# *Topics in Macroeconomics*

# Literacy and Growth

Serge Coulombe[*]          Jean-François Tremblay[†]

[*]University of Ottawa, Serge.Coulombe@uottawa.ca

[†]University of Ottawa, Jean-Francois.Tremblay@uottawa.ca

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## Abstract

From the demographic profile of the 1994-1998 International Adult Literacy Survey, we derive synthetic time series over the 1960–1995 period on the literacy level of labor market entrants. This information is then used as a measure of investment in education in a two-way error correction panel data analysis of cross-country growth for a set of 14 OECD countries. The analysis indicates that direct measures of human capital based on literacy scores contain more information about the relative growth of countries than measures based on years of schooling. The results show that, overall, human capital indicators based on literacy scores have a positive and significant effect on the transitory growth path and on the long-run levels of GDP per capita and labor productivity. Quantitatively, our results indicate that the skills associated with one extra year of schooling increase aggregate labor productivity by approximately 7 %, which is consistent with microeconomic evidence (Psacharopoulos, 1994). Moreover, we find that investment in the human capital of women is more important for growth than investment in the human capital of men and that increasing the average literacy skills over all individuals has a greater effect on growth than increasing the percentage of individuals that achieve high levels of literacy skills.

**KEYWORDS:** human capital, literacy, growth regressions, convergence

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## 1.      Introduction

The role of human capital in explaining cross-country differences in well-being has received considerable attention in recent economic growth literature.[1] In studies of broad sets of countries, including both developed and developing, standard measures of human capital that are based on educational achievement are often found to have a positive and significant long-run level effect on the countries' GDP per capita, and a transitory positive effect on economic growth during the convergence process toward the steady state (Barro 2001). However, when the sample under study is restricted to developed countries, the estimated effect of human capital or education on economic growth is not significant, sometimes null, or even negative (Islam 1995; Barro 2001).[2]

One reason for this puzzling result may be the fact that measuring human capital is not straightforward; human capital is not usually exchanged in markets like other economic goods. For this reason, human capital is typically measured indirectly using educational attainment and/or enrolment rates. But such human capital indicators are often subject to measurement error and comparability problems at the cross-country level, given the wide variety of educational systems around the world and the cross-country heterogeneity in the original schooling data sources.

In a recent contribution to the topic, de la Fuente and Doménech (2002) address the data quality issue and conclude that the growth effect of corrected (for measurement errors) average schooling indicators across 21 OECD countries is positive and significant. Although the data constructed by de la Fuente and Doménech appear to represent an improvement compared with earlier data sets, including those of Barro and Lee (1993, 2001), the data are based on schooling data and are therefore subject to comparability issues.

In this paper, we introduce a novel approach to using human capital indicators in growth empirics. The indicators are based on direct measures of human capital that are constructed from literacy test scores. The literacy raw data, available for 14 OECD countries, come from the 1994–1998 International Adult Literacy Survey (IALS) that tested the skills of individuals between the ages of 16 and 65. A historical perspective on human capital accumulation is needed to test the growth effects of investment in education. We use the age distribution of test

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[1]  See, for example, the pioneering contributions of Mankiw et al. (1992), Benhabib and Spiegel (1994), and Islam (1995), as well as the more recent work of Temple (2000), Bassanini and Scarpetta (2002), Krueger and Lindahl (2001), Pritchett (2001), and Barro and Sala-i-Martin (2004).

[2]   Negative effects of education in cross-country growth studies are not limited to developed countries. See, for example, Benhabib and Spiegel (1994), Islam (1995), Caselli et al. (1996), and Pritchett (2001).

results to construct a synthetic time series of the literacy level of the young cohort entering the labor market in each period. We constructed the series over the 1960–1995 sample using periods of 5 years. The relative literacy level of these cohorts is seen as an indicator of a country's investment in human capital relative to the other countries in the sample. Our estimation procedure also uses in some regressions the schooling data from de la Fuente and Doménech (2002) as the instrument for our literacy variable in order to account for potential measurement errors.

Direct measures of human capital have been used previously in growth regressions by Hanushek and Kimko (2000) and Barro (2001). They consider measures of schooling quality that are based on student performance in international assessments of science and mathematics. They use, however, a single cross-section of human capital indicators. Therefore their analysis abstracts from the time-series dimension of human capital investment. The innovative methodological contribution of our paper consists in deriving time-series data based on direct measures of human capital that are comparable at the cross-country level.

Results indicate that our human capital indicators based on literacy tests have a positive and significant effect on the long-run levels of GDP per capita and labor productivity, and on the growth rate in the transitory process toward steady state. Moreover, in our restricted set of OECD countries, the human capital data based on literacy test scores are found to contain more information about the relative growth of countries than the schooling data of Barro and Lee (2001) and the corrected schooling data of de la Fuente and Doménech (2002). From a quantitative perspective, our results imply that the skills acquired from one extra year of education increase aggregate labor productivity by approximately 7%. This is consistent with returns to education estimated in Mincerian wage regressions.

Interestingly, our results by gender indicate that the growth effects of human capital indicators based on female literacy are stronger than the effects measured from indicators of male literacy. We get this insightful result even when controlling for fertility. While these findings concur with the Mincerian wage regression literature (e.g., Psacharopoulos 1994), they contrast sharply with those of Barro (2001) who found that female education had no significant effect on growth when fertility is included in the set of explanatory variables.

Finally, some of our results also suggest that the distribution of human capital investment may be important for growth. In particular, we find that the relative growth of countries is much more sensitive to the average level of literacy skills than to the proportion of individuals who achieve high levels of literacy skills.

The remainder of the paper is organized as follows. Section 2 presents the literacy data and provides details about the construction of the synthetic time series used in the empirical analysis. The methodology used to conduct the regression analysis is discussed in Section 3. The methodology is straightforward and has been used elsewhere in the literature (Barro and Sala-i-Martin 2004). Results are presented and analyzed in Section 4. We conclude with a discussion of the limitations of our analysis and suggested directions for further research.

## 2.    Data

Human capital indicators are based on the results of the 1994–1998 International Adult Literacy Survey (IALS), which assessed the literacy proficiency of representative samples of individuals aged between 16 and 65 over three skill domains—prose literacy, document literacy, and quantitative literacy.[3] The tests measured the ability of individuals to accomplish various tasks across a range of difficulty levels. The tests were designed to sample everyday tasks that would not provide any advantage or disadvantage to particular groups due to familiarity, language, or culture, among other things.

Synthetic time series for the 1960–1995 period were constructed from the cross-sectional data using the age distribution of test results, under the assumption that the level of human capital remains constant throughout individuals' lives.[4] We use the average literacy test score of individuals who would have been in the 17–25 age group in the first year of the period (such as 1960, 1965, 1970, …) in each country as proxies for the relative (initial) human capital investment in this period. The data on average test scores are available for 14 countries and can be broken down by gender.[5] The data for the three skill domains (prose, document, and quantitative) and the averages over the three tests (literacy) are presented in the Appendix for both genders, men and women.

The IALS was also conducted in several other countries that could not be included in our sample for various reasons. Poland, the Czech Republic, Hungary, and Slovenia do not have reliable estimates of GDP and investment rates. Data for France have not been made public. It was not possible to construct data for Australia due to constraints on availability. Portugal had only a limited sample size that was not sufficient to support the division by cohorts. Japan, Malaysia,

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[3]  Older individuals were tested in some countries.
[4]  See Appendix F in Coulombe et al. (2004) for an overview of the IALS study, how the synthetic estimates were derived, what is known about the relationship of skills to economic growth, and their suitability for the present use.
[5]  These countries are Belgium (Flanders), Canada, Denmark, Finland, Germany, Ireland, Italy, Netherlands, Norway, New Zealand, Sweden, Switzerland, United Kingdom, and the United States.

Mexico, and Canary Islands also had very limited and non-representative samples. Finally, while it would have been possible to use Chile, it would have been quite an outlier in the analysis, given the political and economic turmoil of the 1970s. As shown by Temple (1998), atypical countries may affect considerably the impact of education in growth regressions. As a result, Temple has adopted the approach of considering OECD countries and non-OECD countries separately.

These indicators provide a direct measure of the quality of human capital and are not subject to various problems related to the comparability of education systems across countries. As mentioned previously, this contrasts with human capital indicators based on schooling enrolment or attainment. Moreover, direct measures of human capital capture additional sources of variance not captured by years-of-schooling or enrolment rates. These additional sources include variance in the quality of the educational experience across time, across groups of individuals, and across countries. Hence these indicators are expected to contain more information about the productive capacity of human capital than educational data. In fact, there is microeconomic evidence suggesting that the skills measured by IALS explain a substantial part of wage earnings and labor market outcomes, independent of the effect of education. In particular, Green and Riddell (2001) have found significant wage returns in the Canadian labor market associated with literacy proficiency measured from IALS data, while controlling for educational attainment.

Of course, our human capital indicators are not without shortcomings. For instance, the fact that construction of the synthetic time series from the cross-sectional data cannot take migration flows into account over the period is an important drawback. Moreover, our indicators impute levels of literacy to individuals earlier in their lives, without correcting for the adjustment in the quality of human capital that occurs during an individual's lifetime through learning and human capital depreciation. Hence, given that the literacy tests were conducted at the end of the period under study, if individuals' human capital tends to grow during post-school life, our indicators would tend to overestimate the human capital investment made before individuals entered the labor market, and vice-versa.

Average literacy test scores for the population aged 17–25 relative to the cross-sectional mean are shown in Figure 1. Scandinavian countries perform very well. Sweden has had the highest average score throughout the period. Finland improved from sixth to second place while Norway was second for the first half of the period and third afterwards. Italy, which had the lowest score in 1960, improved substantially from 84% of the average to 94% in 1995. In contrast, the United States recorded the largest decline from 103% of the average to 91%, going from fifth to last place.

