Literacy and Growth:

New Evidence from PIAAC*

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Abstract

Expanded international data from the PIAAC survey of adult skills allow us to replicate the IALS-based analysis by Coulombe, Tremblay and Marchand (2004) as well as Coulombe and Tremblay (2006) based on more recent and more comprehensive data on the literacy skills of the adult population. Results from panel estimations over the period 1970-2010 suggest that literacy skills have become an even more important determinant of economic growth than was suggested by the IALS analysis covering the period 1960-1995. Our estimates imply long-run elasticities of GDP per capita with respect to literacy of about 3. This means that in the long run a one-percent increase in literacy translates into a three-percent increase in GDP per capita. Short-run elasticities are also substantial. The association between labor productivity and literacy is equally strong. This suggests that the effect of literacy on living standards goes beyond its effect on unemployment and participation rates A closer inspection of the data additionally reveals some important heterogeneities: Investment in the human capital of women appears to have a much stronger effect on subsequent growth than investment in the human capital of men. Our results also suggest that underinvestment in human capital hampers growth by more than developing highly talented individuals stimulates it. Specifically, the proportion of adults with low levels of literacy skill – Levels 1 and 2 – appears to have a much larger impact on growth rates than the proportion of adults with Level 4 and 5 literacy proficiency. Thus, policies that serve to reduce the proportion of low skilled adults would likely yield higher returns than those that serve to increase the proportion of high skilled adults.

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Content

I. Introduction

Economic and social policy is guided by policy makers' assumptions about how best to increase wealth and the welfare of populations. Policy makers in the OECD area have long appreciated that human capital – what individuals know and can apply to productive use – is an important enough determinant of long-term growth to justify significant investments that serve to increase the quantity of education. However, policy makers have paid much less attention to understanding how differences in the quality and equity of educational output have influenced key growth rates or how differences in the efficiency of the markets that mediate skill supply and demand influence rates of skill utilization. At the same time, research that can inform policy about the importance of the quality of the educational output for national productivity and economic growth is scarce. At the macro level, the bulk of the empirical literature relies almost exclusively on available quantity-based measures of human capital investment such as educational attainment, which is typically proxied by years of schooling. While such measures are certainly related to human capital and, in fact, have been shown to be economically relevant, they nevertheless might be poor approximations of effective human capital.

Until fairly recently, almost all of the international evidence on quality-based measures of human capital came from the International Adult Literacy Survey (IALS) and the Adult Literacy and Life Skills Survey (ALL). These surveys were the world's first comparative assessments of the cognitive skills of the adult population. Analysis of individual data from these surveys provided evidence of the significant impact that differences in literacy skills on a broad range of individual labor-market, educational, social, and health outcomes. More specifically, literacy skill differences were shown to influence the incidence of employment, working time, the average spell durations of unemployment, as well as income and the probability of receiving social benefits (McCracken and Murray, 2009). Analysis also established that low-skilled adults were 2.5 to 13 times more likely of experiencing poor outcomes even after adjustment for a broad range of other variables known to influence outcomes (DataAngel, 2009). Research undertaken in Canada suggested that these relationships are causal, a finding that suggests that investments in adult skill upgrading might yield significant returns to both individuals and firms (SRDC, 2014).

At the macro-economic level, analysis of the 1994-1998 IALS data established that differences in average adult literacy skills – the ability to read and apply what is read to productive use – was an important determinant of differences in the growth of GDP per capita and labor productivity among OECD economies (Coulombe, Tremblay and Marchand, 2004; Coulombe and Tremblay, 2006). In fact, literacy scores were better predictors of long-run growth of OECD countries than schooling attainment data. Additionally, higher proportions of adults with relatively low skill levels – at levels 1 and 2 on the international proficiency scales – yielded significant reductions in rates of economic growth over the long run.

However, skill measures from almost two decades ago may not accurately capture the situation in economies that have undergone substantial technological change (Autor, Levy, and Murnane, 2003; Goldin and Katz, 2008; Acemoglu and Autor, 2011). Since the analysis of the IALS and ALL data was undertaken, the global economy has been in a state of flux precipitated by a massive increase in the global supply of productive skills, the globalization of markets for raw materials, financial capital, production technology and R&D, reductions in tariff and non-tariff barriers to market entry, and the diffusion of computer technology throughout the world's economies.

Recently, a new large-scale assessment of the skills of the adult population was conducted – the Programme for the International Assessment of Adult Competencies (PIAAC). Compared to IALS and ALL, PIAAC has greater country coverage, considerably larger sample sizes, and tests that cover a wider variety of skills. Analysis of the PIAAC data for Canada confirms that the global changes in the last decades have had a significant impact on the relationship of literacy skill with individual outcomes, including a massive increase in the relative wage premia paid to workers with high literacy skill levels (Canada West Foundation, 2018).

In this report, we seek to determine how the changes to the global economy have shifted the impact that literacy skill has on economic growth. We do so by largely replicating the IALS-based analysis by Coulombe, Tremblay and Marchand (2004) as well as Coulombe and Tremblay (2006), but use the more recent and more comprehensive PIAAC data. Specifically, we construct synthetic time series of literacy skills of labor-market entrants by exploiting the age structure of the PIAAC data. This allows us to conduct a panel data analysis of cross-country growth for 33 developed countries over the period 1970-2010.

Our results suggest that literacy skills have become an even more important determinant of economic growth than was suggested by the IALS analysis covering the period 1960-1995. Across various specifications, we systematically find a strong positive association between literacy and GDP growth. Our estimated coefficients imply long-run (i.e., steady state) elasticities of output with respect to literacy of about 3. In other words, a one-percent increase in literacy test scores translates into a three-percent increase in GDP per capita in the steady state. Using these estimated elasticities, back-of-the-envelope calculations suggest that the skills acquired by an additional year of schooling increase GDP per capita by about 9 percent. Estimated elasticities of output with respect to literacy are very similar when considering labor productivity instead of GDP per capita.

Our results reinforce the conclusion of the earlier analysis with IALS data that literacy skills are an important determinant of economic growth. However, long-run elasticities of GDP growth implied by our estimations are about twice as large as those obtained using IALS; elasticities of labor productivity are also larger. These results document the extent to which modern knowledge-based economies value skills.

In line with Coulombe and Tremblay (2006) and Hanushek and Woessmann (2008, 2012), we find that quality-based measures of human capital (i.e., literacy) are more important for growth than quantity-based measures (i.e., years of schooling). Thus, it is skills, not the number of years spent in school, that drive economic growth.

Text Box: Literacy Skills in PIAAC

The PIAAC literacy measures assess the ability of adults aged 16 to 65 to read information presented in text, charts and graphs and, importantly, to apply what they have read. Defined thus, literacy has been shown to have a significant impact on the efficiency of learning and on the productivity of workers. In an economy in which automation is reducing the demand for workers who are only required to apply routine procedural knowledge and is increasing the demand for workers who are able to fluidly solve information-intense problems with the help of computers and in heterogeneous teams, advanced literacy skill will likely be a prerequisite for getting and maintaining employment and for attracting a living wage.

Our results also indicate some important heterogeneities. First, investment in the human capital of women that precipitates increases in literacy skill levels appears to have a much stronger effect on subsequent growth than investment in the human capital of men. Moreover, our results suggest that underinvestment in human capital (as indicated by a large percentage of adults with low literacy proficiency, conventionally Level 1 and 2) hampers growth by more than developing highly talented individuals (as indicated by a large share of adults with high literacy proficiency, conventionally Level 4 and 5) stimulates it.[1]

The remainder of the report is structured as follows. Section 2 provides an overview of the evolution of research in human capital and growth with a special emphasis on how human capital is measured in various research applications, distinguishing between studies that use quantity-based measures of human capital and those that use direct measure of cognitive skill as proxies for human capital. Section 3 presents the data, while Section 4 lays out our empirical strategy. The main results, together with robustness checks and heterogeneity analysis, are presented in Section 5. There we also discuss the limitations of our analysis. Section 6 concludes with some policy implications of our results.

II. Literature review

Modern human capital research mainly focuses on two complementary aspects. One is reflected in the work of Jacob Mincer, Gary S. Becker, and others, who developed the general theory and focused attention on the study of the relationship between human capital and labor income.[2] The other aspect is reflected in the work of Schultz, Denison, and Griliches, who use the theory of human capital to analyze productivity and economic growth. Given the evidence on individual returns to human capital accumulation, it seems logical that human capital would also matter for the macroeconomic performance of an economy as a whole. In fact, the advent of human capital theory in the 1950s led researchers to attempt a better understanding of the roles education and training play in a country's economic growth. However, from a theoretical point of view, it took some time before the role of human capital investment was well integrated in theories of economic growth. To a considerable extent, this lack of integration can be traced to a general lack of reliable measures of individual skill.

[1] Workers with Level 1 and 2 literacy skill are able to read well enough to learn to apply routine procedural knowledge efficiently but struggle to acquire the information to solve non-routine problems efficiently.

[2] An overwhelming amount of evidence documents non-pecuniary returns to human capital accumulation outside the labor market. For example, Wagstaff (1993) shows that schooling improves health while simultaneously reducing the number of physician visits. In particular, individuals with more schooling react more quickly and more effectively to new information on health (Kenkel, 1991; Glied and Lleras-Muney, 2008). Education matters also in a competitive marriage market (Becker, 1973; Chiappori, Iyigun, and Weiss, 2009) and affects family formation (Rockwell, 1976; Chadwick and Solon, 2002). Moreover, education affects fertility (Black, Devereux, and Salvanes, 2005, 2010), teenage pregnancies (Black, Devereux, and Salvanes, 2008), and divorce rates (Oreopoulos and Salvanes, 2011). Education also appears to affect preferences, risky behavior, crime, and trust (Lee and McCrary, 2005; Oreopoulos and Salvanes, 2011).

Human capital and economic growth

Early neoclassical growth models did not consider education as an input to production. These early theoretical attempts to understand economic growth are based on models characterized by a neoclassical production function with diminishing returns to capital inputs. This functional form, however, implies that in the absence of continuing improvements in technology, per capita growth will cease. This modeling deficiency was initially patched over by assuming that technological progress occurred in an exogenous manner (Solow, 1956). It was not until the late 1980s and 1990s that neoclassical growth models were modified to explain technological progress within the system. Human capital accumulation plays a key role in these models as a main determinant of technological progress and, thus, long-term economic growth.

