# Distinguishing between the effects of primary and post-primary education on economic growth

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**Abstract**

This paper follows Benhabib and Spiegel (1994) in examining the effect of human capital accumulation on economic growth. The paper is innovative in two ways. First, it takes the R&D–based models more seriously. This delivers more structural specifications in which human capital affects growth as an input of final output *and* as a catalyst of technological innovation and imitation. Second, due to data availability it is possible to disaggregate human capital and assign different roles to primary and post–primary education. Regression estimates obtained from these alternative specifications suggest that the relative contribution of human capital to technology adoption and final output production vary by country wealth. More importantly, regression estimates suggest that primary education contributes mainly to production of final output, whereas post–primary education contributes mainly to adoption and innovation of technology.

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# 1 Introduction

Politicians and economists alike are convinced that education is a determining factor of an individual's well–being and more generally a determinant of economic growth. Yet the empirical evidence which relies on a decade–long intense investigation, suggests at best a weak relationship between human capital accumulation and growth. In particular, regression estimates obtained from cross–country growth accounting reveal a puzzling result; that is, human capital accumulation enters growth regressions either significantly with a negative sign, or insignificantly with a positive sign.

This paper proposes modifications to the conventional cross–country growth accounting approach that deliver some new and interesting results.[1] It is important to mention at the outset that the paper investigates the relationship between economic growth and changes in human capital rather than growth and the initial level of human capital. In particular, this paper follows Benhabib and Spiegel (1994) in empirically investigating alternative structural specifications in which the role of human capital in economic growth is partly through output production and partly through facilitating technological innovation and imitation.[2]

This paper takes Benhabib and Spiegel (1994) as its starting point and extends it in three ways. First, it uses a relatively novel World Bank dataset on the stock of physical capital and educational attainment per worker for a panel of 80 countries. Second, it takes the R&D–based model (e.g. Romer (1990)) more seriously. This implies structural specifications in which human capital affects growth through its traditional role as a factor of production and through serving as a means of technological progress. Third, due to data availability it is possible to disaggregate human capital and assign different roles to primary and post–primary education. More precisely, primary education is assumed to enter the final output sector, whereas secondary and tertiary education are assumed to enter the R&D sector.

Theoretically, the model used in this paper is closely related to Veblen (1915), Nelson and Phelps (1966), and more recently Barro and Sala–i–Martin (1997), Perez–Sebastian (2000) and Papageorgiou (forthcoming).

[1] Empirical growth literature is divided into two main classes of cross-country growth regressions. The first class is originated by the pioneer work of Mankiw, Romer and Weil (1992), henceforth MRW, who provide a simple theoretical framework for growth regressions based on the Solow (1956) model. The second class, into which this paper belongs, is based on cross–country growth accounting. Growth accounting provides a decomposition of the observed output growth into components associated with changes in factor inputs and a residual that reflects technological change and other elements. A key difference between the MRW–type regressions and growth accounting regressions is that whereas the former examines the relationship between *levels* of capital and human capital investment and income growth, the latter examines the relationship between *growth rates* of human and physical capital stocks and income growth. In this respect, the two approaches provide springboards on which we can investigate two different yet equally important relationships. This paper adopts the growth accounting approach partly because we possess a novel dataset on *stocks* of physical and human capital and partly because we are interested in examining how human capital accumulation (not investment) is related to economic growth.

[2] Through out the paper the term "innovation" is used to mean development of domestic technology. This term can be interpreted either as actual innovation, or as re–invention of existing technology. The term "imitation" is used to mean adoption of foreign technology.

In terms of the model's implications, it is closer to the work of Baumol, Blackman and Wolff (1989) who argue that the relative returns for various types of educational attainment differ in their contribution to growth. Indeed, one of the key innovations of this paper is to use alternative structural specifications to identify the way by which primary and post–primary schooling impact economic growth.

The main findings of the paper are as follows. Regression estimates obtained from the proposed specifications suggest that the relative contributions of human capital to technology adoption and final–goods production seem to vary by country wealth. Most importantly, the contribution of primary education to output production is substantial whereas its contribution to R&D is limited, especially in developing countries. The reverse is true for post–primary education. There are also a few other findings worth noting. Contrary to most standard growth accounting exercises,[3] human capital enters positively into our growth regressions; this result provides further evidence in favor of Benhabib and Spiegel (1994). Regression estimates obtained from the alternative specifications, present some evidence for a dual role of human capital in economic growth. More precisely, when human capital enters as an input of final–goods production as well as a input in technology production, the resulting specifications perform better than the prevalent specifications in the literature.

The rest of the paper is organized as follows. Section 2 revisits two existing empirical specifications common in the existing literature and proposes three alternative specifications. Section 3 describes the data, discusses estimation issues and presents regression results for the entire sample of 80 countries and three subsamples of countries. Section 4 summarizes and concludes.

## 2 Alternative growth regression specifications

This section describes alternative growth accounting specifications examined in the estimation section of the paper.[4] The proposed specifications are extensions of the Benhabib–Spiegel specification (BS hereafter)[5], and are derived by taking the R&D–based (Romer–type) models' framework more seriously. We start with a brief overview of the R&D–based models' framework and then point out three reduced–form specifications that will be the bases of our empirical work.

The basic R&D–based model can be characterized by two equations and a resource constraint.[6]

[3]An exception is Temple (1999a).

[4]New reliable data on physical and human capital stocks made growth accounting regressions popular. The growth accounting approach has been initially used by Kyriacou (1991) and Benhabib and Spiegel (1994) and more recently by a large number of papers including Barro (1999), and Temple (1999a, 2001), just to name a few. For an excellent discussion on cross–country growth accounting regressions see Temple (1999b pp. 121–125).

[5]The specification that we will be referring to as BS is Eq. (13) in Benhabib and Spiegel (1994).

[6]For a discussion on the detailed structure of the R&D–based model, see the pioneer paper by Romer (1990) or one of the

1. *Aggregate Production Function*: The first equation is the aggregate production function that is implicitly given by

$$Y_{it} = G(A_{it}, K_{it}, L_{it}, H_{Yit}), \tag{1}$$

where $Y_{it}$ is gross output of country $i$ at time $t$, $A_{it}$ is the level of exogenous domestic technology, $K_{it}$ is the stock of physical capital, $L_{it}$ is the labor force, and $H_{Yit}$ is the human capital engaged in final–goods production. Following Romer (1990) the production function is explicitly given by

$$Y_{it} = A_{it}^{\alpha+\beta} H_{Y\,it}^{\alpha} L_{it}^{\beta} K_{it}^{1-\alpha-\beta},\ 0 < \alpha < 1,\ 0 < \beta < 1, \tag{2}$$

where $\alpha$ and $\beta$ are factor shares.