**Figure 1: Average Literacy Score of Population Aged 17-25 Relative to the Cross-Section Mean**
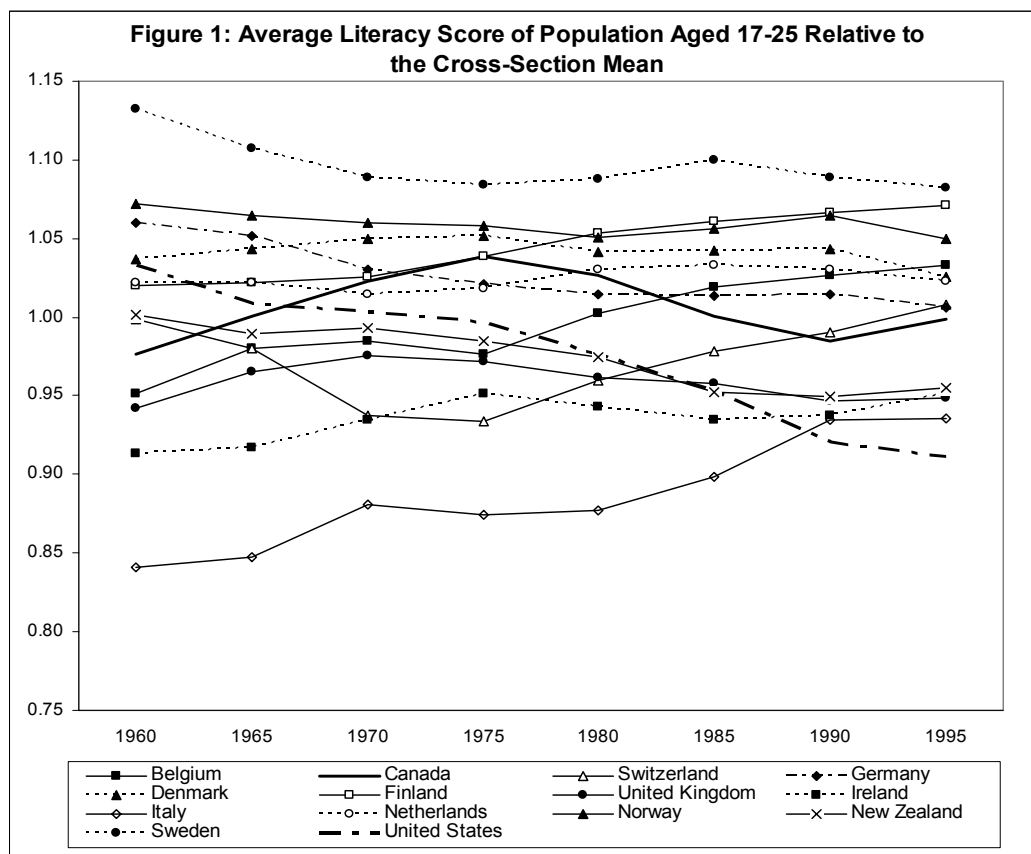


In the study, we also employ data on GDP per capita, GDP per worker, investment as a share of GDP, government expenditures as a share of GDP, and imports and exports, all of which are from the Penn World Tables (Version 6.1).[6] These variables are expressed in purchasing power parities (PPP), which allow real-quantity comparisons across countries. GDP per capita is also adjusted for changes in terms of trade. The openness ratio is the sum of exports and imports as a share of GDP, averaged over 5-year periods and adjusted for the size of countries measured by population and land area. Fertility rates are from the United Nations' database and inflation rates are from the International Monetary Fund (International Financial Statistics). Fertility, investment rates, government expenditures as a share of GDP, and inflation rates are also taken as averages over 5-year periods.

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[6] GDP per worker and labor productivity are considered equivalent expressions in the remainder of the text.

## 3.      Empirical methodology

### 3.1     The pooling of time series/cross-section data

The relationship between various human capital indicators and economic growth is analyzed using the now-standard empirical approach—the convergence-growth regression—that is based on the theoretical analysis of Mankiw et al. (1992) and Barro and Sala-i-Martin (1992). In the convergence-growth framework, the growth rate of the economic indicators such as GDP per capita and labor productivity, $Y_{i,T}$, for country $i$ during period $T$ is determined by its initial level, by a set of environmental and control variables $Z_{i,T}$, and by a stochastic term $v_{i,T}$ that captures the effect of country-specific shocks temporarily affecting economy $i$ during period $T$.

Following Coulombe and Lee (1995), Islam (1995), and many subsequent studies, we pool time-series and cross-country information to study the convergence-growth relationship. The panel data approach to growth regressions is now recognized as having numerous advantages over the pure cross-country approach that was first used by Barro (1991), Barro and Sala-i-Martin (1992), and Mankiw et al. (1992). The panel data approach, discussed in Temple (1999), exploits the information contained in the time-series evolution of the cross-sections of countries during the period under study. Furthermore, the pooling of time-series and cross-sectional information is particularly welcome in the present empirical analysis, given the limited number of cross-sections (14) covered by literacy data. OECD countries such as Spain, Portugal, and Greece that were initially poorer are not in our country sample and the information contained in the time-series evolution is quite comparable to the cross-sectional variance in our sample. In studies of a broad set of countries, such as Barro and Sala-i-Martin (2004), including underdeveloped countries, results are driven mainly by the information contained in the cross-sectional variance.

From a panel data approach, the growth rate of GDP per capita or labor productivity, denoted by $\Delta Y_{i,t}$, is given by the following expression where variables are defined as logarithm deviations from the cross-sectional sample mean:

$$\Delta Y_{i,t} = F(Y_{i,t-1}, Z_{i,t-p}, \varepsilon_{i,t}),$$

where $t = 0,...,T$ and $p$ is the number of lags (usually 0 or 1) used for the $Z$ variables. We use data at 5-year intervals to remove cyclical fluctuations. As is the usual practice, correlations among variables over the business cycle horizon have to be swept out in growth studies. For this reason, data are usually pooled in periods of 5- or 10-year intervals. Given the limited number of cross-sections in

our sample, we pooled the data in 5-year periods to maximize the use of the within-country variation. As Johnson et al. (2004, 103) put it, the use of within-country variation in panel data is the only possible avenue when the number of countries is rather limited in growth empirics. For values of $p$ equal to 0 and 1, the panel data set-up will use $NT$ observations between period 0 and period $T$.

The combination of time-series and cross-sectional information in growth regressions has to be done with great care since the two types of information are not comparable in a straightforward manner. First, common trends and common shocks (such as the productivity slowdown or the oil shock) to the $Y$ and $Z$ variables have to be extracted from the time-series observations in order to obtain unbiased results. To tackle this issue, we follow the familiar approach in panel data analysis of defining the $Y$ and $Z$ variables as deviations from the cross-sectional sample mean. This approach is equivalent to introducing $T$-1 time dummies $\lambda_t$ in the panel data regressions. Second, we control for time-invariant heterogeneity across countries using country-specific fixed-effects $\mu_i$. However, it should be remembered that with a fixed-effect approach, we cannot use time-invariant control variables such as a rule-of-law indicator, a democracy indicator, or country size in the regressions. Our empirical strategy is designed to focus on the time-series dimension embedded in the demographic profile of the literacy score database. In the terminology of Baltagi (1999), our panel data model might be viewed as a two-way error component regression model:

$$\Delta Y_{i,t} = \beta Y_{i,t-1} + Z'_{i,t-P} \phi + v_{i,t},$$
$$\text{where } v_{i,t} = \mu_i + \lambda_t + \varepsilon_{i,t}.$$

The growth-regression equation tested in the first empirical set-up follows directly from Mankiw et al. (1992) and Islam (1995):

$$\Delta Y_{i,t} = \beta Y_{i,t-1} + \varphi_1 S(k)_{i,t} + \varphi_2 S(h)_{i,t-1} + \varphi_3 n_{i,t} + v_{i,t}, \qquad (1)$$

In this set-up, $i = 1, \ldots, 14$ for the 14 OECD countries (only 13 in labor productivity regressions) in the sample and $t = 0, \ldots, 7$ where period 0 corresponds to 1960 and period 7 to 1995 for variables that are measured at one point in time. For variables that are averaged over 5-year intervals, period 1 corresponds to 1960–1964 and period 2 to 1965–1969. The first growth rate used in the regression is for the period 1960–1964 (period 1). The investment ratio $S(k)_{i,t}$ is the 5-year average ratio of investment to GDP in period $t$, and $n_{i,t}$ is the 5-year average fertility rate in period $t$. The key variable of interest in this empirical analysis is the $S(h)_{i,t-1}$ for which a variety of human capital investment indicators will be used; these include indicators based on literacy scores and

others based on schooling attainment. The measures of human capital investment derived from literacy data that entered the regression for the growth rate from 1960 to 1964 are based in this empirical set-up on literacy scores for the 17–25 age group in 1960 (period 0). The point estimate of the $\beta$ parameter is a measure of the average speed of convergence across the 14 countries of the sample.

One apparent difference between specification (1) and Mankiw et al. (1992) and Islam (1995) basic specifications is that we use the fertility rate ($n$) instead of the sum of population growth, depreciation, and technological progress ($n + \delta + g$) in the list of controls. Two points are worth mentioning regarding this. First, since we are using panel data with time dummies in all econometric specifications, we do not have to add 0.05 ($\delta + g$) to the population growth rate in a parsimonious specification of (1). With time dummies, variables are transformed as (logarithm) deviations from the cross-sectional sample mean and factors that are common across countries, such as depreciation and technological progress, are removed from the analysis. Consequently, our specification is similar to Mankiw et al. (1992) and Islam (1995) under the assumption of equal growth rates of technological progress and depreciation rates across countries. With the cross-country fixed effects, we also allow for different levels of technology across countries. This is contrary to Mankiw et al. (1992) but along the line of Islam (1995).

The second apparent departure from Mankiw et al. (1992) is that we use the fertility rate instead of the population growth rate. These two variables are intrinsically related and controlling for both is likely to lead to multicolinearity. We have experience separately with both these variables and not surprisingly, they lead to very similar results. We choose to report only the results for fertility for two reasons. First, the fertility rate was overall more significant than population growth. Second, we thought that it would be appealing to control for fertility since part of our analysis deals with the division between male and female. The effect of female literacy on growth is greater and more robust than for male and it is important to show that female literacy affects growth beyond the effect on fertility.

Mankiw et al. (1992) show that the share of physical capital and human capital in national income, $\alpha$ and $\eta$ respectively, can be computed from the point estimates of the parameters $\beta$, $\phi_1$, and $\phi_2$ of (1) in the following way:

$$\hat{\varphi}_1 = -\hat{\beta}\left(\frac{\alpha}{1 - \alpha - \eta}\right) \qquad (2)$$

$$\hat{\varphi}_2 = -\hat{\beta}\left(\frac{\eta}{1 - \alpha - \eta}\right) \qquad (3)$$

We will be using these relations to provide estimates of human (and physical) capital shares for a variety of human capital indicators.