The idea that human capital could generate long-term sustained growth was one of the critical features of the "new growth" literature initiated by Lucas (1988) and Romer (1986). The initial wave of endogenous growth models (Lucas, 1988; Romer, 1986) did not really provide a theory of technological change, but posited that spillovers of knowledge between producers and external effects from human capital helped avoid the tendency for diminishing returns to the accumulation of capital.

For example, in order to capture the critical role investment in human capital plays in economic growth, Lucas (1988) combined the theory of human capital and Solow's model to show the consequences of technical change for economic growth, and established a model emphasizing human capital accumulation through schooling and learning-by-doing, as well as emphasizing physical capital accumulation and technological change. In Lucas's model, the individual's "human capital" was the embodiment of Schultz's and Becker's human capital concept, Solow's technology change, and Romer's knowledge accumulation. Also, the external effect of human capital was distinguished from its internal effect. The effect of human capital included its effect as labor on production, its external benefit, which spills over from one person to another, and its effect as the source and embodiment of technology innovation, technology shift, and technology change.

The more elaborate incorporation of R&D theories (combined with some form of ex-post monopoly power) in the growth framework (Aghion and Howitt, 1992; Romer, 1987, 1990a) further advanced the theoretical understanding of long-term economic growth. In these models, technological progress results from purposive R&D activity. These models also include some form of ex-post monopoly power to ensure that R&D activity is rewarded. A key implication of these models is that the rate of growth can continue to be positive as long as the economy (in the guise of, for example, entrepreneurs) doesn't run out of ideas.

Empirical research on the effect of human capital accumulation—in particular education—emerged in parallel with theory. However, in this literature, measurement issues were and are a major concern. The various issues in this literature related to measurement of human capital are discussed in the next section.

The traditional approach to investigating effects of human capital on economic growth is to estimate cross-country growth regressions. These growth regression models relate countries' average annual growth in gross domestic product (GDP) per capita over several decades to measures of human capital and a set of other variables that affect economic growth. Following Barro (1991) and Mankiw, Romer, and Weil (1992), most results from early cross-country growth regressions show a significant positive link between quantitative measures of human capital and economic growth. In particular, primary schooling appears to be a highly important factor for growth in GDP per capita (see Sala-i-Martin, Doppelhofer, and Miller, 2004).

An alternative approach to estimating the importance of human capital for economic success is based on panel data models. Many advantages of the panel data approach to growth regressions over the pure cross-country approach have been discussed in the literature. However, the one key advantage of a panel specification is that it no longer requires assuming an identical production function for all countries, which may give rise to the omitted variable bias in a regression analysis. For example, Islam (1995) implemented a panel data specification of the Solow production function augmented by human capital that he estimated by splitting up data covering the 1960-1985 period into five sub-periods for each country. The panel estimation then allows for the inclusion of country-specific fixed effects to correct for the omitted variable bias arising due unobserved country-specific differences or shocks. However, as empirical measure for the steady state level of human capital, Islam (1995) also used a quantitative measure of human capital, namely the average years of schooling as well as the share of individuals with primary, secondary, or tertiary education in total population over 25 years, obtained from Barro and Lee's database.

A potential estimation problem in such a panel framework is that the explanatory variables might be serially correlated. In addressing this problem, Barro (1997) uses an estimation method that takes account of the likely endogeneity of the explanatory variables by using lagged values as instruments. With respect to human capital, Barro (1997) finds that years of schooling at the secondary and higher levels for males aged 25 and over do have a significantly positive effect on growth in the sample of all countries.

Measures of human capital

These days, almost everybody agrees that human capital is highly important, but there is less consensus about what human capital actually is. For example, one definition of human capital is that it is “the knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being” (OECD, 2001a). Clearly, human capital is an extremely broad concept. Hence, it is difficult to measure. In fact, since its inception, the empirical literature on the effects of human capital accumulation and the production of human capital has been plagued with measurement issues. Consequently, much of the academic debate in this literature today focuses on data-quality issues.

This section reviews some of the most important available proxies for human capital commonly used in empirical studies. Please note that this review is not intended to provide a complete survey of all available proxies for human capital; rather, it focuses on selected research questions and discusses different ways of measuring human capital in these applications. In particular, two broad categories of proxies for human capital are discussed: quantity-based measures of human capital and recently available direct measures of cognitive skill.

Quantity-based measures of human capital

Empirical research on economic growth was from the beginning dominated by concerns about the measurement of input factors. Based on the Solow model, a growth accounting framework was developed that breaks down growth in aggregate output into contributions from the growth in inputs. The earliest growth accounting studies included only physical capital and labor as input factors. In these early applications, the sum of employed individuals or the total hours worked served as a proxy for the input embodied in human beings. The residual estimated in such growth accounting exercises is the well–known Solow residual or total factor productivity (TFP) and its interpretation became a famous topic of debate. Many researchers interpret the change in TFP as a proxy for technological progress. Others are more skeptical about this interpretation and call TFP a measure of ignorance (Abramovitz, 1956). Jorgenson and Griliches (1967) even hypothesized that the residual could be eliminated altogether if one properly adjusts the input measures for shifts in quality and composition. As a consequence of these considerations, it is now best practice in any productivity analysis to work with quality-adjusted measures for capital inputs (BLS, 1993; OECD, 2001b).

Jorgenson, Gallop, and Fraumeni (1987) developed a framework that adjusts labor input based on compositional changes. This framework is the foundation for several recent studies analyzing changes in labor quality (Card and Freeman, 2005; Jorgenson, 2005; Schwerdt and Turunen, 2007, 2009, 2010). Their key idea behind this approach is to augment labor input to reflect differences in labor quality by aggregating the input of different categories of labor weighted by their relative contribution to individual productivity. The weights are derived from coefficient estimates of Mincerian wage regressions (similar to Equation (1)) on the basis of survey data that include key indicators (typically gender, age, and educational attainment) for different categories of labor input as explanatory variables. Provided the necessary data are available, this approach can be easily extended to include a myriad of labor input categories (Jorgenson, 1995).

Moreover, this approach can be used to calculate not only average levels of human capital, but also human capital distribution among households (Dagum and Slottje, 2000). The key disadvantage of this approach is that it relies heavily on the assumption that observed wage differences reflect productivity differences. Additionally, the detailed data required for these calculations are available only in a few advanced countries and differences in measurement of key variables (e.g. wages, educational attainment) severely complicate cross-country comparisons.

Measures of human capital also play a prominent role in modern cross-country growth regressions (for a detailed review, see Woessmann, 2003). Following Summers and Heston's (1988, 1991) compilation of national accounts data for a large number of countries and years in the Penn World Table, several early contributions to this employed adult literacy rates as a proxy for human capital (e.g., Azariadis and Drazen, 1990; Romer, 1990b). Literacy rates are defined as the percentage of adults (15 years and over) in the population who are able to read and write a simple statement related to daily life. Obviously, literacy rates are related to the stock of human capital, but they are a very crude measure of it.

Other studies use school enrollment ratios (e.g. Barro, 1991; Mankiw, Romer, and Weil, 1992; Levine and Renelt, 1992) as proxies for an economy's human capital. School enrollment ratios are defined as the share of students enrolled in school at a grade level over the total population of the corresponding age group. However, the use of enrollment ratios has been criticized as a poor measure of the stock of human capital available for current production (see Gemmell, 1996). A primary concern is that students currently enrolled in schools are not yet a part of the labor force and, consequently, their education cannot be a determinant of current production. Moreover, enrollment rates might be a poor proxy for growth in educational capital because growth of educational attainment depends not on the current enrollment rate, but on the difference between the enrollment rate of the cohort leaving the labor force and the cohort entering the labor force (see Pritchett, 2001).

In an attempt to overcome these shortcomings of using enrollment rates as a direct measure of human capital, other studies construct data sets on years of educational attainment based on the perpetual inventory method, which employs data on enrollment ratios, repeater rates, age-specific mortality rates, and drop-out rates (for a detailed description of the perpetual inventory method, see Lau, Jamison, and Louat, 1991; Nehru, Swanson, and Dubey, 1995). The most innovative and important contribution in this field of research was made by Barro and Lee (1993), who, using census or survey data on educational attainment, developed an internationally comparable data set on average years of schooling for a large sample of countries and years.

The Barro and Lee data, which have been updated frequently (see Barro and Lee, 1996, 2001, 2010), are a key data source for empirical studies on cross-country differences in educational attainment. The Barro and Lee data focus on the adult population as a substitute for the actual labor force, which allows constructing data on years of schooling for more countries. Barro and Lee's (1993) attainment levels are based on UNESCO's International Standard Classification of Education (ISCED). When data from censuses or surveys are not available, adult illiteracy rates are used to estimate the fraction of the working-age population with no schooling. Missing observations are estimated based on the perpetual inventory method. Specifically, the researcher's start with the directly observed data points as benchmark stocks and estimate changes from these benchmarks on the basis of school enrollment ratios and data on population by age to estimate survival rates. Repeater ratios and drop-out rates do not enter the estimation in Barro and Lee (1993), but are included in the revised version of the data set (Barro and Lee, 1996). Barro and Lee (2001) additionally account for variations in the duration of schooling levels over time within a country and further improve the estimation by using information from consistent census data, disaggregated by age group, along with new estimates of mortality rates and completion rates by age and education level. The latest version of the data set contains information on educational attainment for 146 countries from 1950 to 2010 disaggregated by sex and by five-year age intervals.

The early Barro and Lee (1993, 2001) schooling data was criticized by Fuente and Doménech (2001) and Cohen and Soto (2007) for containing implausible time-series profiles of educational attainment for some countries. Fuente and Doménech (2006) corrected the Barro and Lee data for inconsistencies and breaks in the time series attributable to changes in the measurement methods and in the criteria used in classification, and constructed an improved time series on schooling attainment levels. They evaluated the performance of their corrected data on average schooling and found that their corrected data are more reliable than earlier data sets. In the recent update to their data, Barro and Lee (2010) address most of the concerns raised by Fuente and Doménech (2006) and Cohen and Soto (2001). Based on the updated data, Barro and Lee (2010) compute reliability ratios and find that theirs are similar to the reliability ratios for the data of Fuente and Doménech (2006).