2. *R&D Equation*: The second equation is the law motion of technology that is implicitly given by

$$A_{it} - A_{i0} = J(H_{Ait}, A_{it}, A_t^*), \tag{3}$$

where $H_{Ait}$ is the human capital engaged in R&D activities, and $A^*$ is the technology frontier. In this model we adopt the explicit R&D equation from Benhabib and Spiegel (1994, Eq. 11) given by

$$A_{it} - A_{i0} = \delta H_{Ait} A_{i0} + \mu H_{Ait}(A_0^* - A_{i0}), \tag{4}$$

where $\delta$ and $\mu$ are the innovation and imitation parameters, respectively. One of the main features of this law of motion, is that technical change is a function of innovation and imitation and is captured by the first and second terms of the right hand side of Eq. (4), respectively.[7]

3. *Resource Constraint*: Finally, we have a human capital constraint given by

$$H_{it} = H_{Yit} + H_{Ait}. \tag{5}$$

Human capital is employed either in the production of final output, or in the production of technology.

Next, we propose three alternative specifications motivated by the model above. We start with a specification that is closest to BS and work towards a more structural specification implied by the Romer model.

To simplify our base regression we start by assuming a production function, $Y_{it} = A_{it}(H_{it}) H_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma}$, that is more flexible than the one given in Eq. (2). Notice that human capital enters the aggregate production

many other papers that followed it. Virtually all R&D–based models share the same structure.

[7] Recently, one of the more popular technology specification is the one used in Jones (1995). We chose to adopt the BS specification because, unlike Jones' specification that allows only for innovation, it allows for imitation as well.

function as an input in final–goods production *and* as an input in technology production. By log–differencing this production function and using the R&D equation given by Eq. (4) obtains the specification

$$\begin{aligned}\log(Y_{it}/Y_{i0}) &= b_0 + b_1 H_{i0} + b_2 H_{i0}(y_0^*/y_{i0}) + b_3 \log(K_{it}/K_{i0}) + \\ &\quad b_4 \log(H_{it}/H_{i0}) + b_5 \log(L_{it}/L_{i0}) + \varepsilon_{it}, \qquad (6)\end{aligned}$$

where $b_1 = (\delta - \mu)$, $b_2 = \mu$, $b_3 = \gamma$, $b_4 = \alpha$, and $b_5 = \beta$. Given technology data constraints, we follow BS in assuming that $y_0^*/y_{i0}$ is a good approximation for $A_0^*/A_{i0}$.

Now working closer to the Romer model given by Eqs. (1)–(5) we allow a portion of human capital to enter in the production of final output, and a portion in the production of technology. The modified aggregate production function is now $Y_{it} = A(H_{Ait})H_{Yit}^{\alpha}L_{it}^{\beta}K_{it}^{\gamma}$. Following the same steps as above we log–difference the modified production function and use Eq. (4) to get the reduced form equation

$$\begin{aligned}\log(Y_{it}/Y_{i0}) &= c_0 + c_1 H_{Ai0} + c_2 H_{Ai0}(y_0^*/y_{i0}) + c_3 \log(K_{it}/K_{i0}) + \\ &\quad c_4 \log(H_{Yit}/H_{Yi0}) + c_5 \log(L_{it}/L_{i0}) + \varepsilon_{it}, \qquad (7)\end{aligned}$$

where $c_1 = (\delta - \mu)$, $c_2 = \mu$, $c_3 = \gamma$, $c_4 = \alpha$, and $c_5 = \beta$. In Eq. (7) we differentiate between $H_{Yit}$ and $H_{Ait}$; the former enters our regression in growth rates where the later enters in levels.

Finally, we constraint the factor coefficients to be consistent with the more rigid production function of Romer (1990) given by Eq. (2). This obtains in the following specification:

$$\begin{aligned}\log(Y_{it}/Y_{i0}) &= d_0 + d_1 H_{Ai0} + d_2 H_{Ai0}(y_0^*/y_{i0}) + d_3 \log(K_{it}/K_{i0}) + \\ &\quad d_4 \log(H_{Yit}/H_{Yi0}) + d_5 \log(L_{it}/L_{i0}) + \varepsilon_{it}, \qquad (8)\end{aligned}$$

where $d_1 = (\alpha + \beta)(\delta - \mu)$, $d_2 = (\alpha + \beta)\mu$, $d_3 = 1 - \alpha - \beta$, $d_4 = \alpha$, and $d_5 = \beta$.

Eqs. (6)–(8) are the empirical specifications used in estimation.

## 3 Data, estimation and results

This section compares the estimates of the standard growth accounting and BS specifications to the estimates obtained from the three alternative specifications given by Eqs. (6)–(8). We begin by briefly describing the data used in our estimation.

## 3.1 Data

Our estimation involved data on 80 countries for the beginning and ending period in our sample (1960, 1987). All of the data used here were obtained from the World Bank's STARS database. From this database we obtained measures of GDP and the aggregate physical capital *stock*, both of which were converted into constant, end of period 1987 U.S. dollars, for all 80 countries for 1960 and 1987. The dataset contained observations on the number of individuals in the workforce between the ages of 15–64, and the mean years of schooling per worker. Further details concerning the construction of these data are provided in Appendix A.

Of interest is the use of a relatively recent data set on *stocks* of physical capital. The relevant reference concerning the construction of these stocks is Nehru and Dhareshwar (1993). The Nehru and Dhareshwar (1993) data on physical capital stocks makes use of World Bank data on gross domestic fixed investment at constant local prices and draws on additional data sources. Nehru and Dhareshwar use the "perpetual inventory method" to calculate capital stocks as briefly discussed in the data appendix. They show that their capital stock estimates are positively correlated with other, more limited, data sets on physical capital stocks. While capital stock estimates necessarily involve some guesswork, by many accounts the Nehru and Dhareshwar data set is the best that is currently available.[8]

We define the stock of human capital in country $i$ as the mean years of schooling of the labor force (workers between the ages of 15–64 as in the measure of $L$) in country $i$ at time $t$. The mean school years of education is defined as the sum of the average number of years of primary, secondary and post–secondary education. The data used on mean years of schooling are also somewhat novel in that they are available *annually* and have been adjusted for differential drop–out and mortality rates and corrected for grade repetition. Details on the construction of this data are provided in Nehru, Swanson and Dubey (1995).