As shown in the work of Barro and Sala-i-Martin (2004), there is no reason to restrict the set of environmental variables $Z$ to the usual one implied by the simple augmented Solow growth model, i.e., population growth (or fertility) and investment ratios for physical and human capital. Other variables that might affect the production function have proven successful in explaining long-run cross-country differences. In this general growth regression set-up, human capital indicators (investment or stock data) might be viewed as one fundamental determinant, among others, of the long-run steady state.[7] For a broad set of countries, including the developed and less developed, many candidate variables can be used as controls for long-run steady states. The choice in our study of 14 developed countries is more limited, for three reasons. First, as shown in Barro (2001), many control variables that are significant in the broad set of countries, including rule-of-law indices and terms of trade changes, are not significant when the sample is restricted to OECD countries. Second, as already mentioned, the use of the two-way error correction model implies that we cannot also control for time-invariant and country-invariant variables. Third, with the small number of cross-sections available (14 for per capita GDP and only 13 for productivity), we cannot control simultaneously for more than five or six time- and country-varying variables with our system estimations that use instrumental variables from iterated weighted two-stage least-squares.

We are, however, able to control for an international openness variable, $OPEN_{i,t}$. The increase in international openness in the period under study is one of the most important macroeconomic developments that affected developed countries. Following Barro (2001), the degree of international openness is first measured as the ratio of exports plus imports over GDP. This measure is then filtered from the effect of population and geographic size from a simple panel data regression. Our benchmark panel data model is the extended version of (1) that includes the openness variable:

$$\Delta Y_{i,t} = \beta Y_{i,t-1} + \varphi_1 S(k)_{i,t} + \varphi_2 S(h)_{i,t} + \varphi_3 n_{i,t} + \varphi_4 OPEN_{i,t} + v_{i,t}, \qquad (4)$$

where the $v_{i,t}$ is defined as in the regression set-up (1).

The long-run level effect of a permanent shock to each of the four variables $z_i$ can be computed from the long-run solution to equation (4), with $\Delta Y_{i,t} = 0$ at $Y = Y*$, where an asterisk on a variable denotes steady-state values. Thus the long-run elasticities for the various $z$ are

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[7]  For a discussion on using investment versus human capital stock data in growth regressions in relation with micro empirical studies, refer to Krueger and Lindahl (2001).

$$\frac{\partial y^*}{\partial z^*} = -\frac{\hat{\varphi}_z}{\hat{\beta}}. \quad (5)$$

We illustrate the robustness of our main result on literacy in Appendix A by adding government expenditures and inflation in the list of controls using weighted least-squares estimations.

## 3.2    Estimation techniques

Many alternative estimation techniques are available for pooled time-series cross-sectional observations in convergence-growth regressions. As the purpose of the analysis is to evaluate the impact of alternative measures of human capital in growth regressions, we follow as closely as possible the estimation techniques used in Barro and Sala-i-Martin (2004) in their empirical analysis of a cross-section of countries. Barro and Sala-i-Martin (2004) present results for pooling at both 5- and 10-year intervals. As mentioned before, we adopt a panel data approach using 5-year intervals to make the best use of the within-country data variations, given the limited number of cross-sections at our disposal.

The per capita GDP ($Y_{i,t-1}$) that enters the regression for the growth rate in the 1960–1964 period is the initial level in 1960. We have included the earlier value ($Y_{i,t-2}$) in the list of instruments in all IV estimations. As pointed out in Barro and Sala-i-Martin (2004), this procedure reduces the tendency to overestimate the convergence speed due to measurement error. Using the two-period lagged dependent variable as instrument also decreases the Nickell bias (Nickell 1981) associated with fixed-effect estimators of dynamic panel data when there are a small number of time periods. This bias is in the same direction as the measurement error bias. Given that per capita GDP (and labor productivity) data were available in 1955 for all countries, the instrumentation of the lagged dependent variable did not translate into a loss of observations in the 1960–1995 sample.

The most common approach to eliminate the Nickell bias in dynamic panel with a large number of cross-sections is to first-difference the data and then use the Generalized Method of Moments (GMM) proposed by Arellano and Bond (1991). Fixed effects are eliminated with first differencing and the lagged levels are used as instruments for the first differences. However, given the short cross-sectional dimension of our panel model (14 countries with per capita GDP; only 13 for productivity regressions), GMM technique is not applicable in our study. Furthermore, taking first differences over short periods of time (5 years) is likely to exacerbate measurement errors in schooling and human capital data.[8]

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[8]  Fixed effects can also increase measurement errors in human capital data since the time-series mean is subtracted from the data. From the point of view of measurement error in the human

The use of instrumental variables may also overcome the problems of endogenous explanatory variables and human capital measurement error.[9] For the first problem, we have included the lagged level of fertility, physical investment, and openness variables in the list of instruments. Lagged instruments are not required for this purpose for the human capital variable since, as is common in growth studies, growth rates are regressed on the initial values of the human capital stock. The use of initial values is a straightforward method of solving the endogeneity problem with standard schooling data in growth regressions. However, as was pointed out in Section 4.1 below, it might not be appropriate for our synthetic human capital data since they are derived from surveys performed in the mid-1990s. Using the literacy variable lagged one other period for initial literacy is not likely to solve this problem since the data also come from the same survey.[10] For this reason, it might be desirable to instrument the initial literacy variable by another contemporaneous schooling indicator to partly overcome the endogeneity problem.

To address the second problem related to measurement errors in the human capital variable and to partly address the endogeneity issue of the literacy variable, we used the schooling variable taken from the de la Fuente and Doménech (2002) data bank as instrument for the human capital investment variables based on literacy scores in a subset of regressions. As pointed out in recent works on education and growth (Krueger and Lindahl 2001; Pritchett 2001), this procedure is an efficient way to account for the measurement error problem of human capital when the measurement errors in the two data sets are uncorrelated. This hypothesis may not hold for various educational data banks since they are often derived from common enrolment data and surveys. In our case, however, we can assume that the measurement errors are not correlated between the two human capital data sets, as the two measures are derived from completely different raw data and methodologies.

We conducted bivariate pooled least-square regressions of the de la Fuente and Doménech (2002) schooling data regressed on our literacy measure. Without country fixed effects, the estimated slope coefficient and t-ratio are 1.25 and 3.76 with a $R^2$ of 0.20. With country fixed effects, the slope coefficient decreases to 0.84 while the $t$-ratio and $R^2$ increase to 5.40 and 0.97, respectively. These results show that a strong covariance exists between the two measures, especially in a

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capital data, it is preferable to take fixed effects over first differencing in a relatively long panel of short periods such as in our study. Subtracting the mean in a long panel corresponds to some extent to taking differences over long periods of time.

[9] For an in-depth analysis of the measurement error issue in various schooling data banks, refer to Krueger and Lindahl (2001) and de la Fuente and Doménech (2002).

[10] It is worth mentioning that our main results are robust to instrumenting the literacy variable by its lagged value.

fixed-effect framework. Thus, as the measurement errors are very likely uncorrelated between the two variables, the schooling data appear to be a very good instrument for our literacy variable. Note that we cannot interpret the above coefficients as reliability ratios as in Krueger and Lindahl (2001), for two reasons. First, literacy and schooling may not necessarily be viewed as measures of the same variable, since literacy is a function of both the quantity and quality of schooling, among other things. Second, schooling and literacy are not measured on the same scale.[11]

    We use system estimations with instrumental variables (IV) from iterated weighted two-stage least-squares (IWTSLS) to account for cross-sectional heteroscedasticity. Breusch-Pagan test for heteroscedasticity from pooled least-square estimation indicate that the null hypothesis of homoscedasticity is rejected at the 1% level. Tests for AR(1) serial correlation using the residuals from IWTSLS-IV regressions based on the *t* statistic of the lagged residuals in modified regressions indicate that the null hypothesis of no serial correlation cannot be rejected.

## 4.    Results

### 4.1    Basic model

Regression results for the conditional convergence of GDP per capita, following equation (1) and using average test scores of the population aged 17–25 as human capital investment measures, are shown in Table 1. The estimated convergence speeds are highly significant and correspond to annual rates of around 5.4%, which are higher than those estimated by Mankiw et al. (1992) for their OECD sample but somewhat below those obtained by Islam (1995).[12] Investment rates are highly significant in all regressions but fertility rates are not, although they have a negative sign as predicted by the neoclassical growth framework.

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[11] The use of literacy test scores as indicators of cross-country relative human capital investment is based on the assumption that the 0 to 500 scale used to measure test scores in IALS is an absolute scale. We have also worked with various rescaling of IALS data and as expected, the estimated coefficients are found to vary significantly when the scale of the literacy variable is adjusted. However, standardized (beta) coefficients change very little.

[12] In the set-up of equation (1) with 5-year time periods, the annual convergence speed is $-\log(1+5\beta)/5$.

**Table 1.  Growth regressions with various literacy indicators – closed-economy version (equation 1)**

| Dependent variable: growth of GDP per capita | | | |
|---|---|---|---|
| | **Literacy** | **Prose** | **Quantitative** | **Document** |
| Initial GDP | -0.047 [a] (0.012) | -0.048 [a] (0.012) | -0.048 [a] (0.012) | -0.046 [a] (0.012) |
| Literacy | 0.085 [b] (0.034) | 0.083 [b] (0.032) | 0.083 [b] (0.035) | 0.084 [b] (0.035) |
| Investment rate | 0.046 [a] (0.008) | 0.048 [a] (0.009) | 0.044 [a] (0.008) | 0.046 [a] (0.008) |
| Fertility rate | -0.012 (0.008) | -0.012 (0.008) | -0.012 (0.008) | -0.013 [c] (0.008) |
| Number of observations | 95 | 95 | 95 | 95 |
| Implied ($\alpha$; $\eta$) | (0.26; 0.48) | (0.27; 0.46) | (0.25; 0.47) | (0.26; 0.48) |

*Notes apply to all tables:*
- Literacy variable is the average of the other three measures of literacy.
- Regressions are over the 1960–1995 sample.
- Data are averaged over 5-year periods.
- System estimations with instrumental variables are from iterated weighted two-stage least-squares.
- All regressions include country fixed effects and time dummies.
- a, b, and c imply significance at the 1%, 5%, and 10% levels, respectively.
- Instruments used are initial GDP per capita of the previous period and the lagged values of the investment rate and of the fertility rate. Initial literacy is instrumented by the initial schooling taken from de la Fuente and Doménech (2002) in Tables 1 and 2 and in columns 1, 2, 4, and 5 in Table 4.
- There is no significant serial correlation in all regressions.
- For regressions with GDP per worker as an independent variable, the sample excludes Germany.
- GDP per capita is not available for Germany before 1970.
- The openness variable is not available for Finland before 1970.