Direct measures of cognitive skills

Until fairly recently, the focus of the empirical literature on human capital has been basically limited to quantity-based measures of human capital both at the micro as well as at the macro level. With data on cognitive skills becoming increasing available and the ability—in at least a few data sets—to link information on cognitive skills to subsequent labor market information, has emerged a new strand of literature that studies the effects of cognitive skills as a direct measure of human capital.

At the macro level, direct measures of cognitive skills prominently entered a growth analysis in Hanushek and Kimko (2000). In this study data from international student achievement tests through 1991 is used to measure labor force quality for 31 countries. They estimate statistical models that relate annual growth rates of real GDP per capita to the measure of cognitive skills, years of schooling, the initial level of income, and other control variables. Their findings suggest that a one country-level standard deviation higher test performance, which is equivalent to forty-seven test-score points in PISA 2000 mathematics, increase annual growth rates by one percentage point. Moreover, when including the measure of cognitive skills in the growth regression, the effect of years of schooling is reduced and becomes mostly insignificant. The inclusion of direct measures of cognitive skills also boosts the explanatory power of the statistical model. Hanushek and Kimko (2000) find that including measures of cognitive skills raises the share of the explained variance by the model from 33 to 73 percent.

Hanushek and Woessmann (2008) extend the analysis of Hanushek and Kimko (2000) by including data from additional international student achievement tests, focusing at an even longer time period (1960–2000) and extending the sample of countries with available test-score and growth information to 50 countries. Their measure of cognitive skills is a simple average of the mathematics and science scores over all several international tests.

The cognitive achievement tests used in Hanushek and Woessmann (2008) stem from a variety of sources. In particular, the data collection in Hanushek and Woessmann (2008) uses information for countries participating in a cooperative venture under the International Association for the Evaluation of Educational Achievement (IEA) and from the OECD. For example, the data set includes information from the Trends in International Mathematics and Science Study (TIMSS) 2003 and from the Programme for International Student Assessment (PISA) studies.

Hanushek and Woessmann (2008) develop a composite measure of performance for each country by aggregating across the variety of tests. To make test results comparable between countries and over time, they develop a common metric. The construction of the common metric builds on data from the U.S. National Assessment of Educational Progress (NAEP), which is conceptually close to the TIMSS tests and provides information over time on a consistent basis.

The results of Hanushek and Woessmann (2008) basically confirm the findings of Hanushek and Kimko (2000). Including measures of cognitive skills in a growth analysis makes the estimated relationship between years of schooling and economic growth insignificant. Hanushek and Woessmann (2008) conclude that “school attainment has no independent effect over and above its impact on cognitive skills” (see Hanushek and Woessmann, 2008, page 639).

Several other studies also confirm the importance of direct measures of cognitive skills for understanding economic growth of countries. Lee and Lee (1995) find an effect size similar to Hanushek and Kimko (2000) using data from the First International Science Study 1970–71 on the participating seventeen countries. The results of Barro (2001) suggest that both the quantity of schooling and test scores matter for economic growth, but measured cognitive skills are more important. Extensions of the measure of Hanushek and Kimko (2000) used in cross-country growth regressions by Bosworth and Collins (2003) and in the cross-country industry-level analysis by Ciccone and Papaioannou (2009) also indicate that measured cognitive skills are more important for economic growth than quantity-based measures of human capital. Recently, Hanushek et al.

(2017) also showed that, on top of levels of cognitive skills, the average individual returns to skills are also systematically larger in countries that have grown faster in the recent past.

Economic growth and human capital measures in adult literacy surveys

Two well-known empirical studies on economic growth based on data from IALS are Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006). These studies build on the idea to construct an aggregate human capital measure using IALS scores and then apply this measure in an analysis of economic growth.[3] In particular, the authors use IALS test scores directly as an indicator for human capital in panel growth regressions similar to Islam (1995). They measure differences in human capital investment by constructing a synthetic time series of the literacy level of the youngest cohort entering the labor market in each period. Construction of the synthetic time series is based on the age distribution of IALS literacy scores. The synthetic time series covers 1960–1995 in five-year intervals. For each starting year of a five-year interval, the authors use the average literacy rate of the cohort of individuals in the age 17–25 group for that year. This human capital measure then directly enters the growth regression equation:

(1) $$\Delta Y_{it} = \beta Y_{it-1} + \varphi_1 S(h)_{it} + \varphi_2 S(k)_{it} + \varphi_3 n_{it} + \nu_{it},$$

where ΔY_{it} represents the growth rate of GDP per capita or labor productivity; Y_{it-1} is the lagged level of GDP per capita or labor productivity in period t–1; $S(k)_{it}$ is the five-year average ratio of investment to GDP in period t; n_{it} is the five-year average fertility rate in period t; and v_{it} is a stochastic error term. The key variable of interest is the measure of human capital, $S(h)_{it,}$ which measures human capital in the beginning of period t. The indicators for human capital investment in the estimation are either standard quantity-based measures of school attainment or the IALS literacy score measures. In the latter case, the human capital measure for the growth rate from 1960 to 1964 is based on literacy scores for the 17–25 age group in 1960 (period 0). The quantity-based measures of school attainment are either average years of schooling from Barro and Lee (2001),

[3] Naturally, literacy and numeracy measures provide a proxy for only a small subset of all relevant cognitive skills, but Hanushek and Zhang (2009) provide some interesting descriptive evidence that shows these literacy test scores from the perspective of cognitive tests requiring deeper content knowledge and analytical skills. In particular, they compare IALS scores of individuals between 16 and 25 years of age to the 1995 Third International Mathematics and Science Study (TIMSS) math scores of students in their final year of upper secondary education, who are between 17 and 20 years of age. The correlation between the average country scores is .73, which suggests that IALS scores are a reasonable proxy for general skill levels.

the corrected schooling data from Fuente and Doménech (2006), or a synthetic time series of the reported years of schooling by cohort in IALS 1994–1998 constructed based on the same methodology as the one used to construct the literacy time series.

The results from estimating Equation (1) with the IALS literacy measures show significant positive effects of literacy rates, as a proxy for human capital investment, on GDP growth and labor productivity. Interestingly, no significant effect on GDP growth or labor productivity can be found when quantity-based measures of school attainment are used to proxy for human capital investments (see Coulombe and Tremblay, 2006, Table 3). Coulombe and Tremblay (2006) conclude that "these findings suggest that literacy scores data contain considerably more information about the relative growth performance of nations than the years-of schooling data" (see Coulombe and Tremblay, 2006, page 19). The authors argue that there are three possible reasons for this finding. First, literacy scores may simply be a more accurate measure of the accumulation of human capital than years of schooling because literacy tests are direct measures of skill. Second, literacy scores in the IALS data at any point in time might be a more comparable measure of human capital on a cross-country basis than years of schooling because skills acquired from a year of schooling might differ significantly across countries. Third, the quality of schooling within countries might change over time. The latter two explanations are clearly supported by the evidence presented in Hanushek and Zhang (2009).

III. Data

To construct a time series of the quality of human capital over the past 40 years, we rely on the Programme for the International Assessment of Adult Competencies (PIAAC), developed by the OECD. PIAAC provides internationally comparable data on the skills of the adult populations. The first round of PIAAC data, administered between August 2011 and March 2012, produced data on 24 (mostly OECD) countries (see OECD, 2013; Hanushek et al., 2015). In a second round, PIAAC administered the same skill survey in an additional nine countries (including both non-OECD countries and new members to the OECD) between April 2014 and March 2015 (see OECD, 2016), extending the usable sample with comparable skill data to 33 countries.[4] At least

[4] Participating countries in the first round were Australia, Austria, Belgium (Flanders), Canada, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (specifically England and Northern Ireland), and the United States. In the second round, the following countries participated: Chile, Greece, Indonesia (Jakarta), Israel, Lithuania, New Zealand, Singapore, Slovenia, and Turkey.

5,000 adults participated in the PIAAC assessment in each country, providing considerably larger samples than in IALS and ALL, the predecessors of PIAAC. In each participating country, a representative sample of adults between 16 and 65 years of age was interviewed at home in the language of their country of residence. The standard survey mode was to answer questions on a computer, but respondents without sufficient computer knowledge could also do a pencil-and-paper survey.

PIAAC was designed to measure key cognitive and workplace skills needed for individuals to advance at work and participate in society. The survey assessed cognitive skills in three domains: literacy, numeracy, and ICT (called "problem solving in technology-rich environments" in PIAAC).[5] The tasks respondents had to solve were often framed as real-world problems, such as maintaining a driver's logbook (numeracy domain) or reserving a meeting room on a particular date using a reservation system (ICT domain). The domains, described in more detail in OECD (2013), refer to key information-processing competencies and are defined as

1. *Literacy*: ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential;
2. *Numeracy*: ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
3. *ICT skills*: ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.

PIAAC measures each of the three skill domains on a 500-point scale.[6] All three scales are intended to measure different dimensions of a respondent's skill set, although a person who performs well in literacy usually tends to have relatively higher numeracy and ICT scores, too. IALS suffered from pairwise correlations of individual skill domains that exceeded 0.9, making it virtually impossible to distinguish between different skills. The skill domains in PIAAC are less

[5] Participation in the ICT domain was optional; Cyprus, France, Italy, and Spain (first round) as well as Indonesia (second round) did not participate in this domain.

[6] PIAAC provides 10 plausible values for each respondent and each skill domain. We follow previous literature in using the first plausible value of the test scores in each domain (Coulombe and Tremblay, 2006; Hanushek et al., 2015, 2017). However, making use of all plausible values does not qualitatively change our results. See Perry, Wiederhold, and Ackermann-Piek (2014) for a discussion of the plausible values in PIAAC.

strongly correlated with an individual-level correlation between numeracy and literacy (ICT skills) of 0.83 (0.75); the correlation between literacy and ICT skills is at 0.80.

We follow Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006) in constructing a synthetic time series of the skill level of the cohort entering the labor market in each period. This synthetic time series is based on the age distribution of PIAAC literacy scores, covering the years 1970-2010 in five-year intervals.[7] For each starting year of a five-year interval, we use the average literacy skill level of the cohort of individuals aged 18–27 in that year. [8] In the analysis, we ask the question “how old was the 18 to 27 year old cohort, for each of the synthetic cohorts, in 2012?” (see Appendix F in Coulombe, Tremblay, and Marchand, 2004, for details of the approach).[9] We use sampling weights provided in PIAAC to construct the average skill measures.

