0}^{t=T-1} \mathrm{var}[a_i t] = (T-1)\mathrm{var}[a_i t] = (T-1)t^2 s^2_a .
$$

APPENDIX 2

One can expand the instrument set proposed in equation (29) by adding instruments of the form:

$$\left[\tilde{X}_{1it-j(t-k)} \quad \tilde{X}_{2it-j(t-k)} \quad X_{1i\bullet(t-k)}\right],\ j>1,\ k>1.$$

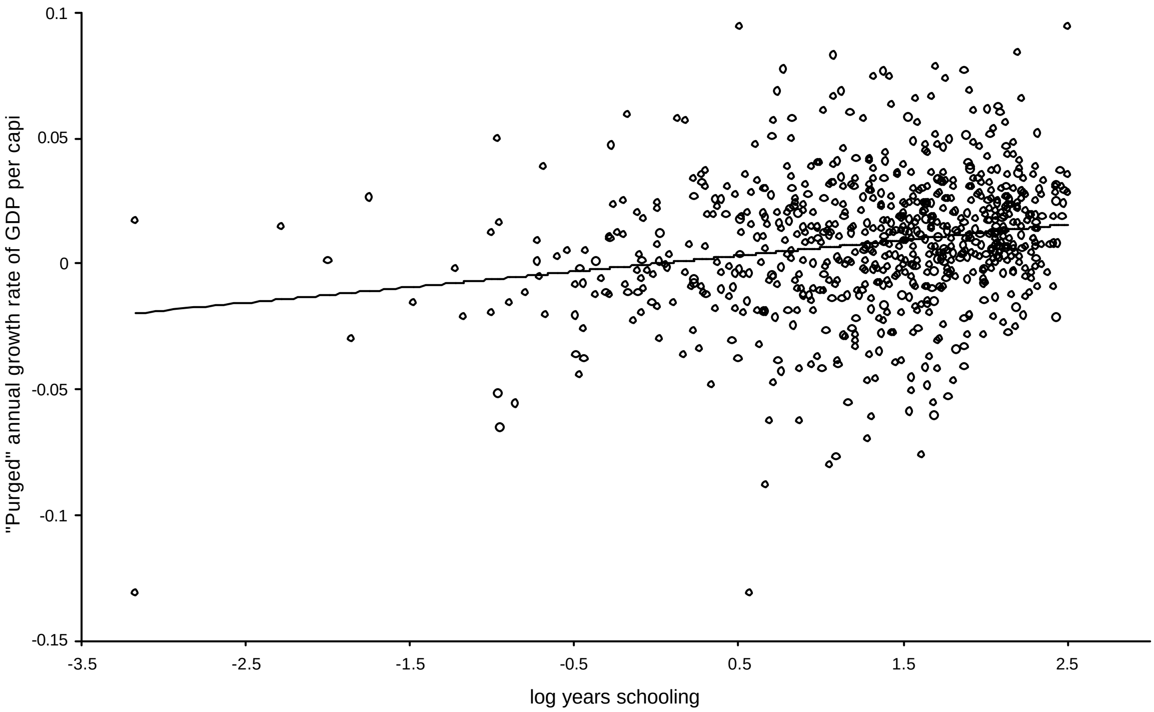
This is easy to set up in a GMM framework with a separate equation for each time period (with cross-equation restrictions on the parameters). One can then test the ensuing overidentifying restrictions. An important concern, however, is that high values of j and k will end up being akin to using successively lagged values of the variables themselves after first-differencing, as in Arellano and Bond (henceforth, AB). As a result, we have preferred to keep things simple, and stick to (29).

As a general econometric point, the issue here is not only to be able to identify the impact of time-invariant variables while controlling for individual effects, but also to be able to precisely identify the impact of particular time-varying variables, correlated with the individual effects, whose variance falls dramatically once first differencing is performed. This suggest that the instrument set proposed in (29) may constitute a possible solution to the problem of weak instruments caused by first-differencing. In some sense, the basic idea is that many time varying variables that are correlated with the individual effect become "almost time-invariant" after first-differencing (as with log human capital in a growth regression) and the only way of estimating the coefficients associated with such a variable while controlling for individual effects is to use a procedure based on Hausman and Taylor, modified to take the correlation between the time varying variable and the time varying component of the error term into account.