Most importantly, the effect of human capital indicators on GDP growth is positive and significant at the 5% level in all cases. This result contrasts sharply with most previous attempts to estimate the effect of human capital on growth across developed countries, de la Fuente and Doménech (2002) being the exception. Interestingly, the estimates are very similar for the different indicators of human capital under consideration, suggesting that the amount of information embedded in the three specific measures of literacy (prose, document, and quantitative) is highly comparable. It is important to point out that this result is not caused by the use of a common instrument (de la Fuente and Doménech,

2002, schooling data). In Coulombe, Tremblay and Marchand (2004), the effect of literacy is also very similar across various literacy indicators when the human capital variable is not instrumented in feasible generalized least-squares estimations (FGLS).[13] Some results with this estimations technique are displayed in Appendix A.

Note that although the estimated coefficient on literacy is positive and significant, the direction of the causality between per capita GDP growth and literacy is *a priori* unclear. Both the initial level of GDP per capita and the literacy indicator are used as explanatory variables, although the level of GDP per capita is itself a function of human capital. For example, in the open-economy growth model of Barro et al. (1995) with perfect capital mobility for the financing of physical capital, the level of GDP per capita is determined entirely by the stock of human capital, and the convergence of GDP per capita is determined by the convergence of the human capital stock. Alternatively, human capital accumulation may be driven by economic growth if, for example, highly educated individuals are attracted and able to migrate to more prosperous countries, or if economic growth generates human capital through learning-by-doing. The possibility of reverse causality is particularly relevant in our analysis. Our human capital investment measures are based on literacy tests performed at the end of the period of analysis and are therefore somewhat distorted by migration flows that occurred over the period, among other things.

We can compute the shares of physical and human capital remuneration in national income, implied by the regression results as shown in equations (2) and (3). For the four literacy measures, these implied shares are between 0.25 and 0.27 for physical capital and between 0.46 and 0.48 for human capital. This estimated share for physical capital is roughly consistent with the observed share of profits in the national income of developed countries, which is typically around 30%. The shares implied by our regression results leave approximately 30% of national income to remunerate raw labor. This implies that two-fifths of wages pay for raw labor and three-fifths represent the return on skill. These results on the human capital share are consistent with the findings of Mankiw et al. (1992) and Coulombe and Tremblay (2001).

Recall that country fixed effects, which account for various forms of heterogeneity across countries, are included in all the regressions. Country fixed effects could also account for heterogeneity in the quality of the literacy data across countries. For example, unlike other countries with complete coverage, Belgium's literacy data cover only the population from the relatively rich and educated Flanders region. The GDP data refer, of course, to the whole country. Thus the relationship between literacy and GDP growth might be substantially

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[13] FGLS regressions correspond to our iterated weighted two-stage least-squares procedure when the variables are not instrumented.

different if literacy data for the entire country were included. Not surprisingly, the fixed effect for Belgium is always negative and significant (with *p*-values around 1%), indicating that growth of the whole country (including Flanders and Walloon) is overestimated by the independent variable (excluding fixed effects) since the literacy indicators are based only on the wealthy region.

## 4.2 GDP per capita versus labor productivity

Following Barro (2001), we have included the openness ratio in our conditional convergence regressions based on the econometric set-up of equation (4) in all the remaining regressions. Results for the convergence of GDP per capita and GDP per worker are presented in Table 2. Germany had to be excluded from the sample in all regressions dealing with labor productivity growth because the time series is not available for the whole country prior to reunification in 1990. As expected, the estimated effect of openness on growth is positive and significant in all cases. The regression results for the other determinants of growth are quite similar in the closed- and open-economy versions of the model, which illustrates the robustness of the estimated relationships.

Interestingly, the point estimates of the literacy variables are higher and the parameters generally estimated with more accuracy (smaller *p*-value) in the regressions dealing with labor productivity than those dealing with GDP per capita. In addition to further illustrating the robustness of the relationship between human capital and growth, these results suggest that the impact of literacy on living standards is not driven by labor market effects. If the effect of literacy on growth were significant only for GDP per capita, one could argue that the underlying augmented neoclassical framework is rejected since the effect of human capital investment on living standards is restricted to its effect on unemployment and participation rates. But the human capital effect is more substantial on labor productivity. This indicates that the primary effect of human capital investment on living standards comes from its role in the broad capital accumulation process, as predicted in the underlying theoretical framework.

To indicate the quantitative implications of our results, in Table 2 we report the long-run elasticities of GDP per capita and GDP per worker with respect to physical and human capital accumulation that is implied by the regression results following equation (5). Before the results are interpreted, however, it is important to point out that in the neoclassical growth framework, as long as the convergence speed is positive, variables such as fertility, literacy (human capital), or the investment rate will affect only the level of long-run GDP per capita or labor productivity. The steady-state growth rate is determined solely by the growth rate of technological progress. But in growth regressions, the convergence speed is typically rather slow, between 2% and 6% per year.

Consequently, it takes a long time period to reach the new steady state and the transitory effect of a human capital shock on GDP per capita or labor productivity can last for an equally long time. In fact, following a human capital shock, with convergence speeds of 2% and 6%, the economy will need respectively 35 and 11⅔ years to close half of the gap to the new steady state. Therefore, in a slow-convergence world, the difference between long-run growth and level effects may not be that important. However, it is more accurate to measure the impact of a shock by its long-run accumulated effect on the steady-state level of GDP per capita or labor productivity than by looking at the impact measured by the point estimate of the human capital variable.

**Table 2. GDP per capita versus GDP per worker – various literacy indicators, open economy version (equation 4)**

| | Dependent variable: growth of GDP per capita | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | **Literacy** | **Prose** | **Quantitative** | **Document** |
| Initial GDP | -0.060[a] | -0.061[a] | -0.062[a] | -0.057[a] |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| Literacy | 0.087[b] | 0.087[a] | 0.084[b] | 0.081[b] |
| | (0.034) | (0.032) | (0.034) | (0.036) |
| Investment rate | 0.036[a] | 0.039[a] | 0.033[a] | 0.037[a] |
| | (0.009) | (0.009) | (0.008) | (0.009) |
| Fertility rate | -0.016[c] | -0.016[c] | -0.017[c] | -0.017[c] |
| | (0.009) | (0.008) | (0.009) | (0.009) |
| Openness ratio | 0.019[b] | 0.019[b] | 0.021[b] | 0.018[b] |
| | (0.009) | (0.009) | (0.008) | (0.009) |
| Number of observations | 93 | 93 | 93 | 93 |
| Elasticities (K; H) | (0.60; 1.45) | (0.64; 1.43) | (0.53; 1.35) | (0.65; 1.42) |

| | Dependent variable: growth of GDP per worker | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | **Literacy** | **Prose** | **Quantitative** | **Document** |
| Initial GDP | -0.046[a] | -0.048[a] | -0.045[a] | -0.044[a] |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Literacy | 0.095[b] | 0.101[a] | 0.079[b] | 0.095[b] |
| | (0.037) | (0.036) | (0.036) | (0.038) |
| Investment rate | 0.025[a] | 0.028[a] | 0.021[b] | 0.025[a] |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Fertility rate | -0.005 | -0.005 | -0.004 | -0.005 |
| | (0.008) | (0.008) | (0.009) | (0.008) |
| Openness ratio | 0.038[a] | 0.038[a] | 0.038[a] | 0.038[a] |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Number of observations | 89 | 89 | 89 | 89 |
| Elasticities (K; H) | (0.54; 2.07) | (0.58; 2.10) | (0.47; 1.76) | (0.57; 2.16) |

Hence, the elasticities implied by our regression results indicate that the long-run effects of human capital investment in literacy are substantial. A country that achieves literacy scores 1% higher than the average ends up in a steady state with labor productivity and GDP per capita respectively higher than other countries by approximately 2% and 1.4% on average. This result holds whether literacy is measured by prose, quantitative, or document skills.

By using an estimate of the marginal return to education in terms of literacy scores, we can translate these elasticities into terms of the macroeconomic return from an extra year of education. The OECD (2000, xiv) estimated that one extra year of schooling increases the literacy score by around 10 points, which is approximately 3.5% of the average literacy score across countries and cohorts in our sample. The elasticities that we found in the regressions of GDP per worker therefore imply that the skills acquired from an extra year of education increase aggregate labor productivity by approximately 7%. This estimate is consistent with the microeconomic return to education found in Mincerian wage regressions, which is typically in the 5% to 15% range (Psacharopoulos 1994). Interestingly, Psacharopoulos reports an estimate of 6.8% for OECD countries only.

## 4.3    Comparison with schooling data sets

Table 3 reports results for the conditional convergence of GDP per capita and GDP per worker using average years of schooling in the population as measures of human capital that were taken from the Barro and Lee (2001) and the de la Fuente and Doménech (2002) data sets. However, we did not use the schooling data of Cohen and Soto (2001) for two reasons. First, it is available only for 10-year intervals whereas our entire analysis is conducted with 5-year periods. Second, although they are quite comparable with the data of de la Fuente and Doménech (2002), their reliability ratios are lower. The average reliability ratios reported in de la Fuente and Doménech (2002) are 0.53 for the Cohen and Soto data compared with 0.72 for the de la Fuente and Doménech data. On the other hand, we have also constructed the synthetic time series for average years of schooling per age cohort from the 1994–1998 IALS using the same methodology based on demographic profiles as the one used for literacy.[14] In each of these regressions, the human capital indicator is used as its own instrument. For comparison purposes, we also report results for the literacy variable when it is used as its own instrument (columns 4 and 8). The reported adjusted $R^2$ are those of the corresponding FGLS regressions.

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[14] Given the organization of the raw micro 1994 IALS data at our disposal, we were not, however, able to extract aggregate data for Canada. Canada is then excluded from the sample in the two regressions dealing with the synthetic schooling data from IALS.