Figure 1 plots average literacy skills for the population aged 18–27 relative to the cross-sectional mean in each period. Canada is shown for comparison in each graph. The only countries whose populations have consistently higher skills than the Canadian population are Australia, Finland, Japan, the Netherlands, New Zealand, Norway, and Sweden. Japan is the international top performer; Indonesia and Turkey perform worst. We also observe that skills develop differently over time across countries. In some countries, such as Greece, Russia, and the United States, skills have decreased over time, indicating that the quality of human capital of workers entering the labor market has declined. Other countries witnessed an increasing skill level of their entry-age workers; examples are Chile, Korea, Singapore, and Spain. However, in the majority of countries, including Canada, the skill level of entry-age workers changed relatively little over time.

[7] We focus on literacy skills to be comparable to the analysis by Coulombe and Tremblay (2006). Results using numeracy skills are qualitatively similar, although the association between numeracy and GDP per capita and especially labor productivity is somewhat weaker than for literacy. See Appendix Tables A-1 and A-2. We do not perform the analysis for ICT skills because of the considerably smaller country coverage.

[8] This slight deviation from Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006), who use individuals aged 17-25 to define their labor-market-entry cohort, was necessary because age in some PIAAC countries is reported only in five-year intervals. As we use 2012 (i.e., the year PIAAC was conducted) as reference year, using an entry age of 17-25 years would not have fitted the age cohorts available in PIAAC.

[9] See Section 5 for a discussion of the shortcomings of constructing a synthetic time series from cross-sectional data.

In the study, we also employ data on GDP per capita, labor productivity[10], investment as a share of GDP, and imports and exports, all of which are from the Penn World Tables 9.0 (see Feenstra, Inklaar, and Timmer, 2015). These variables are expressed in purchasing power parities (PPP), which allow real-quantity comparisons across countries. Fertility rates (live births per woman) are from the United Nations' database.

IV. Estimation

Our preferred estimation strategy uses PIAAC scores as a direct measure of human capital employed in a straightforward dynamic panel framework similar to the model estimated in the seminar work by Islam (1995). As the usual "growth-initial level" regression model, we can derive our panel regression model from the standard conceptual growth framework by collecting terms with lagged outcomes on the right-hand side.[11] We prefer the dynamic panel regression model over the "growth-initial level" model for purely econometric reasons. In particular, using an outcome that is a function of the lagged value of the outcome (as is the case for a growth rate) together with the lagged outcome as explanatory variable is problematic because any measurement error in the outcome would affect both sides of the equation, thereby creating a purely mechanical correlation that does not have any economic interpretation.

More specifically, our dynamic panel model is given by

$$Y_{it} = \beta_1 Y_{it-1} + \beta_2 h_{it} + \beta_3 k_{it} + \beta_4 n_{it} + \tau_t + c_i + \varepsilon_{it}\,, \tag{2}$$

where Y_{it} represents GDP per capita or log labor productivity; Y_{it-1} is the lagged level of GDP per capita or labor productivity in period t–1; h_{it} measures human capital (i.e., literacy skills) in the beginning of period t;[12] k_{it} is the five-year average ratio of investment to GDP in period t; n_{it} is the five-year average fertility rate in period t; τ_t is a period fixed effect, c_i is a country fixed effect, and ε_{it} is a stochastic error term. As is standard in the growth literature, all variables in Equation (2) are in logs. The inclusion of country fixed effects c_i allows to account for the omitted variable bias arising due unobserved country-specific differences or shocks (see Section 2). In particular, c_i pick up all kinds of unobserved country-specific factors that are constant over time. In addition,

[10] Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006) use GDP per worker to measure labor productivity. We instead use GDP per total hours worked to account for the increasing share of flexible working-time arrangements, in particular, part-time workers (e.g., OECD, 2018).

[11] For the derivation of these two alternative regression specifications, see Equations (9) and (10) as well as the accompanying explanation in Islam (1995).

[12] For instance, when considering the five-year period 1970-1974, h_{it} is the literacy score in 1970.

the period fixed effects τ_t absorb all unobserved effects that equally affect all countries; for instance, business cycles or changes in global demand and market conditions.

The choice of control variables exactly follows Coulombe and Tremblay (2006). To account for the increase in international openness in the period under study, we also estimate regression models that include a control for international openness. This variable is measured as the ratio of exports plus imports to GDP (Barro, 2001).[13]

We deal with the potential problem of serially correlated explanatory variables by instrumenting all explanatory variables (except for literacy skills) with their lagged values as instruments.[14] In particular, instrumenting initial GDP by its lagged value reduces the tendency to overestimate the convergence speed due to measurement error and decreases Nickell bias (Nickell, 1981), which potentially occurs in finite samples when the lagged dependent variable is added as a control.

Note that in the analysis of Coulombe and Tremblay (2006), literacy skills are instrumented by years of schooling (corrected for measurement error) from Fuente and Doménech (2006). However, we have severe methodological doubts against using years of schooling as an instrument for skills. Schooling is clearly a choice variable and may proxy some additional component of human capital that is relevant for earnings (at the individual level) and economic growth (at the macroeconomic level) – such as non-cognitive aspects of education that are not captured in the literacy score. If any of these arguments hold true, the exclusion restriction that the instrument affects economic output only through individuals' literacy skills, and not directly in any other way, would be violated.[15] It is neither appropriate to instrument literacy by its lagged value because our synthetic human capital data are derived from the same survey (i.e., they come from one cross-section).[16] We therefore decided not to instrument literacy.

We are particularly interested in calculating the implied long-run elasticities of output with respect to human capital based on our estimates, which can be directly compared to the results of

[13] Coulombe and Tremblay (2006) filter openness from the effect of population and geographic size in a panel regression. We refrain from doing so mainly because the procedure let to a number of negative values for openness, which would have resulted in missing values after the log transformation. Moreover, the exact filtering procedure applied by Coulombe and Tremblay was unclear.

[14] Using lagged values as instruments effectively reduces our analysis period to 1975-2010.

[15] When using years of schooling as an instrument for literacy skills, we find coefficients on literacy of a similar order of magnitude as in our main analysis. However, standard errors are much larger. Results are available on request.

[16] Results are robust to instrumenting literacy by its lagged value. Results are available on request.

Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006). This long-run elasticity can be computed based on the steady state of Equation (2), where $Y_{it} = Y_{it-1}$. Thus, the implied long-run elasticity of output with respect to human capital is given by:

$$\frac{\partial Y_{it}}{\partial h_{it}} = -\frac{\hat{\beta}_2}{(1-\hat{\beta}_1)}. \tag{3}$$

V. Results

Baseline results: GDP per capita

Table 1 shows our baseline results using GDP per capita as dependent variable. In Columns 1 and 2, we estimate OLS regressions with country and period fixed effects; in Columns 3 and 4, we instrument all control variables by their lagged value to alleviate problems of measurement error and, partly, endogeneity (see Section 4).

Most importantly, the association between literacy and GDP growth is positive and statistically significant at the 1 percent level across specifications. Our coefficients imply long-run (i.e., steady state) elasticities of output with respect to literacy of about 3.[17] This indicates that human capital investments have substantial growth effects: a one-percent increase in literacy test scores translates into a three-percent increase in GDP per capita in the steady state. Using back-of-the-envelope calculations, we can also express this elasticity as the macroeconomic return of one additional year of schooling. Schwerdt (2018) estimated that literacy skills increase by about 8 PIAAC points for one additional year of schooling, which amounts to approximately 3 percent of the average literacy score across countries and cohorts in our sample. Given a long-run elasticity of 2.97 in the full-control IV model (Column 4 of Table 1), the skills acquired by an additional year of schooling increase GDP per capita by about 9 percent. Interestingly, this is close to the well-identified microeconomic estimates on the returns to one additional year of schooling in developed countries (e.g., Card, 1999; Heckman, Lochner, and Todd, 2006; Woessmann, 2016).

These effect magnitudes are about twice as large as those obtained by Coulombe and Tremblay (2006) using IALS data from the mid-1990s, suggesting that human capital became even more important for economic growth in recent decades.[18] This conclusion is reinforced by Figure

[17] Long-run elasticities are shown in the bottom of the table.

[18] Note that this comparison implicitly assumes that a one-point change in the IALS score is the same as a one-point change in the PIAAC score. However, while the average literacy skill level in both assessments is very similar, the standard deviations are slighty different (50 points in PIAAC and 62 points in IALS, using the full sample in both

2, which show the specification in Column 2 of Table 1 graphically. We observe a clear positive relationship between literacy and GDP per capita, and there are no apparent outliers which drive this association.

Note that in the neoclassical growth framework, the steady-state growth rate is determined by the growth rate of technological progress alone, meaning that investment in human capital does not affect steady-state growth. However, human capital does affect the growth rate along the transition path to the steady state, and therefore influences the level of output in the steady state. We can easily retrieve the estimated convergence speed to the steady state from the coefficient on initial GDP.[19] We find annual convergence speeds between 8 percent and 11 percent, which are somewhat larger than those reported by Coulombe and Tremblay (2006), but close to those estimated by Islam (1995) in his OECD sample. From these convergence speeds, it follows that the economy will reach a new steady state after a shock rather quickly. In fact, it takes between six and nine years to close half of the gap to the new steady state.

The signs of the other control variables are in line with the neoclassical growth framework (i.e., fertility is negative, investment rate is positive); control variables are also significant in most specifications. In Columns 2 and 4, we add the openness ratio to our panel model. As expected, the estimated effect of openness on output is positive, albeit not always statistically significant. The regression results for the other determinants of output are quite similar in the regression models without openness ("closed economy") and with openness ("open economy").