We denote the GDP data converted into constant 1987 U.S. dollars by $Y_{it}$, and the physical capital stock data in constant U.S. dollars by $K_{it}$, where $i = 1, 2, ..., 80$ indexes each country and $t = 1960$, 1987 indexes the years of our sample. Similarly, we use the notation $L_{it}$ to denote the data on the size of the workforce in country $i$ in year $t$. We use $H_{it}$ to denote the mean years of education, and $H_{Yit}$ and $H_{Ait}$ to denote the mean years of primary and post–primary education, respectively. Finally, we follow Benhabib and Spiegel (1994) and use the ratio $y_t^*/y_{it}$ as a rough proxy for the technological gap, where $y_t^*$ and $y_i$ denote output

[8]A panel version of this data set with 2296 observations (82 countries, 28 years for each country) has been used in Duffy and Papageorgiou (2000). However, Ireland and New Zealand were dropped from the sample used in this paper due to unreliability of their primary education data. Allowing the two countries to enter our sample does not change our results significantly.

per worker in the "technological leader" and country $i$, respectively.[9]

Our estimation involved both ordinary–least–squares (OLS) regressions in combination with panel data estimation techniques and instrumental variable approaches.[10] In contrast to OLS estimation, our panel estimation (with or without instrumental variables) obtained implausible results regarding the role of human capital in the growth process.[11] Even though we have considered a number of different possible explanations for these "odd" panel results, the most convincing to us was an explanation offered by Islam (1995, p. 1153). Islam suggested that the problem lies on the inherent nature of panel data estimation. More precisely, he conjectured that since panel data techniques rely on "within" variation, and since there exists a negative *temporal* relationship between the human capital variable and economic growth within countries, then in panel results the negative temporal relationship is strong enough to outweigh the positive cross–sectional relationship. Given the above estimation constraints, the results presented in this section are obtained using OLS.

## 3.2 Cross–country regressions: Whole sample

This section presents estimates for the whole sample of 80 countries. The regression estimates presented here are without a variety of "ancillary variables" commonly used in the literature. Robustness of our results using different subsamples and ancillary variables will be examined later on in the paper.

In addition to Eqs. (6)–(8), Table 1 presents estimates obtained from the standard Growth Accounting Regression (GAR hereafter)

$$\log(Y_{it}/Y_{i0}) = \log(A_{it}/A_{i0}) + \alpha\log(K_{it}/K_{i0}) + \beta\log(L_{it}/L_{i0}) + \gamma\log(H_{it}/H_{i0}) + \varepsilon_{it}, \tag{9}$$

and the BS specification

$$\log(Y_{it}/Y_{i0}) = a_0 + (\delta - \mu)H_{i0} + \mu H_{i0}(y_0^*/y_{i0}) + \alpha\log(K_{it}/K_{i0}) + \beta\log(L_{it}/L_{i0}) + \varepsilon_{it}. \tag{10}$$

Model 1 in Table 1 provides estimates of the GAR specification given by Eq. (9). Looking at the results of Model 1, we see that the estimated parameters are robust to previous studies. Specifically, the estimated parameter of physical capital is positive and is the only relevant variable that enters significantly in this

[9] In this study, the "technological leader" is Switzerland that experienced the highest initial per capita income ($y^*_{1960}$). In fact, Switzerland was still the per capita income leader in 1987.

[10] The empirical growth literature has pointed out a number of caveats of OLS application in growth regressions. The more serious include the well–documented fixed–effects and endogeneity problems (see Islam (1995) and Caselli et al. (1996)), and measurement errors (see Krueger and Lindahl (1998)).

[11] The panel data estimation involved data on 80 countries for 28 years from 1960 to 1987 (2240 observations).

regression. The labor estimate has a positive sign but is insignificant, and human capital enters negatively and is highly insignificant.

Table 1: Growth regressions for the whole sample

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| *Const.* | 0.12611[a] | -0.04677 | -0.16113[c] | 0.03454 | -0.04165 |
| | (0.03467) | (0.06300) | (0.09394) | (0.05201) | (0.02884) |
| $GK$ | 0.49470[a] | 0.46783[a] | 0.44518[a] | 0.45057[a] | 0.44667[a] |
| | (0.05198) | (0.05000) | (0.04878) | (0.04820) | (0.05639) |
| $GL$ | 0.17990 | 0.39352[a] | 0.41458[a] | 0.31600[b] | 0.53843[a] |
| | (0.13670) | (0.15496) | (0.15660) | (0.15501) | (0.08175) |
| $GH$ | -0.07336 | | 0.16179[c] | | |
| | (0.06304) | | (0.07636) | | |
| $GH_Y$ | | | | -0.00360 | 0.01490 |
| | | | | (0.06459) | (0.06931) |
| $H$ | | 0.02054[a] | 0.03405[a] | | |
| | | (0.00642) | (0.01038) | | |
| $H_A$ | | | | 0.05413[b] | 0.07931[a] |
| | | | | (0.02387) | (0.02319) |
| $H(A^*/A)$ | | 0.00024 | 0.00035[b] | | |
| | | (0.00017) | (0.00017) | | |
| $H_A(A^*/A)$ | | | | 0.00230[a] | 0.00205[c] |
| | | | | (0.00078) | (0.00120) |
| *F-Stat.* | | | | | 1.98 |
| $\overline{R}^2$ | 0.527 | 0.567 | 0.578 | 0.560 | 0.554 |
| *Obs.* | 80 | 80 | 80 | 80 | 80 |

Notes: GX denotes the growth rate of variable X between 1965-1987. Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. Recovered standard errors for $\delta$ and $\mu$ are in brackets: Model 2, $\delta = 0.02077$ [0.00649]; Model 3, $\delta = 0.03440$ [0.01045]; Model 4, $\delta = 0.05643$ [0.02396]; Model 5, $\delta = 0.14704$ [0.04024], $\mu = 0.00370$ [0.00215]. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Model 2 presents estimates of the BS specification. Using our alternative dataset seems to improve Benhabib and Spiegel (1994) estimates in one way. In addition to physical capital entering significantly positive, now also labor enters with the expected sign and it is significant. However, unlike Benhabib and Spiegel (1994) who find the imitation variable, $H(y^*/y)$, to be positive and significant,[12] our Model 2 appears to favor innovation as the process affecting productivity growth in the whole sample. Standard approximation methods, obtain a significantly positive value of the innovation parameter $\delta$ at the 1% level.[13] In general,

[12]This is the result in Benhabib and Spiegel (1994), Model 1 of Table 5, p.162.

[13]The recovered values of $\delta$ and their associated standard errors are reported in the tables' captions.

Model 2 performs notably better than the GAR specification and reinforces the results of Benhabib and Spiegel (1994).