As in the original HT paper, our instrument set suggests the following approach to testing. First, run the regression using the "consistent" instrument set proposed in (29). Concomitantly, run the regression in first differences, using twice-lagged levels (as in Anderson and Hsiao, 1981, 1982, henceforth AH, although their focus is of course on a lagged dependent variable), to control for endogeneity. It is then straightforward to construct a Hausman test of the overidentifying restrictions (whereas the AH estimates will be just-identified). Though not as clean as the original test proposed in HT which uses the "within" estimates (but which cannot be used because of the lack of exogeneity), this is the appropriate procedure. Second, as with conventional consistent HT, carry out (a) a Sargan test of the overidentifying restrictions and, in the spirit of AB, (b) a test for first order serial correlation of the residuals in levels (to test the critical identifying condition given by ASSUMPTION 5). One can check the consistency of the AH counterfactual by doing the usual test for the absence of second order serial correlation and the presence of first-order serial correlation in the first-differenced residuals, given in AB. On the other hand, if AB were the counterfactual used to construct the Hausman test described above, one could perform the same tests for serial correlation in the first-differenced residuals, plus a Sargan test of the overidentifying restrictions of the AB estimator.

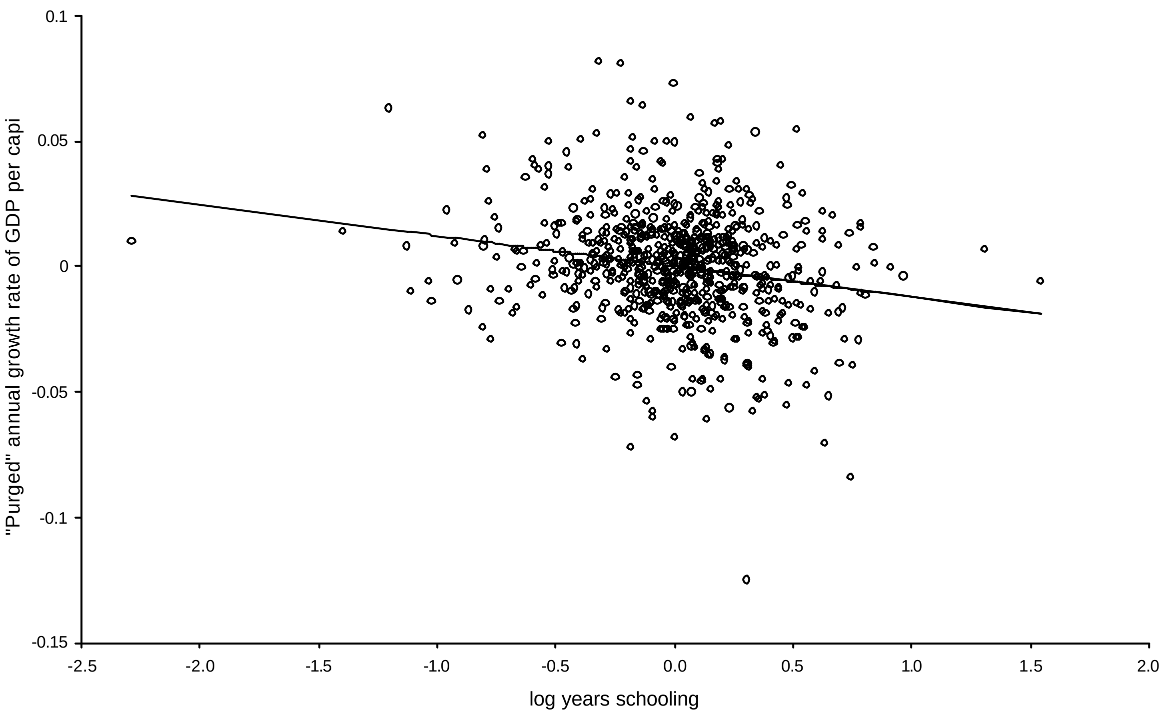
If the results pass this first battery of tests, one can be reasonably confident that one can get consistent estimates of the variance components, and proceed to q -differencing. One can then construct the corresponding Hausman test of the efficient *versus* consistent estimates using the proposed instrument set, or using our efficient modified HT *versus* AH. In the context of a dynamic panel data setup with a lagged dependent variable (as in the growth regressions considered here), one simply adds the lagged dependent variable transformed as in equation (28) to the instrument set. Then the Hausman test proposed above using the AH estimator as the counterfactual really comes into its own.