Baseline results: Labor productivity

Table 2 reports regressions analogous to those in Table 1 using labor productivity as outcome variable. A population's level of literacy skills remains to be a highly significant predictor of economic performance. In fact, the long-run elasticities of output with respect to literacy are very similar when considering labor productivity as when considering GDP per capita. The respective elasticities are again larger than those obtained by Coulombe and Tremblay (2006). The estimated long-run elasticity in the full-control IV model of 2.58 (Column 4 of Table 2) suggests that the

surveys). This implies that a one-point change in PIAAC is the same as a 1.2-point change in IALS expressed in the PIAAC standard deviation. Therefore, our results might not be perfectly comparable to those of Coulombe and Tremblay (2006); in fact, the difference in magnitude of the literacy skill estimates between our studies is likely smaller than noted above if skills would have been adjusted by the test-specific standard deviation.

[19] In our set up with end-of-period GDP as dependent variable and five-year time periods, the annual convergence speed is calculated as $-\frac{\log(\beta_1)}{5}$, with β_1 as the coefficient on initial GDP.

skills acquired through one extra year of schooling increase aggregate labor productivity by 7.7 percent. The positive association between literacy and labor productivity is also indicated by Figure 3, which depicts the specification in Column 2 of Table 2.

The convergence speed is somewhat lower than in the GDP-per-capita regressions, ranging between 6.6 percent and 7.9 percent, which also implies a longer transition to the steady state. Depending on the specification, it takes between 8.7 years and 10.5 years to go half the distance to the steady state. All control variables have the expected signs, but are typically not significant (with the exception of initial labor productivity).

Controlling for the quantity of human capital

To show the empirical relevance of the quantity of human capital in a country, we now add school attainment to the model. We use years-of-schooling data from Barro and Lee because the data are consistently available for our sample countries and periods; the data compiled by Fuente and Doménech, which were used in the Coulombe and Tremblay (2006) analysis, are available only for 22 out of 33 countries.

Table 3 reports the results. When using GDP per capita as outcome variable, we find a positive, but small and insignificant elasticity of output with respect to school attainment in a model without literacy (Column 1). When adding literacy, the coefficient on school attainment becomes even negative and remains insignificant (Column 2). Most importantly, however, the coefficient on literacy changes very little compared to the model without school attainment. The same is true when using labor productivity as outcome (Columns 3 and 4).

These results suggest that quality-based measures of human capital (i.e., literacy) are a better predictor of a country's growth experience than quantity-based measures (i.e., years of schooling). This is in line with earlier comparisons of the growth effects of quantity-based versus quality-based measures of human capital, most prominently, Hanushek and Woessmann (2008). There are several reasons why school attainment might be a poor approximation of effective human capital. For example, the quality of schooling might change over time and might vary across countries (Hanushek and Zhang, 2009). Approximating an individual's stock of human capital with years of schooling is especially problematic for cross-country comparisons. Such comparisons implicitly assume that the contribution of each school year to human capital accumulation is independent of the quality of the education system. Moreover, measures of educational attainment just reflect an individual's human capital at the end of formal schooling, which may not be good indicators of effective human capital when individuals need to constantly adapt their skills to structural and technological change throughout their entire working life, gain skills through adult education, training and work experience, and lose skill through underutilization.

Female versus male literacy

Next, we analyze potential differences in the growth effects of human capital investments of women and men. To do so, we calculated the literacy level of females (males) aged 18–27 in a particular period in order to capture the investment made in the skills of the cohort of women (men) that enters the labor market in that period. Table 4 presents the results when we separately include the average literacy scores of women and men in our growth regressions.

While female and male literacy appear to exert a substantial positive growth impact when they enter separately, the coefficient on male literacy becomes small and insignificant when both human capital indicators are jointly included. Female literacy, however, remains to be strongly and significantly associated with economic growth. This result, which is in line with the IALS analysis by Coulombe and Tremblay (2006), suggests that investment in the human capital of women appears to have a much stronger effect on subsequent growth than investment in the human capital of men.[20] One reason could be that the decision of women to invest in human capital is typically accompanied with relatively more pronounced changes in labor supply or sorting into more productive occupations or firms, while labor supply of men is more inelastic.

Percentage of the population that achieved specific literacy levels

To explore the relevance of the distribution of skills in the population, we make use of the fact that the OECD assigns respondents to different proficiency level depending on their PIAAC score. Proficiency levels are defined as follows: below level 1 (below 176 PIAAC points), level 1 (176-225 points), level 2 (226-275 points), level 3 (276-325 points), level 4 (326-375 points), level 5 (376 points and above).[21] We define low literacy as a proficiency level of at most 2; high literacy is defined as a proficiency level of 4 or 5.

There is considerable variation in the share of low performers across countries (averaged over all time periods), ranging from 25 percent (Japan) to 95 percent (Indonesia). Similarly, Turkey and

[20] Note that since our regressions control for the fertility rate, the estimated effect of women's literacy on growth is not driven by lower fertility that may result from investment in women's human capital.

[21] See OECD (2013, p. 64) for a description of the types of tasks completed successfully at each level of proficiency.

Indonesia have less than 1 percent of high performers, while Finland and Japan have more than 20 percent. Not surprisingly, the share of low performers decreases over time, while the share of high performers increases.

Table 5 reports the results of using the percentage of individuals with low literacy or high literacy instead of average literacy. A larger population share of low performers in literacy is clearly negatively associated with growth, while a larger share of high performers increases a country's growth rate. Magnitude-wise, we find that the negative relation between low literacy and growth is stronger than the positive association between high literacy and growth is. This suggests that underinvestment in human capital (as indicated by low literacy proficiency) hampers growth by more than developing highly talented individuals (as indicated by high literacy proficiency) spurs it. Thus, investments focused on reducing the proportion of low skilled adults in the population seem to be a more viable strategy to improve a country's economic performance than increasing the share of high performers.

Robustness

We performed several checks of the robustness of our main results. First, one might expect that the relationship between literacy and growth is weakened by the financial crisis starting in 2008, which considerably decreased countries' growth performance despite a high skill level of the population. Thus, we re-estimated the specifications in Tables 1 and 2 for the period 1970-2004. The results, shown in Appendix Tables A-3 and A-4, are very similar as in the full sample, indicating that the crisis did not meaningfully affect the literacy-growth relationship.[22]

Second, we test whether the relationship between literacy and growth is driven by influential outliers. To do so, we rerun the regressions dropping each country separately; no matter which country we excluded, literacy retained a positive and significant coefficient. Thus, we conclude that our main results are not driven by specific countries.[23]

Third, we corrected for Nickell bias by applying a Bias-Corrected Least Squares Dummy Variable (LSDVC) estimator (Wilson, 2009). The relationship between literacy and growth gets even stronger in the LSDVC regressions (Table A-5), suggesting that Nickell bias led to a downward bias of the literacy effect in our main estimations, especially for labor productivity.

[22] Note that effects of the crisis that are similar for all countries are already captured by the period fixed effects.

[23] Detailed results are available on request.

Comparison with IALS countries

Except for Switzerland, all countries which participated in IALS also took part in PIAAC. To allow for a direct comparison of the Coulombe and Tremblay (2006) analysis with our results, we re-estimated the main models restricting the set of countries to those which participated in both IALS and PIAAC. The 13 countries included in this analysis are: Belgium, Canada, Denmark, Finland, Germany, Ireland, Italy, Netherlands, New Zealand, Norway, Sweden, United Kingdom, and the United States.

Table 6 reports the results.[24] The relationship between literacy and growth remains positive and sizeable, but becomes weaker than in the full sample and statistically insignificant. The magnitudes of the long-run elasticities are roughly comparable to those reported in Coulombe, Tremblay and Marchand (2004) – we find somewhat larger elasticities for GDP per capita and somewhat smaller elasticities for labor productivity. In general, we are careful not to interpret these results as conclusive evidence because of the severe reduction in sample size compared to our main analysis (from 236 to 104 observations).

Do skills lead or lag growth?

One remaining question, which is also relevant econometrically, is whether skills lead or lag growth. For instance, if we would systematically observe that countries which grow faster subsequently invest more in skills (e.g., greater growth may provide added resources that can be used to improve schools and test scores), the positive association between literacy and growth suggested by our main results may just be driven by reverse causality. This problem is already alleviated by using beginning-of-period literacy scores, but a closer inspection of the issue is still warranted.

Tables 7 and 8 show the results of including literacy with different lags and leads (up to two periods) in models using GDP per capita or labor productivity as outcomes. While the lags and leads, when included without the contemporaneous value of literacy, are sometimes significantly related to growth, their association with growth disappears once we include the contemporaneous literacy values (see Columns 4 and 8 of Tables 7 and 8). Moreover, contemporaneous literacy remains sizable and significant (except for one specification) when different lags or leads are added. This evidence suggests that economic growth during a particular period is mostly strongly

[24] Note that we refrain from performing an IV analysis because of the small number of observations.

affected by the quality of the labor force entering the labor market in the beginning of that period (vis-à-vis by the skills of earlier cohorts). Moreover, it appears that growth follows skills and not vice versa. This result suggests that the link between literacy and economic growth is not severely affected by problems of revere causality.[25]

Methodological concerns

Our estimates are of course subject to questions about causality. Any unobserved drivers of skill accumulation that are not properly captured by the controls and lagged output, while having an independent impact on output, would confound our estimates. Selective migration across countries during our sample period could for example be such a confounding factor. Thus, our results might be seen as largely descriptive in nature, but considering a range of specifications and alternatives does not change our overall finding, which suggests that the overall pattern of results is very robust.

Beyond this more general mythological issue, there are a number of remaining design-specific concerns regarding our empirical methodology, which we share with Coulombe and Tremblay (2006). First, skill accumulation during schooling is also affected by factors such as family inputs, which might change over time. Thus, different cohorts might differ along several unobserved dimensions that also affect skill accumulation during schooling years. Second, individuals might gain or lose skills as they age. Hence, as individuals of a certain cohort are observed only when they are within a certain age range at the time of the survey, the estimated age effect may partly also capture cohort-specific impacts, as well as capturing part of the variation in school quality over time. The cross-sectional nature of the original data prevents us from controlling for age effects non-parametrically. Thus, the validity of our human capital measure crucially depends on the assumption that the level of human capital remains roughly constant throughout an individual's life. Any stark changes in the stock of human capital due to migration or gains and losses of human capital at later stages of life due to adult learning and skill depreciation are likely to bias our estimates.