**Table 3. Comparison with schooling data sets – open-economy version (equation 4)**

| Dependent variable: growth of GDP per capita | | | |
|---|---|---|---|
| | (1) BL2001 | (2) FD2002 | (3) schIALS | (4) Literacy |
| Initial GDP | -0.068 [a] | -0.067 [a] | -0.055 [a] | -0.060 [a] |
| | (0.012) | (0.014) | (0.013) | (0.012) |
| Human capital indicator | -0.004 | 0.040 | 0.045 [c] | 0.095 [a] |
| | (0.012) | (0.029) | (0.024) | (0.034) |
| Investment rate | 0.024 [a] | 0.030 [a] | 0.045 [a] | 0.039 [a] |
| | (0.008) | (0.008) | (0.009) | (0.009) |
| Fertility rate | -0.026 [a] | -0.018 | -0.023 [a] | -0.022 [b] |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Openness ratio | 0.020 [a] | 0.017 [b] | 0.012 | 0.021 [b] |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Adjusted $R^2$ | 0.395 | 0.433 | 0.453 | 0.459 |
| Number of observations | 93 | 93 | 86 | 93 |
| Elasticity K | 0.35 | 0.45 | 0.81 | 0.65 |
| Elasticity H | -0.06 | 0.60 | 0.81 | 1.58 |

| Dependent variable: growth of GDP per worker | | | |
|---|---|---|---|
| | (5) BL2001 | (6) FD2002 | (7) schIALS | (8) Literacy |
| Initial GDP | -0.038 [a] | -0.033 [a] | -0.035 [a] | -0.043 [a] |
| | (0.011) | (0.012) | (0.013) | (0.010) |
| Human capital indicator | 0.009 | -0.030 | 0.013 | 0.098 [a] |
| | (0.013) | (0.036) | (0.031) | (0.037) |
| Investment rate | 0.018 [c] | 0.013 | 0.042 [a] | 0.029 [a] |
| | (0.010) | (0.009) | (0.011) | (0.009) |
| Fertility rate | -0.010 | -0.007 | -0.015 [c] | -0.008 |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Openness ratio | 0.039 [a] | 0.030 [a] | 0.035 [a] | 0.040 [a] |
| | (0.009) | (0.008) | (0.009) | (0.007) |
| Adjusted $R^2$ | 0.494 | 0.491 | 0.541 | 0.581 |
| Number of observations | 89 | 89 | 82 | 89 |
| Elasticity K | 0.47 | 0.39 | 1.20 | 0.68 |
| Elasticity H | 0.24 | -0.91 | 0.37 | 2.28 |

*Note:* The four indicators of human capital are:
- BL2001 is average years of schooling (Barro and Lee 2001);
- FD2002 is corrected schooling data (de la Fuente and Doménech 2002);
- schIALS is the synthetic time series of the reported years of schooling by cohort in IALS 1994-1998, following the same methodology as the one used to construct the literacy variable;
- Literacy is the same (mean) literacy variable as in Tables 1 and 2.
For comparison purposes, each initial human capital indicator has been used as its own instrument.

The first four regressions in Table 3 pertain to per capita GDP growth. In the regression reported in the column (1), the point estimate of the human capital indicator based on Barro and Lee (2001) schooling data is negative and not significant. In column (2), the point estimate of de la Fuente and Doménech (2002) corrected schooling data is positive but not significant (*p*-value of 17%). The adjusted $R^2$ is a little higher for the regression using the de la Fuente and Doménech (2002) data than for the Barro and Lee (2001) data (0.433 versus 0.395). In the regression reported in column (3), the synthetic schooling variable of labor market entrants is positive and significant at the 10% level and the adjusted $R^2$ (0.453) is higher than for the other two schooling data sets. In column (4), the literacy variable is positive and significant at the 1% level and the adjusted $R^2$ is higher (0.459) than for the schooling data.

Regression results reported in columns (5) to (8) pertain to labor productivity growth. The effect of human capital is not significant (and negative in the case of the de la Fuente and Doménech data) for the three schooling data. The adjusted $R^2$ is almost the same in the two regressions based on Barro and Lee (2001) and de la Fuente and Doménech (2002), taking a value of around 0.49, which is below the one obtained for the synthetic data. When the literacy variable is used as an alternative indicator of human capital, the effect of human capital is again positive and significant at the 1% level and the adjusted $R^2$ increases to 0.58.

Note that the sample used in de la Fuente and Doménech (2002) includes Greece, Portugal, and Spain, which have substantially lower levels of schooling and GDP per capita than the rest of OECD countries. These countries could drive, to some extent, the positive and significant effect of schooling obtained by de la Fuente and Doménech (2002). In contrast, the sample of countries that we use is more homogenous in terms of levels of human capital and GDP per capita.

These findings suggest that literacy scores data contain considerably more information about the relative growth performance of nations than the years-of-schooling data. We believe that this is the central result of our study and we suggest three possible explanations for it. First, literacy scores might be a more accurate measure of the accumulation of human capital than years of schooling. This may result simply from the fact that literacy tests are direct measures of skills, as opposed to years of schooling. Second, at a given point in time, literacy data might be more comparable on a cross-country basis than years of schooling, given that educational systems vary considerably across countries. Skills acquired from a year of schooling might differ significantly across countries. Third, literacy data in a given country might be more comparable on a time-series basis than years of schooling. Therefore, the skills acquired from one year of schooling in 1960 in a given country may not be directly comparable with the skills acquired from one year of schooling in 1990.

These findings also illustrate the robustness of the results obtained in Tables 1 and 2 since the results do not change significantly when the literacy variable is instrumented by its own value.

It is important to mention that the results using our human capital indicator and schooling data are not comparable in a straightforward manner. Our literacy variable may be seen as an investment variable while the schooling data essentially measure a stock. We defined our human capital indicator as the literacy level of individuals aged 17–25 in a particular period in order to capture the investment made in the skills of the cohort that enters the labor market in each period. The human capital indicator reflects the investments made in the previous two decades or so. In contrast, average years of education in the entire working-age population reflect the human capital investment made in the previous four or five decades. The fact that our literacy variable appears to contain more information about future growth than the schooling data could therefore suggest that the investments made in the previous two decades are more important to growth than the total investments made in the previous four or five decades. However, the fact that our synthetic schooling variable does not have a strong effect on growth is inconsistent with this interpretation since it also reflects investment made in the previous two decades.

## 4.4     Results based on female versus male literacy

In order to compare the relative contribution to growth of investment in the human capital of men and women, we analyzed the conditional convergence of GDP per capita and of labor productivity, using the average literacy scores of men and women as human capital investment measures separately. These regression results are presented in columns (1), (2), (4), and (5) of Table 4.

**Table 4.  Male versus female literacy – open-economy version (equation 4)**

|  | Dependent variable: growth of GDP per capita | | | Dependent variable: growth of GDP per worker | | |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Initial GDP | -0.052 [a] | -0.073 [a] | -0.067 [a] | -0.038 [a] | -0.055 [a] | -0.062 [a] |
|  | (0.012) | (0.012) | (0.013) | (0.011) | (0.011) | (0.012) |
| Male literacy | 0.058 [c] |  | -0.004 | 0.068 [b] |  | -0.006 |
|  | (0.031) |  | (0.039) | (0.033) |  | (0.039) |
| Female literacy |  | 0.094 [a] | 0.095 [b] |  | 0.099 [a] | 0.123 [a] |
|  |  | (0.032) | (0.041) |  | (0.034) | (0.043) |
| Investment rate | 0.034 [a] | 0.037 [a] | 0.044 [a] | 0.023 [b] | 0.023 [a] | 0.032 [a] |
|  | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) | (0.008) |
| Fertility rate | -0.017 [b] | -0.017 [b] | -0.021 [b] | -0.008 | -0.000 | 0.003 |
|  | (0.009) | (0.008) | (0.008) | (0.009) | (0.008) | (0.008) |
| Openness ratio | 0.017 [b] | 0.020 [b] | 0.014 | 0.038 [a] | 0.039 [a] | 0.036 [a] |
|  | (0.009) | (0.008) | (0.010) | (0.006) | (0.007) | (0.007) |
| Number of observations | 93 | 93 | 93 | 89 | 89 | 89 |

*Note:*  For comparison purposes, we have used the initial values of male and female literacy as their own instruments in the regressions reported in columns (3) and (6).

Investment in the human capital of women undoubtedly appears to have a much stronger effect on subsequent growth than investment in the human capital of men. For both GDP per capita and GDP per worker, the estimated coefficients are larger and more significant for the literacy levels of women compared with men. While investment in male literacy has a significant effect at the 10% level on GDP growth and at the 5% level on the growth of productivity, investment in women's literacy has a significant effect at the 1% level on both productivity growth and GDP per capita growth. In columns (3) and (6), we report the results of regressions that include both male and female literacy as explanatory variables. In this case, the coefficients on male literacy become negative and insignificant, while those on female literacy remain positive and highly significant. From an econometric point of view, this further indicates that the effect of investment in the literacy of women on growth is more robust than the effect of investment in the literacy of men. Note as well that since our regressions control for the fertility rate, the estimated effect of women's literacy on growth is independent of the impact of lower fertility that may result from investment in women's education.[15]

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[15] More results dealing with the comparison between male and female literacy can be found in Coulombe et al. (2004). The results of regressions with the participation rate of women relative to that of men as an additional regressor are also reported. Despite controlling for the effect of women's literacy on their labor market participation, the literacy of women is still found to have a stronger impact on growth than men's literacy.

These results about male and female literacy are consistent with the Mincerian wage regression literature, in particular that of Psacharopoulos (1994) who provides microeconomic evidence that the rate of return on women's education is slightly higher than that of men. Our results also concur with the gender-specific effects of educational attainment found in other studies of economic growth. For example, Hill and King (1995) provide evidence that women's education has a positive and significant effect on GNP and that gender gaps in enrolment rates are detrimental to growth.[16] Schultz (1995) finds that female school enrolments have a greater positive effect on growth than male enrolments. Dollar and Gatti (1999) report, for a sample of developed countries only, that indicators of female educational attainment have a positive and significant effect on growth in contrast to the effect estimated from indicators of male education.[17,18]

## 4.5    Results based on the percentage of individuals who achieved high literacy levels

The results from the IALS are also available as percentages of individuals who have attained different literacy levels (1 to 5) thought to be associated with particular sets of skills. In order to briefly explore how the distribution of human capital investment may affect the relative growth of countries, we conducted conditional convergence regressions in which the human capital measures are based on the percentages of individuals who attained at least level 4 in a particular skill domain. Interestingly, only the indicator based on prose skills is found to have a significant effect on growth, and the long-run elasticities of these human capital measures are much lower than those based on average scores. The estimated elasticities are equal to 0.18, 0.12, and 0.06 for the prose, document, and quantitative indicators, respectively. These exploratory results suggest that the distribution of human capital investment may be important for long-run standards of living. In particular, it is consistent with the view that human capital investment increases growth, mostly by making the overall labor force more

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[16] Galor and Weil (1996) and Knowles et al. (2002) present theoretical models consistent with a negative relationship between the gender gap in education and economic growth.