The most important finding in Table 1 is delivered by Model 3. Model 3 is based on Eq. (6), and extends the BS specification by allowing human capital to enter the growth regression not only as a facilitator of technological progress but also as an input of final–goods production. The coefficient estimates for physical capital growth and labor growth, enter with the expected signs and are significant at the 1% level. Most interestingly, the estimated coefficients of domestic innovation ($\delta$), imitation ($\mu$), and human capital are all positive and significant at the 1%, 5%, and 10% levels, respectively. There are several points worth noticing here. First, the labor growth coefficient estimate increases dramatically from 0.17990 in Model 1 to 0.41458 in Model 3. Second, human capital accumulation in output production ($GH$), enters significantly positive in Model 3 and in great contrast to the estimate of Model 1. Third, both domestic innovation ($H$) and imitation ($H(y^*/y)$) terms enter significantly positive and the magnitude of both terms is higher than those in Model 2.

Models 4 and 5 (based on Eq. (7) and Eq. (8), respectively) extend Model 3 by disaggregating human capital into primary and post–primary education as discussed in the previous section. Making this adjustment to human capital, results in primary education growth ($GH_Y$) entering insignificantly in both models. However, the magnitude of both the innovation and imitation terms has become notably higher than those in Model 3.[14] As a final step, we apply a diagnostic test to determine which one of Models 3, 4, or 5 is preferable. Using the maximum–likelihood criterion reveals that for the whole sample Model 3 is preferable.[15]

In summary, the results of Table 1 provide additional evidence supporting human capital as a facilitator of innovation and imitation. Furthermore, Model 3 presents first evidence for a dual role of human capital in economic growth. Most importantly, Model 4 suggests that the effect of primary and post–primary education maybe different between final production and R&D activity.

### 3.3 Cross–country regressions: Subsamples

In this section, we considered our findings for certain subsamples of countries. In particular, we have divided the sample of 80 countries up into three subsamples of roughly equal size and we have re–estimated the structural specifications given by Models 1–5 for each of these subsamples. The subsamples have been

[14] In Model 4, $\delta$ is positive and significant but at the 5% level. In Model 5, $\delta$ and $\mu$ are positive and significant at the 1% and 10% levels respectively.

[15] In particular, log–likelihood functions are 57.8 for Model 3, 56.1 for Model 4, and 55.0 for Model 5.

constructed by ranking the entire sample of countries by their initial per capita GDP ($y_{1960}$) in 1987 U.S. dollars, and then dividing this ranking of countries up into three income classes: *high–income*, *middle–income*, and *low–income*. A list of the countries in each subsample appears in Appendix A.

Table 2: Growth regressions for the high–income countries

| | Model 1a | Model 2a | Model 3a | Model 4a | Model 5a |
|---|---|---|---|---|---|
| *Const.* | 0.17125[a] | -0.11156 | -0.09770 | 0.10276[c] | -0.00782 |
| | (0.03430) | (0.09571) | (0.10057) | (0.05249) | (0.06041) |
| $GK$ | 0.45123[a] | 0.39384[a] | 0.39813[a] | 0.39069[a] | 0.37758[a] |
| | (0.04887) | (0.05295) | (0.06353) | (0.06175) | (0.09922) |
| $GL$ | 0.15477 | 0.39568[b] | 0.42895[c] | 0.41258[c] | 1.0311[a] |
| | (0.16782) | (0.18112) | (0.21402) | (0.23858) | (0.22994) |
| $GH$ | -0.16248 | | -0.04671 | | |
| | (0.19408) | | (0.27643) | | |
| $GH_Y$ | | | | -0.24644 | -0.40870[c] |
| | | | | (0.25931) | (0.08722) |
| $H$ | | 0.02433[b] | 0.02215[c] | | |
| | | (0.00962) | (0.01226) | | |
| $H_A$ | | | | -0.01368 | -0.00332 |
| | | | | (0.02717) | (0.04141) |
| $H(A^*/A)$ | | 0.00013[b] | 0.00364[b] | | |
| | | (0.00005) | (0.00144) | | |
| $H_A(A^*/A)$ | | | | 0.01792[b] | 0.02074[b] |
| | | | | (0.00685) | (0.00956) |
| *F-Stat.* | | | | | 4.33 |
| $\overline{R}^2$ | 0.502 | 0.599 | 0.581 | 0.551 | 0.483 |
| *Obs.* | 27 | 27 | 27 | 27 | 27 |

Notes: GX denotes the growth rate of variable X between 1965-1987. Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. Recovered standard errors for $\delta$ and $\mu$ are in brackets: Model 2a, $\delta = 0.02792$ [0.00987]; Model 3a, $\delta = 0.02579$ [0.01304]; Model 4a, $\delta = 0.00425$ [0.02367]; Model 5a, $\delta = 0.02798$ [0.06020], $\mu = 0.03332$ [0.01499]. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 2 presents the results of the specifications for the wealthiest third of countries in our sample. Model 1a performs poorly with human capital entering even more negatively than Model 1. Models 2a and 3a obtain similar estimates. These two models suggest that the wealthy countries benefit both from innovation and imitation. The innovation term is substantially higher in magnitude than the imitation term, and the recovered $\delta$ is significantly positive in both models. More importantly, human capital growth ($GH$) in Model 3a, and primary education growth ($GH_Y$) in Models 4a and 5a enter negatively (and are insignificant in Models 3a and 4a). This implies that wealthy countries' income growth is not influenced by the accumulation of human capital in the output sector. A maximum–likelihood test reveals that for the rich sample, Model 3 is most preferable.[16]

Table 3: Growth regressions for the middle–income countries

| | Model 1b | Model 2b | Model 3b | Model 4b | Model 5b |
|---|---|---|---|---|---|
| *Const.* | 0.08668 | -0.02571 | -0.18301 | -0.09400 | -0.09689 |
| | (0.07556) | (0.11208) | (0.19625) | (0.14547) | (0.05036) |
| *GK* | $0.57088^a$ | $0.51359^a$ | $0.44716^a$ | $0.41801^a$ | $0.41785^a$ |
| | (0.08378) | (0.08900) | 0.08971 | (0.08666) | (0.10535) |
| *GL* | 0.19364 | 0.17872 | 0.24949 | $0.48834^c$ | $0.49516^a$ |
| | (0.16364) | (0.18143) | (0.19946) | (0.26991) | (0.10952) |
| *GH* | -0.07207 | | 0.21920 | | |
| | (0.10111) | | (0.18665) | | |
| $GH_Y$ | | | | 0.08574 | 0.08699 |
| | | | | (0.10973) | (0.10871) |
| *H* | | 0.00015 | 0.01818 | | |
| | | (0.01300) | (0.02359) | | |
| $H_A$ | | | | 0.11096 | 0.11328 |
| | | | | (0.13017) | (0.14130) |
| $H(A^*/A)$ | | 0.00204 | $0.00254^c$ | | |
| | | (0.00130) | (0.00142) | | |
| $H_A(A^*/A)$ | | | | 0.01171 | 0.01164 |
| | | | | (0.00785) | (0.00936) |
| *F-Stat.* | | | | | 0.00 |
| $\overline{R}^2$ | 0.564 | 0.612 | 0.624 | 0.640 | 0.657 |
| *Obs.* | 27 | 27 | 27 | 27 | 27 |