In fact, several studies based on IALS data suggest that gains and losses of skills over the life cycle do indeed occur. For example, Edin and Gustavsson (2008) provide evidence that

[25] However, other problems of reverse causality still exist, given that our human capital investment measures are based on literacy tests performed at the end of the period of analysis, and may therefore be distorted, among other things, by the migration flows that occurred over the period.

depreciation of general skills is economically important. Based on two waves (1994 and 1998) of IALS data for Sweden, Edin and Gustavsson (2008) investigate the role of skill depreciation in the relationship between work interruptions and subsequent wages. Analyzing changes in individuals' skills as a function of time out of work, they find strong evidence for a negative relationship between work interruptions and skills. Cascio, Clark, and Gordon (2008) investigate the effects of post-secondary education on cognitive skills using IALS data. While U.S. students score below their OECD counterparts on international achievement tests, U.S. native adults ultimately catch up. Cascio, Clark, and Gordon (2008) show that cross-country differences in the age profile of literacy skills explain a good part of the U.S. "catch up." However, one concern with their study is, once again, that the cross-sectional design of the IALS data does not allow controlling directly for cohort effects. Several other studies based on IALS more generally document gains and losses of skills over the life-cycle (see Willms and Murray, 2007; Green and Ridell, 2003; Kamp and Boudard, 2003).

The average human capital of specific cohorts might also be affected by differences in migration patterns over time when migrants are associated, on average, with different skills than natives. Several studies based on IALS and ALL data investigate native-migrant differences in literacy skill. For example, Ferrer, Green and Ridell (2006) and Bonikowska, Green and Ridell (2008) find the native-born literacy distribution dominates that for immigrants in Canada. However, the immigrant-native literacy skill gap varies significantly between countries (see Kahn, 2004), which could reflect differences in the average skills of migrants migrating to different countries. Thus, differences in migration patterns over time and between countries might complicate the construction of synthetic time series of human capital investments.

While these findings cast some doubt on the validity of certain key assumptions made by Coulombe and Tremblay (2006) and in our study, the consistency of findings across periods, countries, and skills assessments is striking. Our basic result that modern knowledge-based societies highly value skills is also supported by several other studies based on PIAAC data that suggest a causal relationship between skills and economic outcomes (Hanushek et al., 2015; Falck, Heimisch, and Wiederhold, 2016).

VI. Conclusions

The availability of new information about growth and skills in a broader set of 33 countries permits closer investigation than previously possible of the hypothesis that higher average literacy of the population stimulates economic growth. In terms of methodology, our analysis directly builds on the IALS-based analysis by Coulombe, Tremblay and Marchand (2004) as well as Coulombe and Tremblay (2006); which we largely replicate based on the more recent and more comprehensive PIAAC data on the level of literacy skills of the adult population.

In line with previous results, we find evidence for a strong positive link between literacy and GDP growth. However, our estimated effects are about twice as large as those obtained by Coulombe and Tremblay (2006). We find an implied long-run (i.e., steady state) elasticity of output with respect to literacy of about 3. In other words, a one-percent increase in literacy skills translates into a three-percent increase in GDP per capita in the steady state. This suggests that the skills generated by one additional year of schooling (8 PIAAC points or 3 percent of mean PIAAC skills) lead to a nine-percent increase in GDP per capita. The technology to improve adult literacy skill already exists. Recent experiments in Canada realized considerable increases in adult literacy skills from as little as 15 hours of high quality, focused instruction (ACCC, 2013; AWES, 2018). The same studies indicate, however, that the growth potential associated with higher skills will only be realized if employers ensure that their work processes, work organizations, and production technologies make full use of the newly created skill supply. Where this is not the case, any newly created skill will evaporate almost as rapidly as it was created.

Our results also extend to other indicators of economic prosperity. In particular, the long-run elasticities of output with respect to literacy are very similar when considering labor productivity instead of GDP per capita. The respective elasticities are again larger than in the earlier study by Coulombe and Tremblay (2006). This suggests that human capital became even more important for economic growth in recent decades.

A closer inspection of the data additionally reveals some important heterogeneities: Investment in the human capital of women appears to have a much stronger association with subsequent growth than investment in the human capital of men. Moreover, we our findings suggest that underinvestment in human capital (as indicated by a low literacy proficiency) hampers growth by more than developing highly talented individuals (as indicated by high literacy proficiency) spurs it. This finding suggests that policy makers should pay more attention to improving the skills of the lower end of the literacy skill distribution than has traditionally been the case. Because of the cumulative nature of literacy skill acquisition such a refocusing would involve the implementation of skill-enhancing measures from pre-school through post-secondary entry and graduation. By definition, such measures will take a long time to yield material reductions in the proportions of youth entering the labor market with low skills. Thus, measures that serve to reduce the proportions of low-skilled working-age adults are needed. Cost-benefit analysis undertaken by DataAngel that is based upon a highly differentiated classification of learning need and instructional costs suggests that rates of return would be highest for those adults with the greatest skill shortages (DataAngel, 2010; DataAngel, 2014).

Overall, our results suggest that investments that serve to increase literacy skills would yield material improvements in growth rates, particularly if they were focused on reducing the proportion of low skilled adults in the population. However, recent research by DataAngel undertaken for the Canada West Foundation suggests a need for measures that go beyond simply increasing the skill supply. Measures that improve the fit between employer demands and worker skills, such as credentials that reliably signal key cognitive skills, would improve market efficiency and lead to higher productivity. These same measures would also attenuate skill loss associated with low levels of skill utilization that are themselves a product of a large proportion of employers reducing the cognitive demands of jobs to avoid having to pay the rapidly rising wage premia for workers with high levels of literacy skill. These rising premia are likely too large to be attributed to skill-based improvements in marginal productivity of skilled workers alone, but also reflect wage increases driven by a shortage of highly skilled/literate workers.

Finally, the analysis suggests a need for economic policy makers to implement measures that serve to induce employers to increase the knowledge and skill intensity of work so that newly developed literacy skills get utilized at work. Evidence of massive adult skill loss in some countries, including Canada and the US, suggests a demand deficiency that is itself a product of several linked market failures of the type that only governments have the tools – information and incentives – to correct (AIR, 2015; IRPP, 2017). On a positive note, the governments which implement such measures the most rapidly are likely to realize material and rapid increases in both labor productivity and GDP per capita.

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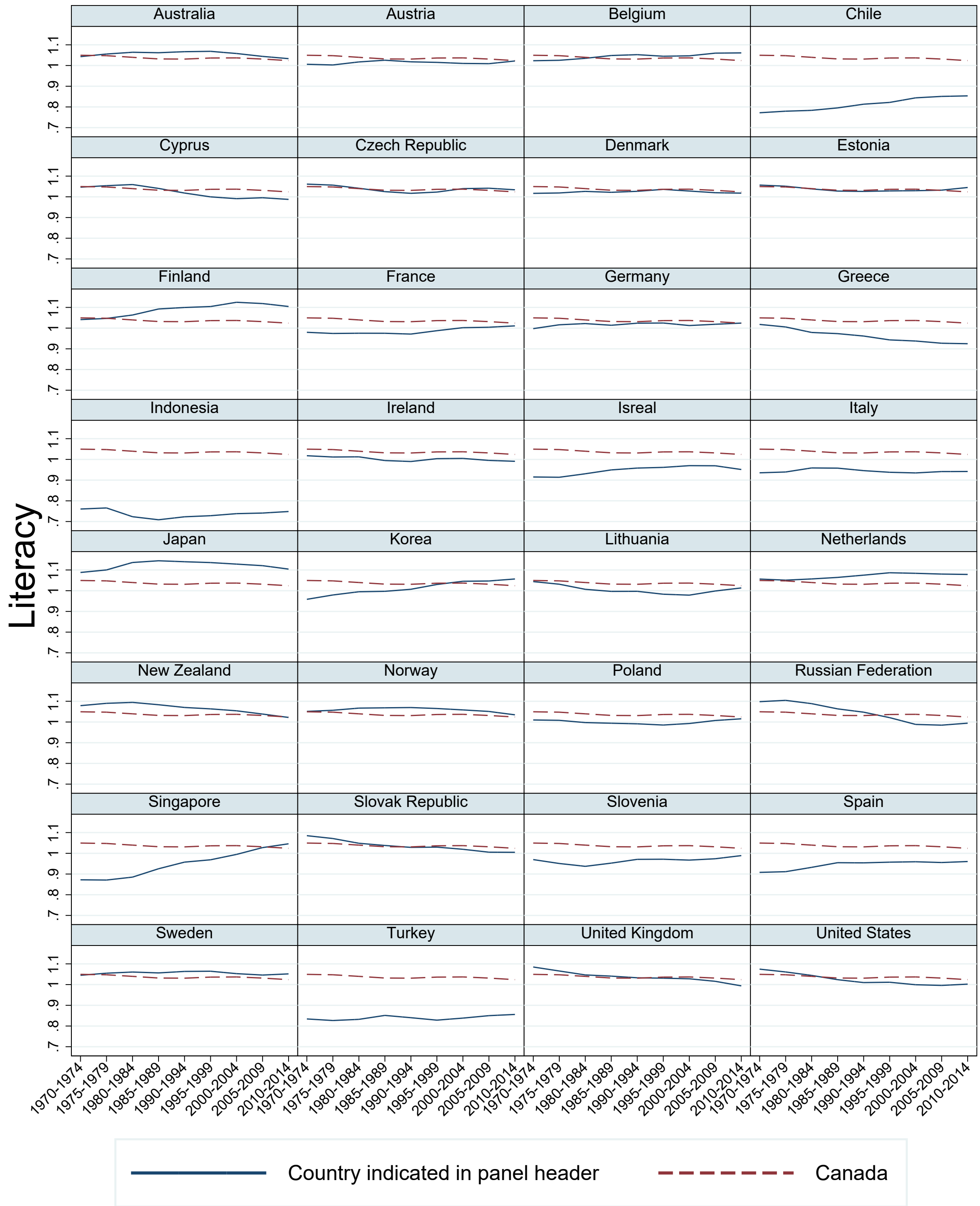
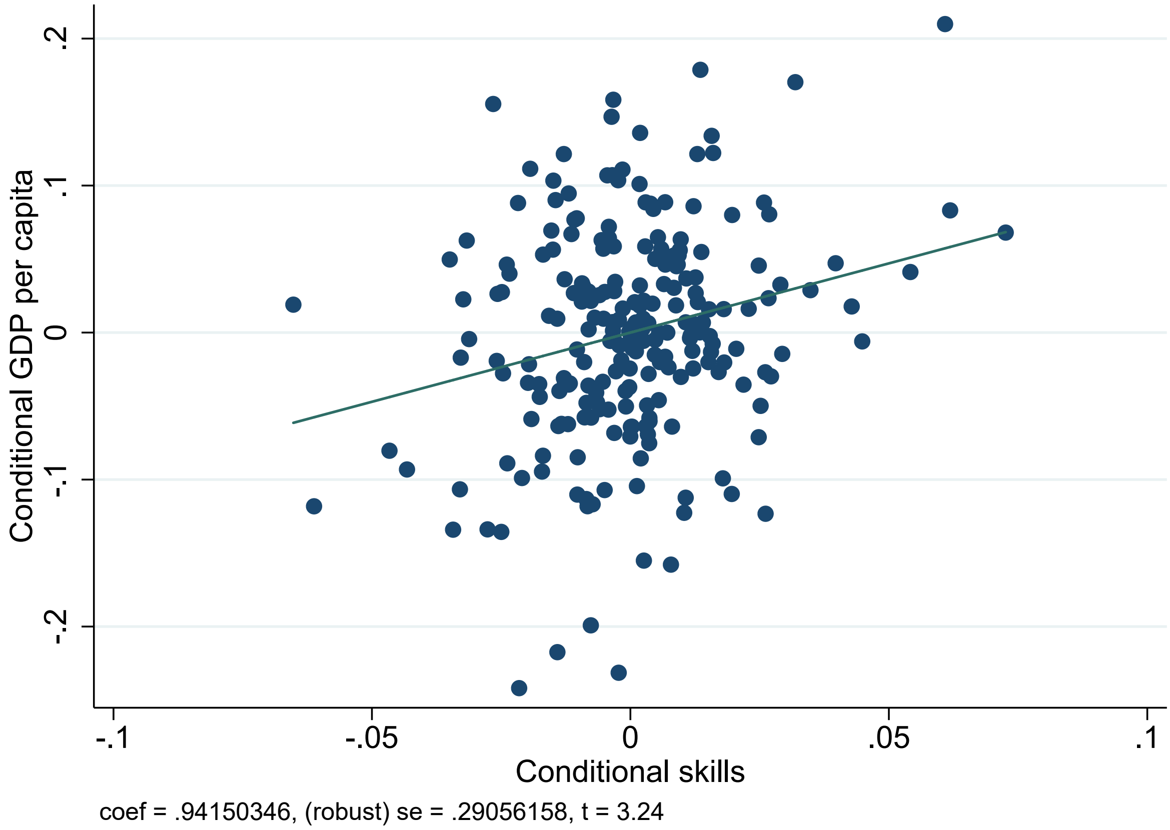
Figure 1: Literacy Skills Over Time