[17] Similar results are found in Caselli et al. (1996), although the effect of male schooling is both negative and significant.

[18] The results of an analysis of robustness to sample composition are reported in Appendix E of Coulombe et al. (2004). FGLS were performed with the full set of explanatory variables, removing one country in each regression. The estimated effect of literacy for the whole population was found to be robust in all cases except when the United Kingdom is removed from the sample, in which case the *p*-value on the literacy variable is around 0.10. Results for female literacy are extremely robust, unlike those for male literacy. Moreover, the long-run elasticity of literacy is highly stable across regressions.

productive as opposed to developing highly talented individuals who may, among other things, have a positive impact on growth through their contribution to innovation and technological progress.

## 5. Conclusions

Literacy tests scores are direct measures of the quality of human capital and likely capture the sources of variance in productive human capital across countries more accurately than schooling data. However, unlike schooling data, these measures are not yet available over long periods of time. To circumvent this problem, we construct synthetic time series of human capital investment indicators by exploiting the demographic profile of literacy test scores. This allows us to extract the information about long-run economic growth that is contained in a single cross-section of data on literacy skills. Hence, part of our purpose is to make a methodological contribution to the measurement of human capital.

The key result of our analysis is that our synthetic measures of human capital are found to contain more information about the relative growth of 14 OECD countries than the information in schooling data. In our view, this may reflect the fact that literacy test scores are more direct and accurate measures of human capital than schooling data; they are also more comparable across countries and across time. In the process, our analysis indicates that investment in human capital does matter for the relative growth of developed countries, in contrast to most previous findings in the economic growth literature. In particular, we find that the skills generated by one additional year of education increase aggregate labor productivity by approximately 7%. Moreover, our results suggest that investment in the human capital of women is much more important for growth than investment in the human capital of men, and that increasing the average level of literacy will have a greater effect on growth than increasing the percentage of individuals who achieve high levels of literacy skills.

Our analysis has two important limitations. First, deriving measures of past investment in the human capital of an age-cohort from literacy tests taken later on in their life provides an imperfect measure of the skills they had when they entered the labor force. In particular, the indicators are distorted by the migration process that occurred over the period as well as by the learning and human capital depreciation that takes place over the course of individuals' active life in the labor market.

Secondly, some caution is required in modeling the effect of human capital investment on the growth of open economies. In the open-economy, neoclassical growth framework with perfect capital mobility for the financing of physical capital but imperfect mobility for the financing of human capital, Barro et al. (1995) show that the convergence of human capital is the driving force for

the convergence of GDP per capita during the transition process toward the steady state. In this context, the initial level of human capital may be seen as a proxy for the initial level of GDP per capita. As pointed out by Coulombe and Tremblay (2001) and Coulombe (2001), it may therefore be inappropriate to include both the initial level of GDP per capita and human capital as explanatory variables. To the extent that financial capital is imperfectly mobile, as may have been the case between World War II (WWII) and the 1970s, Barro and Sala-i-Martin (2004) argue that the positive effect of human capital on growth may be capturing an imbalance in the relative stocks of human and physical capital. Such an imbalance may have characterized several OECD countries in the 1950s and 1960s where WWII had destroyed primarily physical capital. However, as we move away from the transition period following WWII, the role of human capital investment in growth may need to be modeled differently, from an empirical perspective.

Our analysis is an initial attempt to exploit synthetic time-series data based on direct measures of skills to estimate the effect of human capital accumulation on growth, as opposed to the traditional approach based on schooling data. To shed additional light on the relative merits of the two types of human capital measures, it may be interesting in future research to compare the performance of human capital indicators based on literacy test scores with those based on schooling data in the empirical analysis of growth for sub-national economies. Educational systems of sub-national economies are likely to be more comparable than educational systems across countries. This research may provide some indication whether literacy test scores are in fact better measures of the productive human capital of an economy or whether they are simply more comparable across countries.

# Appendix A
## Controlling for government expenditures and inflation: GLS estimations

The results presented in Tables 1 through 4 come from system estimations with instrumental variables. Given the limited number of cross-sections in our sample, we cannot use this two-stage weighted least-squares technique with additional controls that have within- and between-country variability. The list of controls, however, can be stretched to a limited extent if instrumental variables and two-stage least-squares are not used. In Table A, we present results from generalized least-squares (GLS) estimations using cross-sectional weighted regressions to account for cross-sectional heteroscedasticity. The 5-year average value in the

current period of government expenditures as a share of GDP and of the inflation rate are entered as additional control variables in separate regressions. White heteroscedasticity consistent standard errors are also reported.

The results from columns (1) and (4) illustrate that our main results regarding the growth effect of literacy is not driven by the use of schooling data as instruments. The results could be directly compared with those for per capita GDP and GDP per worker displayed in column (1) of Table 2. The only notable difference is that without instrumental variables, the long-run elasticity of GDP per worker with respect to literacy is higher (2.5) compared with two-stage least-squares (2). In columns (2) and (5), the government expenditure variable is negative and highly significant. The effect of the literacy variable remains highly significant and its long-run elasticity is not much affected. The inflation variable is not significant and not surprisingly, both the significance and the long-run elasticity of literacy remain comparable with columns (1) and (4).

**Table A.  Average literacy scores of individuals aged 17–25**

| | Dependent variable: growth of GDP per capita | | | Dependent variable: growth of GDP per worker | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Initial GDP | -0.065 [a] | -0.060 [a] | -0.068 [a] | -0.049 [a] | -0.033 [a] | -0.049 [a] |
| | (0.013) | (0.012) | (0.013) | (0.010) | (0.010) | (0.011) |
| Literacy | 0.096 [a] | 0.099 [a] | 0.113 [a] | 0.121 [a] | 0.081 [b] | 0.122 [a] |
| | (0.035) | (0.035) | ((0.039) | (0.034) | (0.035) | (0.039) |
| Investment rate | 0.037 [a] | 0.037 [a] | 0.037 [a] | 0.036 [a] | 0.036 [a] | 0.037 [a] |
| | (0.008) | (0.008) | (0.009) | (0.008) | (0.007) | (0.009) |
| Fertility rate | -0.016 [c] | -0.009 | -0.016 | -0.002 | 0.010 | -0.002 |
| | (0.009) | (0.010) | (0.010) | (0.009) | (0.010) | (0.009) |
| Openness ratio | 0.021 [a] | 0.024 [a] | 0.024 [a] | 0.036 [a] | 0.039 [a] | (0.036) [a] |
| | (0.007) | (0.008) | (0.006) | (0.006) | (0.007) | (0.006) |
| Government expenditures | | -0.012 [a] | | | -0.019 [a] | |
| | | (0.004) | | | (0.005) | |
| Inflation | | | -0.06 | | | -0.000 |
| | | | (0.05) | | | (0.002) |
| Elasticities (H) | 1.48 | 1.65 | 1.66 | 2.47 | 2.45 | 2.49 |
| Adjusted $R^2$ | 0.46 | 0.51 | 0.53 | .58 | .70 | .57 |
| Number of observations | 95 | 95 | 92 | 90 | 90 | 90 |