Notes: GX denotes the growth rate of variable X between 1965-1987. Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. Recovered standard errors for $\delta$ and $\mu$ are in brackets: Model 2b, $\delta$ = -0.00189 [0.01394]; Model 3b, $\delta = 0.0156$ [0.02358]; Model 4b, $\delta = 0.09924$ [0.13440]; Model 5b, $\delta = 0.21458$ [0.23279], $\mu = 0.01999$ [0.01512]. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 3 presents estimates of the five specifications for the middle–income group of countries. Physical

[16]Log–likelihood functions for the rich sample are 25.8 for Model 3a, 24.9 for Model 4a, and 22.3 for Model 5a.

capital enters, once again, significantly positive in all models. Estimates of Model 3b show that the imitation term enters positively and is significant at the 10% level, whereas innovation enters positively but is insignificant. This is weak evidence that the middle–income group benefits more from imitation than innovation. It is, however, obvious that for this subsample of countries our results are more ambiguous. The ambiguity of the estimates is also revealed by the diagnostic test which fails to determine the most preferable model.[17]

Table 4: Growth regressions for the low–income countries

| | Model 1c | Model 2c | Model 3c | Model 4c | Model 5c |
|---|---|---|---|---|---|
| *Const.* | -0.29670$^c$ | -0.30312$^c$ | -0.46252$^a$ | -0.49585$^a$ | -0.05055 |
| | (0.16348) | (0.15465) | (0.13953) | (0.13779) | (0.05067) |
| $GK$ | 0.46048$^a$ | 0.39890$^a$ | 0.41052$^a$ | 0.38008$^a$ | 0.37711$^a$ |
| | (0.11209) | (0.10727) | (0.11228) | (0.10204) | (0.11170) |
| $GL$ | 1.3958$^a$ | 1.4990$^a$ | 1.5112$^a$ | 1.8235$^a$ | 0.56515$^a$ |
| | (0.47578) | (0.52530) | (0.47804) | (0.46679) | (0.16714) |
| $GH$ | 0.05924 | | 0.19927$^c$ | | |
| | (0.10751) | | (0.10580) | | |
| $GH_Y$ | | | | 0.17678$^c$ | 0.05774 |
| | | | | (0.08670) | (0.11503) |
| $H$ | | -0.01176 | 0.00740 | | |
| | | (0.01840) | (0.02298) | | |
| $H_A$ | | | | -0.13773 | -0.09256 |
| | | | | (0.08777) | (0.14959) |
| $H(A^*/A)$ | | 0.00045 | 0.00055$^b$ | | |
| | | (0.00030) | (0.00024) | | |
| $H_A(A^*/A)$ | | | | 0.00666$^a$ | 0.00504$^c$ |
| | | | | (0.00166) | (0.00260) |
| *F-Stat.* | | | | | 7.22 |
| $\overline{R}^2$ | 0.500 | 0.515 | 0.533 | 0.649 | 0.545 |
| *Obs.* | 26 | 26 | 26 | 26 | 26 |

Notes: GX denotes the growth rate of variable X between 1965-1987. Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. Recovered standard errors for $\delta$ and $\mu$ are in brackets: Model 2c, $\delta$ = -0.01130 [0.01824]; Model 3c, $\delta$ = 0.00795 [0.02282]; Model 4c, $\delta$ = -0.13107 [0.08651]; Model 5c, $\delta$ = -0.14050 [0.23929], $\mu$ = 0.00809 [0.00423]. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 4 presents estimates for the poorest third of countries. Labor in all four models enter significantly

[17]In particular, the log–likelihood functions for the middle–income sample are 21.1 for Model 3b, 21.7 for Model 4b, and 21.7 for Model 5b.

but with large estimates. Models 1c and 2c perform poorly with only physical capital entering significantly positive. As expected, the results of Model 3c suggest that the poorest third of countries benefit from imitation but not from innovation. Of interest is the significantly positive coefficient estimate of the growth of human capital in output production, $GH$. This result points out that the poorest countries in our sample benefit from human capital as an input of final production.

Most important is the finding obtained in Model 4c in which growth in primary education, $GH_Y$, enters significantly positive. This result suggests that LDCs benefit most from the accumulation of primary education employed in final good production. One possible explanation for this result is Rostow's development stages. Primitive economies benefit more from the accumulation of primary education as they rely heavily on final good production. Developing and developed economies benefit more from the accumulation of highly educated workers as they depend heavily on R&D. In addition to primary education, it is important to notice that the imitation variable ($H_A(y^*/y)$) enters significantly positive. Even though the magnitude of this estimate is small, it shows that LDCs can rip off the return from educated workers who can adopt existing technology. The more structural specification of the Romer model given by Model 5c results in positive but insignificant estimates of $GH_Y$. In the poor subsample, the maximum likelihood ratio test reveals that Model 4c is most preferable.[18]

In summary, our subsample estimation reveals that the relative contribution of human capital to technology adoption ($H(y^*/y)$ in Models 3a, 3b and 3c) increases with country wealth. This finding suggests that a country may need to reach a certain threshold of economic development before R&D activities begin to affect growth. Also, consistent with casual observation, it is found that the innovation variable ($H$ in Model 3a) contributes significantly only to the growth of the high–income countries. Most importantly, it is shown that the growth rate in primary education ($GH_Y$ in Model 4c) has a positive and significant effect on the income growth of the low–income countries, whereas for the other two subsamples it is insignificant. This result suggests that distinguishing between the effects of primary and post–primary education on growth is essential in our understanding of the development process.

### 3.4 Robustness of the results

In addition to testing the robustness of the empirical findings using different structural specifications and subsamples, we also examine the sensitivity of our results to including a range of "ancillary variables". First, we have included sub–Sahara African and Latin–American country dummies in the whole–sample

[18]Log–likelihood functions for the low–income sample are 19.5 for Model 3c, 23.6 for Model 4c, and 19.2 for Model 5c.

estimation (Table 5), to capture regional effects that have been found to be important in other studies. The main observation is that where the African–country dummy entered negative and significant the Latin American country dummy was always insignificant.