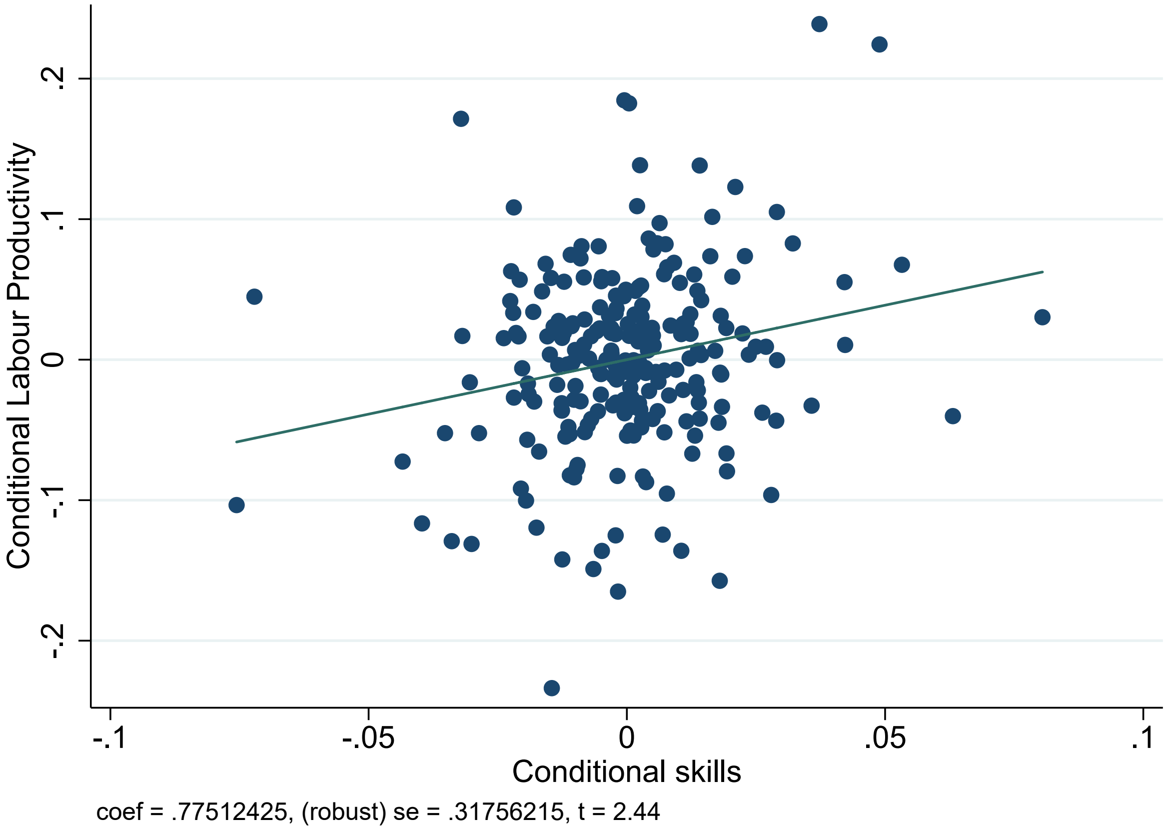
Notes: Graph shows average literacy skills of the population aged 18 to 27 years in five-year periods from 1970 to 2010. Canada (represented by the dashed red line) is included in all panels as benchmark. *Data source:* PIAAC.

Figure 2: Literacy Skills and GDP per Capita



Notes: Added-variable plot of a regression of end-of-period GDP per capita on initial level of GDP per capita, fertility rate, investment rate, openness, and average literacy scores. All variables are in logarithm. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Figure 3: Literacy Skills and Labor Productivity



Notes: Added-variable plot of a regression of end-of-period labor productivity on initial labor productivity, fertility rate, investment rate, openness, and average literacy scores. All variables are in logarithm. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 1: Baseline Results: GDP per Capita

	(1)	(2)	(3)	(4)
Literacy	1.044***	.942***	1.206***	.970***
	(.285)	*(.291)*	*(.272)*	*(.280)*
Initial GDP per capita	.646***	.671***	.576***	.673***
	(.046)	*(.050)*	*(.071)*	*(.077)*
Fertility rate	−.140***	−.119**	−.240***	−.143
	(.052)	*(.054)*	*(.082)*	*(.092)*
Investment rate	.160***	.153***	.124**	.079
	(.051)	*(.052)*	*(.058)*	*(.062)*
Openness ratio		.057		.106**
		(.035)		*(.050)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	236	236	236	236
R-squared	.985	.986	.985	.985
Implied long-run elasticity of outcome to literacy	2.95	2.86	2.85	2.97

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita. All variables are in logarithm. Instruments used in Columns 3 and 4 are initial GDP per capita of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 2: Baseline Results: Labor Productivity

	(1)	(2)	(3)	(4)
Literacy	.823**	.775**	.859***	.744***
	(.319)	*(.318)*	*(.317)*	*(.285)*
Initial labor productivity	.710***	.718***	.672***	.711***
	(.054)	*(.053)*	*(.091)*	*(.087)*
Fertility rate	−.072	−.066	−.134*	−.097
	(.050)	*(.050)*	*(.070)*	*(.069)*
Investment rate	.070	.068	.078	.066
	(.050)	*(.051)*	*(.058)*	*(.058)*
Openness ratio		.030		.061
		(.032)		*(.043)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	231	231	229	229
R-squared	.987	.987	.987	.987
Implied long-run elasticity of outcome to literacy	2.84	2.75	2.62	2.58

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period labor productivity. All variables are in logarithm. Instruments used in Columns 3 and 4 are initial labor productivity of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 3: Controlling for Quantity-based Measure of Human Capital

	GDP per Capita		Labor Productivity	
	(1)	(2)	(3)	(4)
Literacy		1.008***		.681**
		(.307)		*(.290)*
Average years of schooling, Barro and Lee	.062	–.029	.111	.046
	(.085)	*(.097)*	*(.092)*	*(.097)*
Initial GDP per capita	.731***	.674***		
	(.072)	*(.077)*		
Initial labor productivity			.751***	.709***
			(.078)	*(.087)*
Fertility rate	–.112	–.149	–.064	–.086
	(.096)	*(.095)*	*(.071)*	*(.072)*
Investment rate	.098	.076	.097	.071
	(.065)	*(.066)*	*(.061)*	*(.059)*
Openness ratio	.123**	.108**	.066	.058
	(.048)	*(.050)*	*(.042)*	*(.043)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented	X	X	X	X
Observations	236	236	229	229
R-squared	.984	.985	.987	.987
Implied long-run elasticity of outcome to literacy		3.09		2.34

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note: Dependent variable: end-of-period GDP per capita (Columns 1–2) and end-of-period labor productivity (Columns 3–4). All variables are in logarithm. Instruments used are initial GDP per capita (Columns 1–2) or labor productivity (Columns 3–4) of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* Barro and Lee, International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 4: Female vs Male Literacy