Figure 1. Annual growth rate of GDP per capita and human capital: Pooling ($g_{2OLS} = 0.0062$)



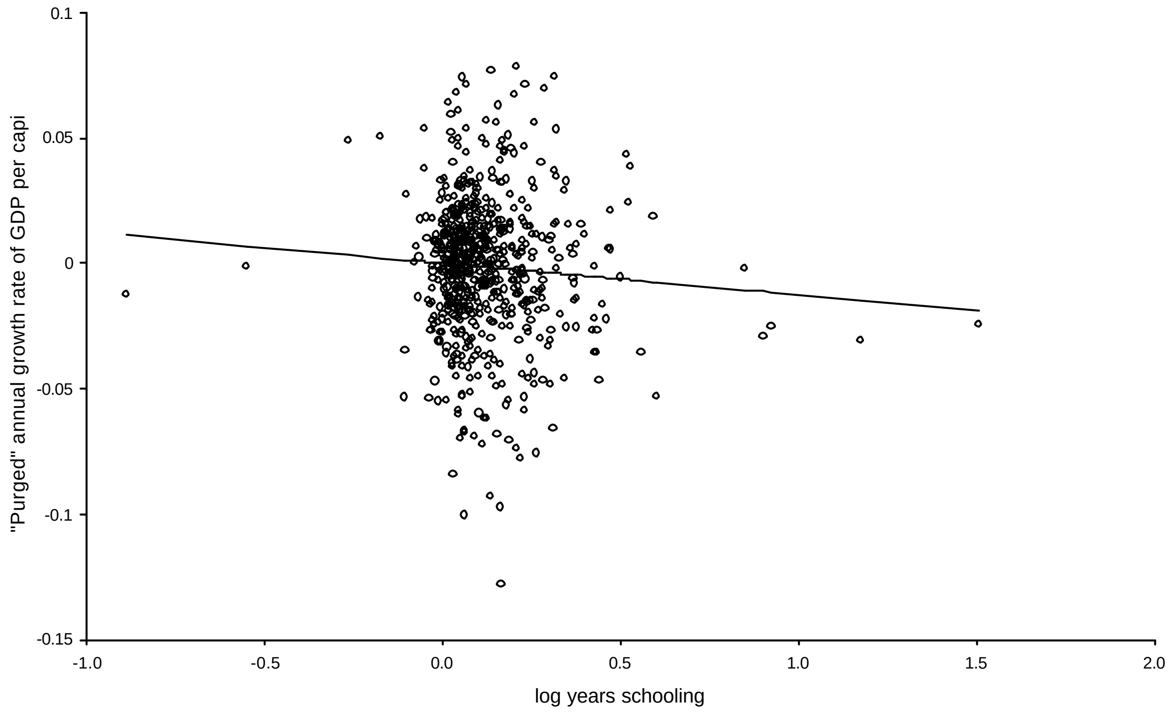
Note: "Purged" growth rate of GDP per capita plotted on vertical axis obtained after purging it of the effects of initial GDP per capita, the investment ratio, population growth rate and time dummies; based on the parameter estimates presented in column 1 of Table 2.