**APPENDIX B**

**Table B.1. Average literacy scores of individuals aged 17–25**

|  | Belgium | Canada | Switzer-land | Germany | Denmark | Finland | U.K. | Ireland | Italy | Nether-lands | Norway | New Zealand | Sweden | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **POPULATION** | | | | | | | | | | | | | | |
| **1960** | 248.9 | 255.2 | 261.0 | 277.2 | 271.1 | 266.8 | 246.4 | 238.8 | 220.0 | 267.1 | 280.3 | 261.9 | 296.0 | 270.1 |
| **1965** | 266.1 | 271.8 | 266.2 | 285.6 | 283.2 | 277.6 | 262.2 | 249.0 | 230.1 | 277.6 | 289.0 | 268.6 | 300.7 | 273.9 |
| **1970** | 273.9 | 284.4 | 260.6 | 286.5 | 291.9 | 285.2 | 271.2 | 259.9 | 244.9 | 282.0 | 294.9 | 276.1 | 302.8 | 279.0 |
| **1975** | 275.2 | 292.6 | 263.1 | 287.6 | 296.3 | 292.8 | 273.9 | 268.0 | 246.4 | 287.0 | 298.2 | 277.4 | 305.4 | 280.8 |
| **1980** | 286.4 | 293.5 | 274.3 | 289.9 | 297.7 | 301.0 | 274.7 | 269.4 | 250.6 | 294.4 | 300.3 | 278.4 | 310.8 | 279.1 |
| **1985** | 293.5 | 288.0 | 281.7 | 291.8 | 300.1 | 305.6 | 276.0 | 269.1 | 258.8 | 297.6 | 304.1 | 274.2 | 316.7 | 274.5 |
| **1990** | 297.6 | 285.5 | 287.0 | 294.0 | 302.5 | 309.2 | 274.5 | 271.7 | 270.9 | 298.7 | 308.6 | 275.3 | 315.4 | 267.0 |
| **1995** | 298.0 | 288.0 | 290.8 | 290.2 | 295.8 | 308.8 | 273.5 | 274.3 | 269.9 | 295.0 | 302.8 | 275.6 | 312.2 | 262.8 |
| **WOMEN** | | | | | | | | | | | | | | |
| **1960** | 235.3 | 254.9 | 255.7 | 273.5 | 266.0 | 266.8 | 240.9 | 234.9 | 202.9 | 259.9 | 278.0 | 260.2 | 287.7 | 270.9 |
| **1965** | 258.2 | 276.8 | 257.0 | 279.8 | 277.4 | 277.9 | 255.6 | 248.0 | 218.5 | 270.4 | 288.0 | 266.2 | 299.4 | 268.8 |
| **1970** | 267.7 | 291.2 | 256.3 | 283.3 | 286.4 | 285.4 | 265.0 | 257.4 | 238.3 | 275.6 | 290.8 | 272.0 | 301.4 | 276.8 |
| **1975** | 273.2 | 293.2 | 264.1 | 284.9 | 291.1 | 294.4 | 267.9 | 267.6 | 242.4 | 284.5 | 293.8 | 273.6 | 304.3 | 280.1 |
| **1980** | 287.6 | 295.6 | 272.4 | 289.2 | 294.7 | 304.0 | 269.4 | 268.1 | 248.3 | 294.6 | 300.4 | 276.1 | 308.3 | 280.3 |
| **1985** | 292.4 | 288.7 | 276.6 | 289.9 | 298.0 | 307.5 | 269.4 | 267.5 | 254.9 | 296.1 | 305.8 | 273.1 | 313.3 | 279.5 |
| **1990** | 299.7 | 277.1 | 282.5 | 291.4 | 300.5 | 314.5 | 270.4 | 274.2 | 266.8 | 297.6 | 309.9 | 277.0 | 312.3 | 269.0 |
| **1995** | 297.2 | 283.6 | 291.8 | 286.9 | 296.8 | 312.6 | 272.4 | 276.7 | 269.8 | 293.2 | 303.3 | 277.5 | 308.8 | 262.4 |
| **MEN** | | | | | | | | | | | | | | |
| **1960** | 265.7 | 255.5 | 266.9 | 280.7 | 276.5 | 266.9 | 252.3 | 243.2 | 238.8 | 274.1 | 282.1 | 263.5 | 304.8 | 269.1 |
| **1965** | 273.7 | 266.3 | 277.3 | 291.3 | 288.8 | 277.3 | 269.4 | 250.0 | 242.6 | 284.6 | 289.8 | 271.0 | 302.0 | 280.3 |
| **1970** | 280.2 | 276.3 | 265.2 | 290.1 | 297.2 | 284.9 | 277.9 | 262.2 | 251.3 | 288.0 | 298.5 | 280.2 | 304.0 | 281.4 |
| **1975** | 277.1 | 292.1 | 262.0 | 290.3 | 301.3 | 291.2 | 279.9 | 268.4 | 250.1 | 289.4 | 302.5 | 281.4 | 306.5 | 281.5 |
| **1980** | 285.3 | 291.2 | 276.4 | 290.5 | 300.6 | 298.1 | 280.1 | 270.8 | 252.7 | 294.2 | 300.3 | 281.0 | 313.3 | 277.8 |
| **1985** | 294.6 | 287.4 | 286.0 | 293.7 | 302.2 | 303.7 | 282.7 | 270.7 | 262.6 | 299.0 | 302.5 | 275.3 | 319.9 | 268.5 |
| **1990** | 295.5 | 293.3 | 290.6 | 296.6 | 304.4 | 304.3 | 278.5 | 269.3 | 275.5 | 299.8 | 307.3 | 273.7 | 318.7 | 264.6 |
| **1995** | 300.9 | 292.3 | 290.0 | 292.8 | 294.8 | 305.2 | 274.5 | 272.0 | 270.0 | 296.6 | 302.3 | 273.6 | 315.4 | 263.3 |

## Table B.2. Average prose scores of individuals aged 17–25

| | Belgium | Canada | Switzer-land | Germany | Denmark | Finland | U.K. | Ireland | Italy | Nether-lands | Norway | New Zealand | Sweden | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POPULATION | | | | | | | | | | | | | | |
| 1960 | 243.3 | 257.6 | 252.9 | 267.0 | 259.8 | 265.8 | 245.3 | 241.6 | 217.9 | 263.0 | 273.5 | 268.0 | 290.6 | 274.0 |
| 1965 | 260.4 | 273.3 | 259.9 | 276.7 | 270.0 | 276.3 | 261.3 | 250.5 | 228.8 | 274.1 | 281.1 | 272.9 | 295.7 | 276.3 |
| 1970 | 269.3 | 285.5 | 253.5 | 277.2 | 277.7 | 284.2 | 270.4 | 261.8 | 245.3 | 278.8 | 287.5 | 279.5 | 298.7 | 280.8 |
| 1975 | 271.0 | 290.8 | 256.2 | 278.8 | 281.7 | 292.4 | 272.6 | 270.0 | 246.8 | 284.3 | 292.5 | 280.5 | 302.1 | 282.5 |
| 1980 | 280.3 | 289.9 | 267.3 | 282.0 | 282.4 | 301.8 | 273.4 | 271.8 | 251.1 | 291.4 | 294.0 | 281.0 | 307.7 | 280.0 |
| 1985 | 286.7 | 284.7 | 274.1 | 283.4 | 284.4 | 307.3 | 275.0 | 271.5 | 260.4 | 295.1 | 297.9 | 276.3 | 313.5 | 274.7 |
| 1990 | 290.9 | 284.3 | 279.8 | 284.9 | 287.3 | 311.4 | 274.4 | 274.6 | 274.2 | 296.9 | 303.4 | 277.5 | 314.0 | 267.0 |
| 1995 | 292.7 | 287.1 | 284.0 | 282.5 | 282.3 | 314.0 | 273.9 | 277.6 | 274.4 | 292.1 | 300.0 | 278.1 | 312.7 | 263.2 |
| WOMEN | | | | | | | | | | | | | | |
| 1960 | 233.7 | 264.4 | 251.0 | 265.1 | 259.9 | 270.2 | 244.3 | 242.2 | 205.8 | 260.9 | 275.9 | 271.7 | 287.2 | 279.3 |
| 1965 | 257.6 | 284.3 | 253.9 | 273.1 | 270.1 | 281.2 | 259.7 | 254.0 | 222.1 | 272.2 | 284.9 | 275.9 | 300.1 | 276.5 |
| 1970 | 267.5 | 296.0 | 251.0 | 276.4 | 277.8 | 288.7 | 269.1 | 262.9 | 244.3 | 277.1 | 289.4 | 281.3 | 303.2 | 283.5 |
| 1975 | 273.0 | 292.9 | 258.8 | 278.3 | 282.5 | 298.3 | 272.6 | 273.4 | 248.2 | 286.2 | 294.7 | 282.3 | 306.3 | 286.4 |
| 1980 | 285.5 | 297.3 | 268.4 | 284.4 | 284.8 | 309.2 | 274.2 | 274.7 | 255.1 | 296.8 | 300.2 | 284.1 | 310.9 | 285.0 |
| 1985 | 288.7 | 290.3 | 271.7 | 285.3 | 287.6 | 314.0 | 274.2 | 274.5 | 262.4 | 298.1 | 304.5 | 280.0 | 314.7 | 282.4 |
| 1990 | 296.3 | 280.9 | 277.6 | 286.4 | 290.5 | 321.4 | 275.3 | 280.6 | 275.1 | 300.4 | 309.6 | 284.1 | 314.4 | 271.9 |
| 1995 | 294.7 | 287.7 | 288.1 | 282.7 | 287.3 | 322.6 | 277.2 | 283.7 | 278.7 | 295.4 | 304.9 | 285.8 | 313.3 | 265.5 |
| MEN | | | | | | | | | | | | | | |
| 1960 | 255.2 | 252.4 | 254.9 | 268.9 | 259.7 | 260.8 | 246.4 | 240.9 | 231.3 | 265.1 | 271.5 | 264.4 | 294.2 | 267.5 |
| 1965 | 263.0 | 261.3 | 267.1 | 280.2 | 269.9 | 271.5 | 263.2 | 247.2 | 236.0 | 276.0 | 277.7 | 269.9 | 291.4 | 276.1 |
| 1970 | 271.2 | 272.8 | 256.1 | 278.1 | 277.6 | 279.8 | 271.7 | 260.8 | 246.1 | 280.3 | 285.8 | 277.8 | 294.8 | 278.0 |
| 1975 | 269.0 | 288.6 | 253.5 | 279.3 | 281.0 | 286.7 | 272.5 | 266.6 | 245.4 | 282.5 | 290.5 | 278.6 | 297.9 | 278.4 |
| 1980 | 275.8 | 282.1 | 266.1 | 279.6 | 280.0 | 294.3 | 272.5 | 268.6 | 247.5 | 286.5 | 288.2 | 277.5 | 304.5 | 274.6 |
| 1985 | 284.8 | 278.9 | 276.2 | 281.3 | 281.3 | 300.8 | 275.8 | 268.4 | 258.5 | 292.1 | 291.9 | 272.3 | 312.3 | 265.2 |
| 1990 | 285.6 | 287.5 | 281.6 | 283.4 | 284.2 | 302.3 | 273.5 | 268.7 | 273.2 | 293.7 | 297.4 | 270.8 | 313.6 | 261.1 |
| 1995 | 293.0 | 286.6 | 280.9 | 282.3 | 277.5 | 305.7 | 270.7 | 271.7 | 270.2 | 289.0 | 295.2 | 270.1 | 312.0 | 260.8 |