In both our entire sample and the three subsamples we have also examined the sensitivity of our results to a large number of variables including a new set of variables that is becoming standard in the literature and borrows from the work of Hall and Jones (1999). The set of ancillary variables used in estimation includes (a) The type of economic organization (i.e. "capitalist" countries have a value of 4–5) variable reported by the Freedom House (1994) (b) The fraction of GDP produced in mining and quarrying sector (c) The fraction of the population speaking one of the major languages of Western Europe (d) An index of political stability and social infrastructure that is the average indicator of 5 political risks facing international investors, and a measure of openness. For additional discussion on these variables see Hall and Jones (sec. 4.3, 1999).

In virtually all of the models and sample sizes our proxy for mining enters significantly negative and our proxy for political stability and social infrastructure enters significantly positively reconfirming the importance of political stability on growth. The rest of the ancillary variables obtain mixed results. As it is shown in Tables 5–8 in Appendix B, the main results of the paper are robust to this list of variables.[19]

# 4 Conclusion

This paper has empirically tested three structural specifications in which human capital affects economic growth as a factor of final production and as a facilitator of technological change. Estimates obtained from the proposed specifications were then compared to estimates from two specifications prevalent in the literature; the standard growth accounting specification and the Benhabib–Spiegel specification. The main findings are:

1. Regression estimates from using a novel World Bank dataset confirm that the standard growth accounting specification performs poorly. Our results obtained from using the whole sample of 80 countries confirm and reinforce the results obtained by Benhabib and Spiegel (1994); that is, structural specifications that allow human capital to operate as a facilitator of technological progress are more successful in explaining growth than the standard growth accounting specification.

[19] In addition to the above mentioned ancillary variables a list of others have been used, such as a political instability variable that accounts for the number of coups that occurred in each country from 1960-1982 (data from Alesina, Özler, Roubini and Swagel (1996)), an inflation variable that is intended to capture macroeconomic instability, the fraction of years during the period 1965-1990 in which the country is rated as an open economy, the share of exports of primary products in GDP in 1970, the central government savings and an institutional quality index, all taken from Sachs and Warner (1997). These results are available by the author upon request.

2. When we divide our entire sample of countries into three subsamples based on their initial per capita income, estimates from our proposed specifications suggest that for the wealthiest group of countries the role of human capital is only as a facilitator of innovation and imitation of technology. On the contrary, for the poorest group of countries the role of human is as an input of final output production *and* as a facilitator of imitation. In addition, regression estimates suggest that the relative contribution of human capital to technology adoption increase by country wealth. This finding suggests a country may need to reach a certain threshold before the returns to engaging in R&D activities become significant.

3. The most important finding of the paper is that primary education contributes mainly to production of final output, whereas post–primary education contributes mainly to adoption and innovation of technology.

The conclusions of this paper for future research are threefold: First, greater attention should be given to empirically investigating the role of human capital as a facilitator of innovation and imitation. Our work is a step towards this direction. Second, in recent contributions, Temple (1998, 1999a, 2001) shows that the correlation between human capital accumulation and growth may be hidden in the data by a number of unrepresentative observations. Given this new finding, an extension of this paper worthy of future work is to apply least–trimmed–squares as an additional robustness check to our OLS estimates. Third, careful consideration of the finding summarized in point 3 above may lead to attractive theoretical models with serious policy implications.

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# Appendix A

## Data

The data used in this paper were obtained from the STARS database of the World Bank. This data set was recently revised to include comparable annual data on physical capital stocks, and the average numbers of years of education of the workforce (used as a proxy for the stock of human capital) for a large number of countries. Both gross domestic product and the stock of physical capital were denominated in constant 1987 local currency units. For cross country comparability purposes and the common econometric issues that might arise without it, we made transformations to these data sets and converted the series on GDP and physical capital into constant 1987 U.S. dollars.[20]

## Data obtained from STARS

*Income (GDP)*: Gross domestic product at the end of each period in constant 1987 local currency units. For comparisons across countries, GDP measured in local constant 1987 currency was converted into constant 1987 U.S. dollars amounts ($US) using official exchange rates for 1987 (Ex87).

*Exchange Rate (Ex87)*: Official end–of–period exchange rate (foreign exchange per U.S. dollar) in 1987. In some cases an alternative rate was used when the official rate had been revalued (e.g. for Brazil, Argentina etc.).

*Human Capital (H)*: Mean years of education is the sum of the average number of years of primary, secondary and tertiary education in labor force. These series were constructed from enrollment data using the perpetual inventory method, and they were adjusted for mortality, drop–out rates and grade repetition. For a detailed discussion on the sources and methodology used to build this data set see Nehru, Swanson, and Dubey (1995).

*Primary Education ($H_Y$)*: Mean years of primary education in labor force. These series were constructed as described above.

*Post–Primary Education ($H_A$)*: Total mean years of post–primary education is the sum of the average number of years of secondary and tertiary education in labor force. These series were constructed as described above.

*Physical Capital (K)*: Data on physical capital stocks are taken from the data set compiled by Nehru and Dhareshwar (1993). Estimation of the stock of physical capital was based on the Harberger–Armington technique for initial capital stocks for each country. Given an initial capital stock, $K_0$, and a sequence of annual investment amounts, $\{I_{t-i}\}_{i=0}^{t-1}$, the perpetual inventory method was used to calculate the capital stock in period $t$, $K_t$, according to:

$$K_t = \sum_{i=0}^{t-1} (1-\lambda)^i I_{t-i} + (1-\lambda)^t K_0,$$

where the rate of decay of the capital stock, $\lambda$, was set at .04. Physical capital stocks were calculated at the end of each period and are in constant, 1987 local currency units. As was the case for GDP, the value of the physical capital stocks was converted into constant 1987 U.S. dollar amounts using official exchange rates for 1987 (Ex87).

*Labor Force (L)*: Population between the ages of 15 and 65.

[20]The dataset used in this study is available by the author upon request.

### Countries in the subsamples

The comprehensive sample of 80 countries was divided into three subsamples based on the initial period, 1960, level of per capita income in each country in constant 1987 U.S. dollars. Below is a list of the countries in each of the three subsamples. The ordering of countries within each subsample reflects their 1960 per capita income ranking.

*High–Income Subsample: (27 countries)*
Switzerland, United States, Denmark, Sweden, Iceland, Germany, Netherlands, Norway, Canada, France, Finland, Australia, United Kingdom, Austria, Belgium, Italy, Japan, Iraq, Israel, Venezuela, Spain, Argentina, Iran, Algeria, Uruguay, Singapore, Cyprus.

*Middle–Income Subsample: (27 countries)*
Greece, Jamaica, Costa Rica, Chile, Panama, Portugal, Peru, Mexico, Mauritius, Brazil, Sudan, El Salvador, Uganda, Malaysia, Jordan, Colombia, Honduras, Guatemala, Senegal, Ecuador, Cameroon, Bolivia, Côte d'Ivoire, Paraguay, Turkey, Tunisia, Korea Rep.