Figure 2. Annual growth rate of GDP per capita and human capital: Within ($g_{2w} = -0.0122$)



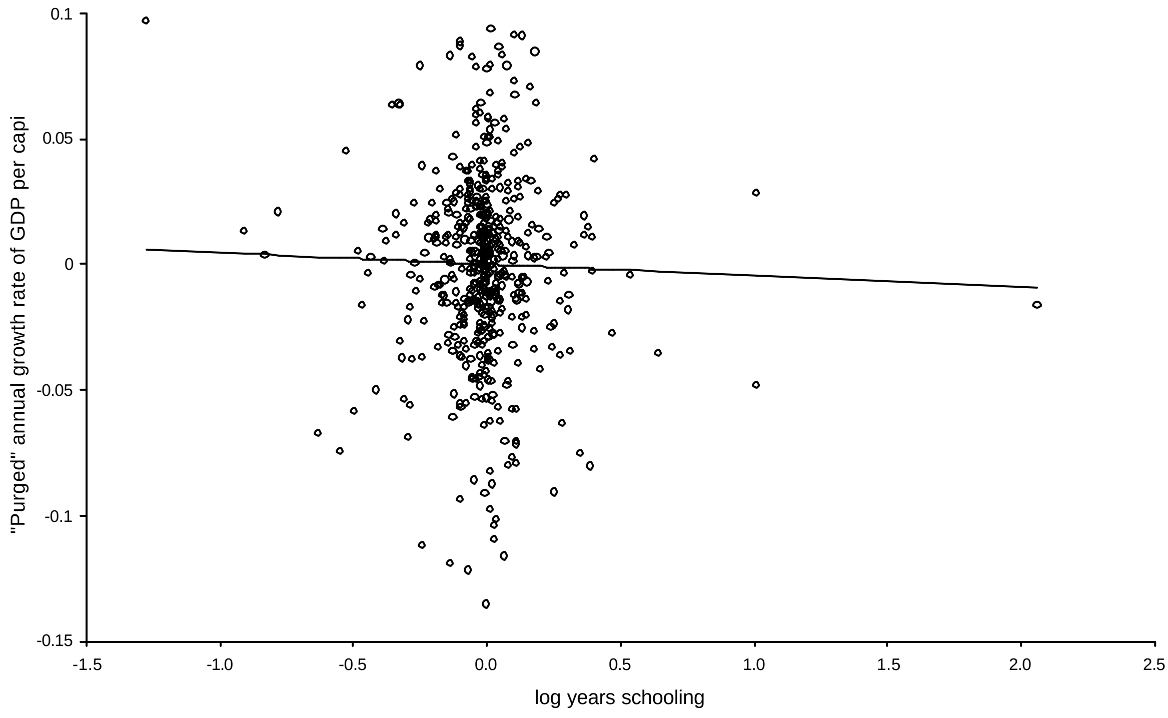
Note: based on the parameter estimates presented in column 2 of Table 2.

Figure 3. Annual growth rate of GDP per capita and human capital: First-differences ($g_{2d} = -0.0125$)



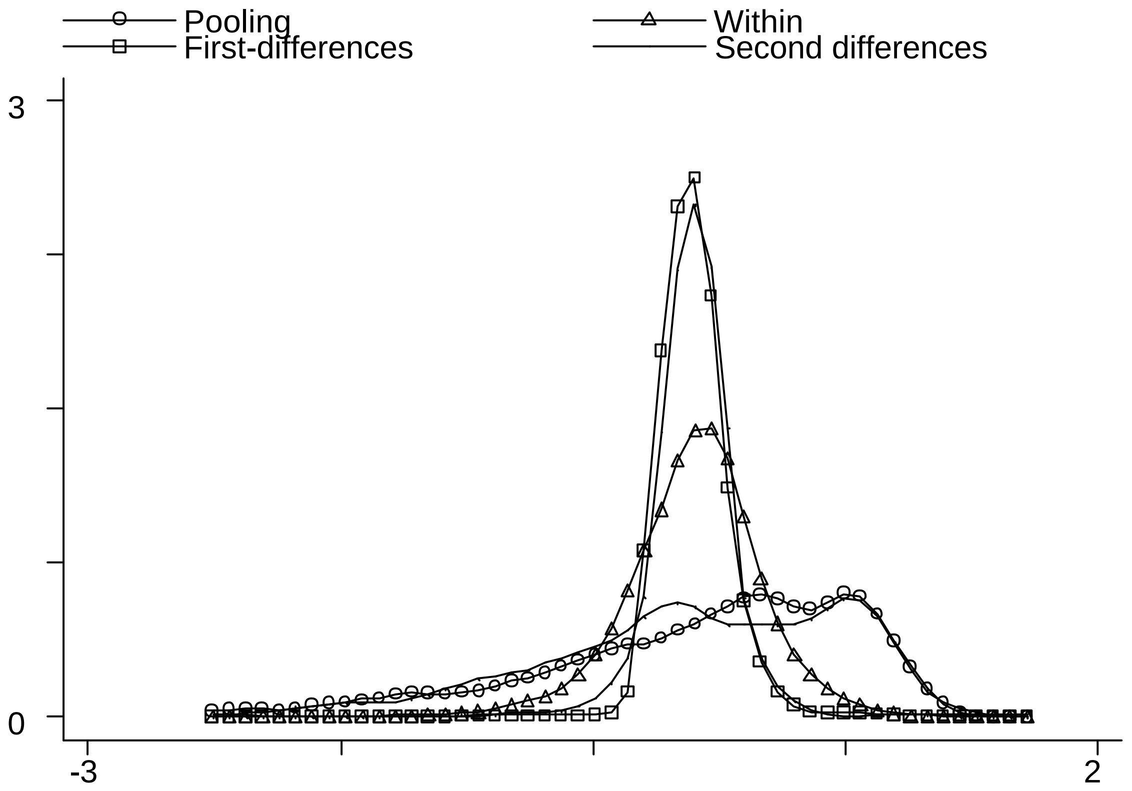
Note: based on the parameter estimates presented in column 3 of Table 2.