**Table B.3. Average quantitative scores of individuals aged 17–25**

| | Belgium | Canada | Switzer-land | Germany | Denmark | Finland | U.K. | Ireland | Italy | Nether-lands | Norway | New Zealand | Sweden | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **POPULATION** | | | | | | | | | | | | | | |
| **1960** | 252.5 | 256.2 | 271.7 | 288.8 | 282.6 | 270.0 | 251.2 | 241.2 | 227.5 | 272.8 | 287.4 | 261.4 | 301.0 | 273.1 |
| **1965** | 271.1 | 270.8 | 275.2 | 296.4 | 294.7 | 279.9 | 265.7 | 251.8 | 237.4 | 281.4 | 295.4 | 268.7 | 305.2 | 277.7 |
| **1970** | 279.5 | 288.9 | 270.4 | 295.9 | 302.8 | 286.5 | 274.3 | 262.7 | 250.8 | 284.8 | 299.6 | 276.8 | 306.3 | 283.1 |
| **1975** | 279.9 | 294.4 | 271.8 | 295.9 | 305.9 | 292.3 | 276.6 | 270.1 | 251.7 | 288.8 | 301.0 | 277.3 | 307.7 | 284.7 |
| **1980** | 291.6 | 295.6 | 281.8 | 297.1 | 305.8 | 297.6 | 276.7 | 270.8 | 254.4 | 296.3 | 302.7 | 277.6 | 312.1 | 283.3 |
| **1985** | 299.9 | 288.9 | 288.2 | 299.1 | 307.4 | 299.5 | 276.9 | 269.9 | 261.6 | 298.4 | 305.1 | 273.0 | 316.7 | 277.4 |
| **1990** | 303.3 | 284.0 | 291.5 | 301.2 | 308.2 | 301.4 | 273.3 | 271.5 | 271.6 | 297.9 | 307.7 | 272.7 | 313.8 | 267.5 |
| **1995** | 300.6 | 283.2 | 292.9 | 295.4 | 300.3 | 298.1 | 268.8 | 274.0 | 268.3 | 292.9 | 299.1 | 272.2 | 309.3 | 262.1 |
| **WOMEN** | | | | | | | | | | | | | | |
| **1960** | 235.8 | 251.9 | 263.0 | 284.3 | 273.9 | 265.3 | 241.4 | 232.2 | 207.0 | 261.0 | 282.0 | 255.1 | 289.0 | 269.5 |
| **1965** | 258.7 | 272.7 | 262.8 | 289.8 | 284.6 | 275.4 | 254.4 | 246.7 | 222.6 | 269.5 | 291.0 | 261.1 | 299.7 | 267.9 |
| **1970** | 267.3 | 294.8 | 263.3 | 290.5 | 293.0 | 282.6 | 263.7 | 256.6 | 240.4 | 273.8 | 291.8 | 266.6 | 300.5 | 276.6 |
| **1975** | 272.1 | 293.0 | 270.4 | 291.2 | 295.9 | 289.6 | 265.7 | 266.2 | 244.6 | 282.1 | 292.6 | 268.7 | 301.5 | 279.4 |
| **1980** | 287.8 | 294.9 | 277.7 | 293.7 | 298.3 | 295.9 | 265.9 | 266.2 | 248.4 | 292.0 | 298.5 | 270.7 | 304.9 | 280.4 |
| **1985** | 295.8 | 286.9 | 280.7 | 294.0 | 301.0 | 297.6 | 265.2 | 265.0 | 254.0 | 292.6 | 303.4 | 267.7 | 310.0 | 279.2 |
| **1990** | 303.2 | 273.4 | 285.7 | 295.5 | 302.5 | 302.8 | 265.0 | 271.3 | 263.8 | 292.0 | 305.4 | 269.8 | 307.7 | 265.5 |
| **1995** | 297.2 | 274.6 | 292.0 | 289.1 | 298.2 | 297.2 | 264.2 | 273.8 | 264.7 | 286.4 | 296.2 | 269.3 | 302.7 | 257.5 |
| **MEN** | | | | | | | | | | | | | | |
| **1960** | 273.4 | 259.6 | 281.1 | 293.3 | 292.1 | 275.4 | 261.5 | 250.8 | 250.3 | 284.3 | 291.7 | 267.5 | 313.8 | 277.6 |
| **1965** | 283.0 | 268.7 | 290.0 | 302.8 | 304.5 | 284.3 | 278.1 | 256.6 | 253.5 | 293.1 | 299.3 | 276.6 | 310.6 | 290.1 |
| **1970** | 291.9 | 281.8 | 278.0 | 301.6 | 312.2 | 290.3 | 285.7 | 268.3 | 261.0 | 294.9 | 306.7 | 286.9 | 311.5 | 290.1 |
| **1975** | 287.2 | 295.8 | 273.3 | 300.6 | 315.5 | 294.9 | 287.6 | 273.9 | 258.5 | 295.2 | 309.1 | 286.4 | 313.7 | 290.2 |
| **1980** | 295.0 | 296.3 | 286.3 | 300.6 | 313.0 | 299.3 | 287.6 | 276.0 | 259.9 | 300.2 | 306.6 | 285.3 | 319.2 | 286.5 |
| **1985** | 303.7 | 290.9 | 294.5 | 304.5 | 313.7 | 301.4 | 289.0 | 275.0 | 269.1 | 304.0 | 306.5 | 278.6 | 323.3 | 275.1 |
| **1990** | 303.4 | 293.9 | 296.2 | 306.8 | 313.7 | 300.2 | 281.5 | 271.6 | 280.1 | 303.3 | 309.9 | 275.6 | 320.0 | 270.0 |
| **1995** | 306.2 | 291.4 | 293.5 | 300.5 | 302.3 | 298.9 | 273.2 | 274.2 | 271.7 | 299.1 | 302.0 | 275.3 | 315.5 | 266.7 |

**Table B.4.  Average document scores of individuals aged 17–25**

| | Belgium | Canada | Switzer-land | Germany | Denmark | Finland | U.K. | Ireland | Italy | Nether-lands | Norway | New Zealand | Sweden | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **POPULATION** | | | | | | | | |
| 1960 | 250.7 | 251.8 | 258.6 | 275.7 | 270.8 | 264.7 | 242.8 | 233.8 | 214.5 | 265.6 | 280.0 | 256.2 | 296.3 | 263.2 |
| 1965 | 266.9 | 271.3 | 263.6 | 283.7 | 284.9 | 276.6 | 259.5 | 244.8 | 224.0 | 277.2 | 290.4 | 264.1 | 301.3 | 267.5 |
| 1970 | 272.9 | 278.8 | 258.0 | 286.5 | 295.2 | 284.8 | 269.1 | 255.2 | 238.6 | 282.5 | 297.5 | 272.2 | 303.2 | 273.1 |
| 1975 | 274.9 | 292.8 | 261.2 | 288.1 | 301.2 | 293.7 | 272.4 | 264.0 | 240.7 | 287.9 | 301.2 | 274.4 | 306.4 | 275.2 |
| 1980 | 287.3 | 294.9 | 273.8 | 290.5 | 305.0 | 303.8 | 274.1 | 265.6 | 246.2 | 295.5 | 304.3 | 276.6 | 312.7 | 273.9 |
| 1985 | 294.0 | 290.6 | 282.7 | 292.8 | 308.6 | 309.9 | 276.0 | 265.8 | 254.4 | 299.3 | 309.2 | 273.2 | 319.8 | 271.5 |
| 1990 | 298.6 | 288.2 | 289.5 | 296.0 | 311.9 | 314.7 | 275.8 | 269.1 | 267.1 | 301.4 | 314.6 | 275.8 | 318.5 | 266.5 |
| 1995 | 300.6 | 293.9 | 295.5 | 292.7 | 304.8 | 314.4 | 277.8 | 271.4 | 267.1 | 299.9 | 309.3 | 276.4 | 314.6 | 263.3 |
| | | | | | | **WOMEN** | | | | | | | | |
| 1960 | 236.5 | 248.3 | 253.1 | 271.2 | 264.3 | 264.8 | 237.0 | 230.2 | 196.0 | 258.0 | 276.2 | 253.7 | 286.8 | 264.0 |
| 1965 | 258.4 | 273.4 | 254.3 | 276.4 | 277.4 | 277.0 | 252.6 | 243.3 | 210.8 | 269.5 | 288.1 | 261.7 | 298.6 | 261.9 |
| 1970 | 268.3 | 282.7 | 254.7 | 282.8 | 288.3 | 284.9 | 262.2 | 252.7 | 230.3 | 275.7 | 291.2 | 268.2 | 300.5 | 270.3 |
| 1975 | 274.6 | 293.6 | 263.0 | 285.2 | 294.9 | 295.3 | 265.3 | 263.3 | 234.6 | 285.1 | 294.2 | 269.9 | 305.0 | 274.5 |
| 1980 | 289.6 | 294.6 | 271.2 | 289.6 | 301.0 | 306.9 | 268.1 | 263.4 | 241.3 | 295.1 | 302.5 | 273.4 | 309.2 | 275.4 |
| 1985 | 292.7 | 288.8 | 277.4 | 290.5 | 305.6 | 311.0 | 268.8 | 262.9 | 248.2 | 297.7 | 309.4 | 271.7 | 315.2 | 276.8 |
| 1990 | 299.7 | 277.0 | 284.2 | 292.3 | 308.5 | 319.4 | 271.0 | 270.7 | 261.4 | 300.3 | 314.8 | 277.0 | 314.7 | 269.7 |
| 1995 | 299.7 | 288.5 | 295.4 | 289.0 | 304.9 | 318.0 | 275.7 | 272.8 | 266.0 | 297.8 | 308.8 | 277.6 | 310.4 | 264.2 |
| | | | | | | **MEN** | | | | | | | | |
| 1960 | 268.5 | 254.6 | 264.7 | 280.0 | 277.8 | 264.5 | 249.0 | 237.7 | 234.9 | 273.0 | 283.1 | 258.5 | 306.4 | 262.4 |
| 1965 | 275.0 | 269.0 | 274.8 | 290.9 | 292.0 | 276.2 | 267.0 | 246.2 | 238.3 | 284.8 | 292.5 | 266.6 | 304.0 | 274.6 |
| 1970 | 277.4 | 274.2 | 261.7 | 290.5 | 301.8 | 284.8 | 276.4 | 257.5 | 246.8 | 288.9 | 303.2 | 276.1 | 305.6 | 276.1 |
| 1975 | 275.2 | 291.9 | 259.2 | 291.0 | 307.4 | 292.1 | 279.6 | 264.8 | 246.3 | 290.5 | 307.9 | 279.2 | 307.7 | 275.9 |
| 1980 | 285.2 | 295.2 | 276.7 | 291.4 | 308.8 | 300.6 | 280.1 | 267.9 | 250.7 | 295.8 | 306.0 | 280.2 | 316.1 | 272.3 |
| 1985 | 295.3 | 292.4 | 287.3 | 295.4 | 311.6 | 308.9 | 283.3 | 268.8 | 260.4 | 300.8 | 309.0 | 274.9 | 324.3 | 265.1 |
| 1990 | 297.5 | 298.6 | 293.9 | 299.6 | 315.2 | 310.3 | 280.5 | 267.6 | 273.4 | 302.4 | 314.4 | 274.6 | 322.5 | 262.7 |
| 1995 | 303.6 | 299.0 | 295.6 | 295.7 | 304.8 | 310.9 | 279.8 | 270.0 | 268.1 | 301.8 | 309.8 | 275.3 | 318.6 | 262.4 |

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