*Low–Income Subsample: (26 countries)*
Zimbabwe, Ghana, Philippines, Zambia, Haiti, Morocco, Madagascar, Rwanda, Thailand, Nigeria, Zaire, Egypt, Kenya, Sri Lanka, India, Mali, Myanmar, Indonesia, Pakistan, Mozambique, Bangladesh, Tanzania, Sierra Leone, Malawi, Ethiopia, China.

## Appendix B

The following exercise assesses the robustness of the results to a common set of "ancillary variables". The ancillary variables used are: 1) Dummies for sub–Sahara African countries ($AFRICA$) and Latin American countries ($LAMER$) that account for regional–specific effects. 2) The type of economic organization ($ECONORG$) 3) The fraction of GDP produced in mining and quarrying sector ($MINING$) 4) The fraction of the population speaking one of the major languages of Western Europe: English, French, German, Portuguese, or Spanish ($EURLANG$) and 5) An index of social infrastructure and political stability that is the average an indicator of 5 political risks facing international investors and a measure of openness ($SOCINF$). In addition to the above mentioned ancillary variables a list of others have been used without changing our main results qualitatively. All of these results are available by the author upon request.

Table 5: Growth regressions for the whole sample with ancillary variables

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| *Const.* | -0.05895 | -0.03572 | -0.18067$^b$ | -0.13512$^b$ | -0.10680$^b$ |
| | (0.06108) | (0.06665) | (0.08475) | (0.06207) | (0.05283) |
| $GK$ | 0.34823$^a$ | 0.35794$^a$ | 0.33125$^a$ | 0.33255$^a$ | 0.33774$^a$ |
| | (0.05654) | (0.05407) | (0.05207) | (0.05239) | (0.05125) |
| $GL$ | 0.64241$^a$ | 0.60368$^a$ | 0.61016$^a$ | 0.59300$^a$ | 0.51289$^a$ |
| | (0.14896) | (0.15894) | (0.15152) | (0.14563) | (0.07414) |
| $GH$ | 0.11922 | | 0.23176$^b$ | | |
| | (0.07177) | | (0.09002) | | |
| $GH_Y$ | | | | 0.15919$^b$ | 0.14936$^b$ |
| | | | | (0.07100) | (0.06382) |
| $H$ | | -0.00841 | 0.00879 | | |
| | | (0.00719) | (0.00955) | | |
| $H_A$ | | | | -0.00747 | -0.01291 |
| | | | | (0.01766) | (0.02480) |
| $H(A^*/A)$ | | 0.00033$^a$ | 0.00051$^a$ | | |
| | | (0.00013) | (0.00015) | | |
| $H_A(A^*/A)$ | | | | 0.00317$^a$ | 0.00322$^a$ |
| | | | | (0.00099) | (0.00120) |
| $AFRICA$ | -0.11099$^b$ | -0.09168$^b$ | -0.11082$^a$ | -0.07235 | -0.07029$^c$ |
| | (0.04383) | (0.03972) | (0.03256) | (0.04522) | (0.04014) |
| $LAMERICA$ | 0.02876 | 0.03390 | 0.03392 | 0.04282 | 0.04627 |
| | (0.03081) | (0.03123) | (0.03256) | (0.03270) | (0.04046) |
| $MINING$ | -0.66275$^a$ | -0.59299$^a$ | -0.65360$^a$ | -0.55409$^a$ | -0.53506$^a$ |
| | (0.17782) | (0.16549) | (0.14401) | (0.16327) | (0.19955) |
| $EURLANG$ | -0.05745$^c$ | -0.05186$^c$ | -0.03309 | -0.03196 | -0.03252 |
| | (0.02977) | (0.02999) | (0.03052) | (0.03020) | (0.03738) |
| $ECONORG$ | 0.01009 | 0.01150 | 0.01303 | 0.01262 | 0.01238 |
| | (0.00961) | (0.00933) | (0.00875) | (0.00860) | (0.01001) |
| $SOCINF$ | 0.25022$^a$ | 0.28602$^a$ | 0.26496$^a$ | 0.33013$^a$ | 0.31938$^a$ |
| | (0.06763) | (0.07849) | (0.07376) | (0.07468) | (0.01001) |
| *F-Stat.* | | | | | 0.32 |
| $\overline{R}^2$ | 0.682 | 0.682 | 0.712 | 0.705 | 0.708 |
| *Obs.* | 80 | 80 | 80 | 80 | 80 |

Notes: Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 6: Growth regressions for the high–income countries with ancillary variables

| | Model 1a | Model 2a | Model 3a | Model 4a | Model 5a |
|---|---|---|---|---|---|
| *Const.* | 0.04666 | -0.03888 | -0.05763 | 0.02409 | -0.00563 |
| | (0.07032) | (0.06086) | (0.08548) | (0.05790) | (0.08187) |
| $GK$ | $0.26690^a$ | $0.23692^a$ | $0.23118^a$ | $0.21709^a$ | $0.20518^a$ |
| | (0.06074) | (0.04872) | (0.05318) | (0.05562) | (0.07118) |
| $GL$ | $0.43865^b$ | $0.72678^a$ | $0.68674^a$ | $0.64882^a$ | $0.77712^a$ |
| | (0.16850) | (0.15584) | (0.18874) | (0.18423) | (0.19511) |
| $GH$ | 0.12573 | | 0.05576 | | |
| | (0.17139) | | (0.19561) | | |
| $GH_Y$ | | | | 0.02236 | 0.01771 |
| | | | | (0.18543) | (0.20650) |
| $H$ | | 0.04687 | 0.00598 | | |
| | | (0.00640) | (0.00784) | | |
| $H_A$ | | | | -0.01704 | -0.01546 |
| | | | | (0.01448) | (0.02610) |
| $H(A^*/A)$ | | $0.00335^a$ | $0.00329^a$ | | |
| | | (0.00068) | (0.00076) | | |
| $H_A(A^*/A)$ | | | | $0.01560^a$ | $0.01613^b$ |
| | | | | (0.00367) | (0.00613) |
| $MINING$ | $-0.71584^a$ | $-0.62645^a$ | $-0.62405^a$ | $-0.64130^a$ | $-0.68687^b$ |
| | (0.16709) | (0.15458) | (0.15597) | (0.16117) | (0.24544) |
| $EURLANG$ | $-0.10759^a$ | $-0.11627^a$ | $-0.11294^a$ | $-0.11150^a$ | $-0.11185^a$ |
| | (0.03468) | (0.03229) | (0.03104) | (0.03100) | (0.03782) |
| $ECONORG$ | 0.02323 | 0.00784 | 0.00828 | 0.01406 | 0.01269 |
| | (0.01576) | (0.01372) | (0.01485) | (0.01383) | (0.01804) |
| $SOCINF$ | $0.16031^c$ | $0.20476^b$ | $0.21619^a$ | $0.20432^a$ | $0.22889^c$ |
| | (0.08354) | (0.07971) | (0.07070) | (0.06416) | (0.11656) |
| *F-Stat.* | | | | | 0.51 |
| $\overline{R}^2$ | 0.759 | 0.821 | 0.811 | 0.805 | 0.810 |
| *Obs.* | 27 | 27 | 27 | 27 | 27 |