Figure 4. Annual growth rate of GDP per capita and human capital: Second-differences ($g_{22d} =$ x.xxxx)



Note: based on the parameter estimates presented in column 6 of Table 2.

Figure 5. The changing distribution of $\ln h_{it}$. Kernel density estimates of log education : Pooling, within, first-difference, second-difference and Hausman-Taylor transformations



Note: the lower kernel density with no symbol corresponds to the standard Hausman-Taylor transformation.

Figure 6. The growth of human capital as a country-specific, exponential process: $h_{it} = h_{i0}\exp\{(a_i + q_{it})t\}$; actual *versus* predicted value of $\ln h_{it}$

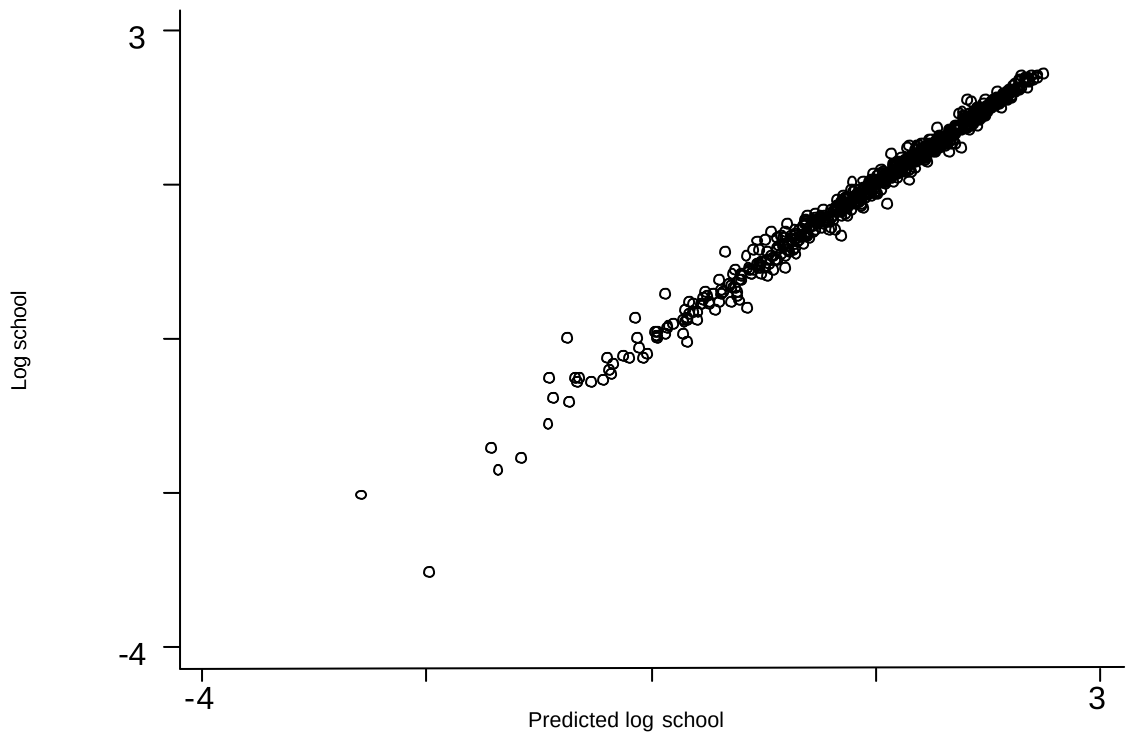


Table 1. Cross-Section *versus* Panel: A Summary of the Human Capital Puzzle

Authors	Type of estimation	Sample	Estimation method	Additional explanatory variables	Coeff. on human capital	Education variable	Implied α (s.e.) where available	Implied ϕ (s.e.) where available
MRW (1992) Table II	Cross-section, 1960-85		OLS		Pos. & signif.	Sec. enrol. rate	0.31	0.28
Islam (1995) Table V, col. 1	Cross-section, 1960-85	non-oil	OLS		Pos. & signif.	Barro-Lee	0.686 (0.069)	0.235 (0.101)
Islam (1995) Table V, col. 2	Panel, 5 periods, 1960-85	non-oil	Pooling-OLS		Insignif.	Barro-Lee	0.801 (0.053)	0.054 (0.102)
Benhabib & Spiegel (1994)	Panel, 2 periods, 1960-1980		First differences		Insignif.	Barro-Lee		
Islam (1995) Table V, col. 3		non-oil	Chamberlain min. dist.		Neg. & signif.	Barro-Lee	0.522 (0.064)	-0.199 (0.109)
Islam (1995) Table V, col. 3		Intermediate	Chamberlain min. dist.		Insignif.	Barro-Lee	0.494 (0.059)	-0.006 (0.126)
Islam (1995) Table V, col. 3		OECD	Chamberlain min. dist.		Insignif.	Barro-Lee	0.207 (0.105)	-0.045 (0.145)
Knowles & Owen (1995)								
Caselli, Esquivel & Lefort (1996), Table 3	Panel, 5 periods, 1960-85		Arellano-Bond GMM		Neg. & signif.	Sec. enrol. rate	0.491 (0.114)	-0.259 (0.124)
Hamilton & Monteagudo (1998), eq. (16)	Panel, 2 periods: 1960-70 and 1975-85	Same as MRW	First differences		Neg. & signif.	% of work. age pop. in sec. sch.	0.468 (0.084)	-0.121 (0.079)
Temple (1999b), Table 1, col. 4	Benhabib-Spiegel Cross-section, 1960-85	Different subsamples	LTS-OLS (RWLS)	Region. dum.	Pos. and signif.	Sec. enrol. rate		0.15 to 0.38
Bond, Hoeffler &Temple (2001), Table 2	Panel, 5 periods, 1960-85	Same as Caselli, Esquivel & Lefort	Arellano-Bover GMM		Insignif.	Sec. enrol. rate		
Bräuninger & Pannenberg (2002), Table 2, col. 1	Panel, 6 periods: 5 year intervals, 1960-90	13 OECD countries	Within	Unempl.	Insignif.	Barro-Lee	0.23	
Table 2, col. 2			Arellano-Bond GMM	Unempl.	Insignif.	Barro-Lee	0.48	
McDonald & Roberts (2002) Table 1, col. 1	Panel, 6 periods: 5 year intervals, 1960-90	MRW with available human cap.	Within	Infant mort. or life expect.	Insignif.	Nehru *et al*	0.40	0.00
Table 1, col. 7		OECD	Pooling		Pos. and signif.	Nehru *et al*	0.53	0.19