Notes: Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 7: Growth regressions for the middle–income countries with ancillary varibales

| | Model 1b | Model 2b | Model 3b | Model 4b | Model 5b |
|---|---|---|---|---|---|
| *Const.* | -0.18189 | -0.28673 | -0.38801$^c$ | -0.30215 | -0.23925 |
| | (0.19896) | (0.22485) | (0.18893) | (0.18793) | (0.16122) |
| *GK* | 0.50561$^a$ | 0.52133$^a$ | 0.44190$^a$ | 0.44289$^a$ | 0.44599$^a$ |
| | (0.07845) | (0.08540) | (0.07087) | (0.07522) | (0.10610) |
| *GL* | 0.43625$^c$ | 0.31551 | 0.31178 | 0.52252$^b$ | 0.38525$^b$ |
| | (0.22769) | (0.22584) | (0.19268) | (0.19615) | (0.14705) |
| *GH* | 0.17676 | | 0.34149$^b$ | | |
| | (0.11349) | | (0.13922) | | |
| $GH_Y$ | | | | 0.19724 | 0.16876 |
| | | | | (0.11932) | (0.14092) |
| *H* | | -0.03028$^c$ | -0.00523 | | |
| | | (0.01748) | (0.01851) | | |
| $H_A$ | | | | 0.01467 | -0.02581 |
| | | | | (0.10859) | (0.16419) |
| $H(A^*/A)$ | | 0.002835$^c$ | 0.00323$^b$ | | |
| | | (0.00149) | (0.00138) | | |
| $H_A(A^*/A)$ | | | | 0.01394$^c$ | 0.01565 |
| | | | | (0.00812) | (0.01147) |
| *MINING* | 0.04338 | -0.40760 | -0.38018 | -0.24031 | -0.22655 |
| | (0.60758) | (0.42956) | (0.45527) | (0.54785) | (0.71145) |
| *EURLANG* | 0.08689 | 0.12086 | 0.14548$^c$ | 0.12881$^c$ | 0.12681 |
| | (0.07548) | (0.08391) | (0.07142) | (0.07020) | (0.07444) |
| *ECONORG* | -0.02727 | 0.03397 | 0.00090 | 0.00782 | 0.00843 |
| | (0.02980) | (0.03577) | (0.03221) | (0.03245) | (0.04772) |
| *SOCINF* | 0.44473$^a$ | 0.25350$^c$ | 0.29592$^b$ | 0.20638 | 0.18526 |
| | (0.14741) | (0.13888) | (0.12324) | (0.14135) | (0.21851) |
| *F-Stat.* | | | | | 0.18 |
| $\overline{R}^2$ | 0.642 | 0.639 | 0.680 | 0.653 | 0.669 |
| *Obs.* | 27 | 27 | 27 | 27 | 27 |

Notes: Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.

Table 8: Growth regressions for the low–income countries with ancillary variables

| | Model 1c | Model 2c | Model 3c | Model 4c | Model 5c |
|---|---|---|---|---|---|
| *Const.* | -0.23884 | $-0.25219^{c}$ | $-0.41883^{a}$ | $-0.50436^{a}$ | $-0.16305^{c}$ |
| | (0.13902) | (0.13413) | (0.14168) | (0.12198) | (0.08010) |
| $GK$ | $0.35297^{a}$ | $0.29286^{b}$ | $0.32930^{a}$ | $0.27999^{a}$ | $0.24597^{b}$ |
| | (0.11782) | (0.11484) | (0.11573) | (0.08745) | (0.10858) |
| $GL$ | $1.1907^{a}$ | $1.3815^{a}$ | $1.4190^{a}$ | $1.5858^{a}$ | $0.63984^{a}$ |
| | (0.37929) | (0.40974) | (0.37864) | (0.31798) | (0.15854) |
| $GH$ | 0.06544 | | $0.19070^{c}$ | | |
| | (0.07824) | | (0.09279) | | |
| $GH_Y$ | | | | $0.21786^{b}$ | 0.11418 |
| | | | | (0.07874) | (0.11167) |
| $H$ | | -0.02647 | -0.00776 | | |
| | | (0.01900) | (0.02283) | | |
| $H_A$ | | | | $-0.19030^{c}$ | -0.16750 |
| | | | | (0.09322) | (0.13073) |
| $H(A^*/A)$ | | $0.00049^{c}$ | $0.00059^{b}$ | | |
| | | (0.00024) | (0.00022) | | |
| $H_A(A^*/A)$ | | | | $0.00736^{a}$ | $0.00616^{b}$ |
| | | | | (0.00146) | (0.00238) |
| $MINING$ | $-0.91432^{b}$ | $-0.87357^{a}$ | $-0.94250^{a}$ | $-0.58149^{c}$ | -0.61618 |
| | (0.35187) | (0.30543) | (0.32391) | (0.30692) | (0.41583) |
| $EURLANG$ | -0.73788 | -0.37888 | 0.08618 | 0.47173 | 0.09071 |
| | (0.86599) | (0.82881) | (0.76473) | (0.46145) | (1.2217) |
| $ECONORG$ | 0.00972 | 0.00676 | 0.01251 | $0.01870^{c}$ | 0.01752 |
| | (0.01543) | (0.01336) | (0.01377) | (0.01070) | (0.01586) |
| $SOCINF$ | $0.30693^{c}$ | $0.36553^{b}$ | 0.27679 | $0.36789^{a}$ | $0.46509^{a}$ |
| | (0.16670) | (0.17243) | (0.16435) | (0.12161) | (0.16832) |
| *F-Stat.* | | | | | 5.12 |
| $\overline{R}^2$ | 0.561 | 0.586 | 0.593 | 0.729 | 0.663 |
| *Obs.* | 26 | 26 | 26 | 26 | 26 |

Notes: Dependent variable is GY. The standard errors are given in parentheses. White's heteroscedasticity correction has been used. a: 1 % confidence level. b: 5 % confidence level. c: 10 % confidence level.