Table 2. Restricted Estimation of the Augmented Solow Models: 1960-2000
Eight five-year periods. Simple covariance transformations
(p-values in parentheses below coefficients)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	Pooling	Within	First diff.	First diff. corrected for first order serial corr.	Between on first diff.	Second diff.	Second diff. + multiplic. country eff.
a	0.8447	0.4974	0.2250	0.3042	0.5301	0.1075	0.1636
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
j	0.1459	-0.1925	-0.0839	-0.2205	-0.0730	-0.0189	0.0380
	(0.003)	(0.001)	(0.101)	0.001)	(0.749)	(0.612)	(0.357)
l	0.0066	0.0327	0.1228	0.0891	0.0250	0.2442	0.3104
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)
$\mathbf{H}_0 : a + j - 1 = 0$	0.0092	-0.6951	-0.8588	-0.9163	-0.5428	-0.9114	-0.7982
[p-value]	0.795	0.000	0.000	0.000	0.053	0.000	0.000
$\bar{R}^2$	0.4769	0.2452	0.3453	0.3076	0.0845	0.5205	0.7080
s	0.0265	0.0219	0.0285	0.0269	0.0088	0.0410	0.0358
Variance of fixed effects	n.a.	0.0527	n.a.	n.a.	n.a.	n.a.	n.a.
First-order r	0.2350	-0.0452	-0.2442	n.a.	n.a.	-0.5329	-0.3843
	(4.74)	(0.316)	(0.000)			(0.000)	(0.000)
Variance of human capital	0.6935	0.1321	0.0230	0. 0230	0.0063	0.0383	0.0383
Skewness of human capital	-1.231	-0.525	2.048	2.048	1.078	1.529	1.529
Kurtosis of human capital	5.040	5.931	20.753	20.753	4.076	29.205	29.205
VIF (collinearity diagnostic)	3.008	3.008	1.068	1.068	1.134	1.051	1.112
Var. of res. from aux. reg.	0.486	0.041	0.021	0.021	0.0720	0.038	0.031
No. of observations	737	737	635	535	100	535	535

Note: a is the coefficient associated with physical capital in the Cobb-Douglas production function; j is the coefficient associated with human capital; l is the annual rate of convergence. Time dummies included in all specifications. Correction for 1st-order serial correlation carried out using a simple Cochrane-Orcutt transformation (hence the reduction in the number of observations); VIF is the "variance inflation factor"; variance of residuals from auxiliary regression corresponds to that of the human capital variable on the other explanatory variables.

Table 3. Restricted Estimation of the Augmented Solow Models: 1960-2000
Eight five-year periods. Arellano-Bond GMM, Hausman-Taylor, and AH HT-GMM estimators
(p-values in parentheses below coefficients)

	(1)	(2)	(3)	(4)
Estimation method	Arellano-Bond GMM	Conventional Hausman-Taylor	AH Hausman-Taylor-GMM (earliest dev.)	AH Hausman-Taylor-GMM (2 earliest dev.)
a	0.5403	0.5099	0.6523	0.5027
	(0.017)	(0.000)	(0.000)	(0.000)
j	-0.4906	0.4909	0.4812	0.9817
	(0.008)	(0.065)	(0.093)	(0.011)
l	0.0308	0.0049	0.0033	0.0064
	(0.296)	(0.000)	(0.010)	(0.005)
$\mathbf{H}_0 : a + j - 1 = 0$	-0.9502	-0.0391	0.1336	0.4844
[p-value]	[0.000]	[0.852]	[0.485]	[0.065]
Sargan test of overid. restrict.: p-value	0.0357	0.008	0.0541	0.6013
No. of observations	535	737	420	420

Note: 1st column is Arellano-Bond estimator as in Caselli, Esquivel and Lefort; p-value associated with the test for first-order serial correlation in Δe_{it} is equal to 0.0000 ; for the corresponding test for second order serial correlation in Δe_{it}, the associated p-value is equal to 0.3200 ; 2nd column is the conventional Hausman-Taylor (1981) estimator where education is assumed to be correlated with country-specific effect; 3rd and 4th columns correspond to our GMM-based Hausman-Taylor type estimator based on internal instruments constructed from deviations with respect to country-specific conditional means; in column 3, only the deviation of the observation for 1960 with respect to the conditional mean is used as an instrument; in column 4, both 1960 and 1965.