	GDP per Capita			Labor Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)
Female literacy	.932***		.811**	.806***		1.206***
	(.251)		*(.383)*	*(.266)*		*(.411)*
Male literacy		.875***	.157		.589**	−.502
		(.291)	*(.454)*		*(.282)*	*(.431)*
Initial GDP per capita	.682***	.672***	.677***			
	(.075)	*(.080)*	*(.078)*			
Initial labor productivity				.711***	.718***	.725***
				(.085)	*(.088)*	*(.086)*
Fertility rate	−.132	−.153	−.136	−.088	−.102	−.075
	(.090)	*(.094)*	*(.092)*	*(.068)*	*(.071)*	*(.070)*
Investment rate	.093	.069	.089	.077	.062	.095
	(.062)	*(.063)*	*(.064)*	*(.058)*	*(.060)*	*(.062)*
Openness ratio	.104**	.109**	.104**	.055	.068	.051
	(.050)	*(.049)*	*(.050)*	*(.043)*	*(.043)*	*(.042)*
Country fixed effects	X	X	X	X	X	X
Period fixed effects	X	X	X	X	X	X
Controls instrumented	X	X	X	X	X	X
Observations	236	236	236	229	229	229
R-squared	.985	.985	.985	.988	.987	.988
Implied long-run elasticity of outcome to female literacy	2.93		2.51	2.79		4.39
Implied long-run elasticity of outcome to male literacy		2.67	.48		2.09	-1.82

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita (Columns 1–3) and end-of-period labor productivity (Columns 4–6). All variables are in logarithm. Instruments used are initial GDP per capita (Columns 1–3) or labor productivity (Columns 4–6) of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 5: High Versus Low Literacy

	GDP per Capita		Labor Productivity	
	(1)	(2)	(3)	(4)
Low literacy	−.147**		−.170***	
	(.059)		*(.057)*	
High literacy		.043*		.048**
		(.025)		*(.024)*
Initial GDP per capita	.691***	.707***		
	(.080)	*(.080)*		
Initial labor productivity			.663***	.718***
			(.096)	*(.087)*
Fertility rate	−.182*	−.150	−.175**	−.118
	(.103)	*(.100)*	*(.085)*	*(.077)*
Investment rate	.134**	.122*	.124**	.114*
	(.066)	*(.067)*	*(.059)*	*(.061)*
Openness ratio	.126***	.097*	.081*	.043
	(.048)	*(.055)*	*(.043)*	*(.046)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented	X	X	X	X
Observations	236	236	229	229
R-squared	.985	.985	.987	.987
Implied long-run elasticity of outcome to literacy	−.48	.15	−.50	.17

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita (Columns 1–2) and end-of-period labor productivity (Columns 3–4). "Low literacy" is defined as the share of the population with proficiency levels 1 and 2 in PIAAC (i.e., below 276 points); "High literacy" is the share of the population with proficiency levels 4 and 5 in PIAAC (i.e., 326 points and above). All variables are in logarithm. Instruments used are initial GDP per capita (Columns 1–2) or labor productivity (Columns 3–4) of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 6: Comparison with IALS

	GDP per Capita		Labor Productivity	
	(1)	(2)	(3)	(4)
Literacy	.599	.692	.327	.455
	(.427)	*(.423)*	*(.454)*	*(.451)*
Initial GDP per capita	.745***	.714***		
	(.073)	*(.092)*		
Initial labor productivity			.746***	.721***
			(.078)	*(.082)*
Fertility rate	–.122	–.143	–.067	–.086
	(.097)	*(.104)*	*(.102)*	*(.109)*
Investment rate	–.068	–.059	–.088	–.083
	(.080)	*(.080)*	*(.078)*	*(.076)*
Openness ratio		–.053		–.063
		(.071)		*(.061)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Observations	104	104	104	104
R-squared	.974	.974	.978	.979
Implied long-run elasticity of outcome to literacy	2.35	2.42	1.29	1.63

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita (Columns 1–2) and end-of-period labor productivity (Columns 3–4). All variables are in logarithm. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 7: Do Skills Lead or Lag Growth: GDP per Capita

	Lag Literacy				Lead Literacy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Literacy two periods lag	.725**		−.042	.450				
	(.368)		*(.654)*	*(.698)*				
Literacy one period lag		.768***	.940	−.652				
		(.277)	*(.627)*	*(.841)*				
Literacy two periods lead					.515		−.579	−.291
					(.604)		*(.832)*	*(.940)*
Literacy one period lead						1.019***	1.177*	.352
						(.353)	*(.707)*	*(1.166)*
Literacy				1.684***				.671
				(.595)				*(.635)*
Initial GDP per capita	.661***	.687***	.646***	.597***	.667***	.595***	.668***	.665***
	(.087)	*(.078)*	*(.089)*	*(.095)*	*(.122)*	*(.102)*	*(.122)*	*(.120)*
Fertility rate	−.163	−.148	−.164	−.168	−.146	−.223**	−.157	−.161
	(.109)	*(.094)*	*(.108)*	*(.108)*	*(.114)*	*(.105)*	*(.116)*	*(.117)*
Investment rate	.080	.092	.073	.037	.024	.001	.017	.021
	(.086)	*(.063)*	*(.085)*	*(.087)*	*(.083)*	*(.066)*	*(.081)*	*(.079)*
Openness ratio	.163***	.110**	.153**	.158**	.130	.091	.133	.122
	(.060)	*(.049)*	*(.061)*	*(.063)*	*(.090)*	*(.071)*	*(.090)*	*(.091)*
Country fixed effects	X	X	X	X	X	X	X	X
Period fixed effects	X	X	X	X	X	X	X	X
Controls instrumented	X	X	X	X	X	X	X	X
Observations	209	236	209	209	172	204	172	172

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita. All variables are in logarithm. Instruments used are initial GDP per capita of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table 8: Do Skills Lead or Lag Growth: Labor Productivity

	Lag Literacy				Lead Literacy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Literacy two periods lag	.515		−.247	.060				
	(.318)		*(.606)*	*(.625)*				
Literacy one period lag		.611**	.917	−.136				
		(.276)	*(.574)*	*(.774)*				
Literacy two periods lead					.582		−.449	−.043
					(.610)		*(.795)*	*(.866)*
Literacy one period lead						.789*	1.124	−.141
						(.429)	*(.744)*	*(1.123)*
Literacy				1.102*				1.087*
				(.569)				*(.593)*
Initial labor productivity	.679***	.720***	.671***	.643***	.758***	.670***	.751***	.733***
	(.075)	*(.087)*	*(.075)*	*(.081)*	*(.153)*	*(.126)*	*(.155)*	*(.151)*
Fertility rate	−.128	−.102	−.122	−.120	−.037	−.113	−.050	−.065
	(.081)	*(.072)*	*(.079)*	*(.079)*	*(.101)*	*(.085)*	*(.103)*	*(.104)*
Investment rate	.106	.080	.094	.059	−.024	−.016	−.034	−.031
	(.077)	*(.059)*	*(.077)*	*(.083)*	*(.085)*	*(.069)*	*(.081)*	*(.078)*
Openness ratio	.100*	.062	.090	.098*	.072	.077	.072	.048
	(.056)	*(.042)*	*(.056)*	*(.059)*	*(.076)*	*(.057)*	*(.075)*	*(.074)*
Country fixed effects	X	X	X	X	X	X	X	X
Period fixed effects	X	X	X	X	X	X	X	X
Controls instrumented	X	X	X	X	X	X	X	X
Observations	204	229	204	204	165	197	165	165

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period labor productivity. All variables are in logarithm. Instruments used are initial labor productivity of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table A-1: Baseline Results With Numeracy Skills: GDP per Capita

	(1)	(2)	(3)	(4)
Numeracy	.657**	.549*	.733**	.579*
	(.295)	*(.300)*	*(.312)*	*(.296)*
Initial GDP per capita	.660***	.689***	.598***	.696***
	(.050)	*(.054)*	*(.074)*	*(.079)*
Fertility rate	–.113**	–.093*	–.211**	–.115
	(.054)	*(.055)*	*(.084)*	*(.093)*
Investment rate	.159***	.152***	.118*	.072
	(.052)	*(.052)*	*(.061)*	*(.064)*
Openness ratio		.066*		.112**
		(.035)		*(.049)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	236	236	236	236
R-squared	.985	.985	.984	.984
Implied long-run elasticity of outcome to numeracy	1.93	1.76	1.82	1.91

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita. All variables are in logarithm. Instruments used in Columns 3 and 4 are initial GDP per capita of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table A-2: Baseline Results With Numeracy Skills: Labor Productivity

	(1)	(2)	(3)	(4)
Numeracy	.489	.441	.402	.342
	(.305)	*(.304)*	*(.323)*	*(.300)*
Initial labor productivity	.732***	.741***	.711***	.748***
	(.053)	*(.052)*	*(.087)*	*(.084)*
Fertility rate	−.050	−.044	−.111	−.073
	(.050)	*(.050)*	*(.069)*	*(.069)*
Investment rate	.073	.071	.086	.072
	(.050)	*(.050)*	*(.061)*	*(.060)*
Openness ratio		.037		.068
		(.032)		*(.042)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	231	231	229	229
R-squared	.987	.987	.987	.987
Implied long-run elasticity of outcome to numeracy	1.83	1.70	1.39	1.36

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period labor productivity. All variables are in logarithm. Instruments used are initial labor productivity of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table A-3: Excluding the Crisis Period: GDP per Capita

	(1)	(2)	(3)	(4)
Literacy	1.022***	1.043**	1.109***	.802**
	(.371)	*(.406)*	*(.344)*	*(.381)*
Initial GDP per capita	.587***	.583***	.567***	.660***
	(.058)	*(.064)*	*(.093)*	*(.110)*
Fertility rate	–.158***	–.162**	–.241**	–.161
	(.059)	*(.065)*	*(.099)*	*(.117)*
Investment rate	.055	.055	.014	.020
	(.060)	*(.060)*	*(.074)*	*(.076)*
Openness ratio		–.010		.117
		(.054)		*(.091)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	172	172	172	172
R-squared	.987	.987	.987	.986
Implied long-run elasticity of outcome to literacy	2.48	2.50	2.56	2.36

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Notes: Regressions are analogous to those presented in Table 1 for the period 1970–2004. Dependent variable: end-of-period GDP per capita. All variables are in logarithm. Instruments used in Columns 3 and 4 are initial GDP per capita of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table A-4: Excluding the Crisis Period: Labor Productivity

	(1)	(2)	(3)	(4)
Literacy	1.167***	1.194**	1.122***	.970**
	(.426)	*(.472)*	*(.389)*	*(.398)*
Initial labor productivity	.648***	.643***	.683***	.728***
	(.077)	*(.081)*	*(.149)*	*(.147)*
Fertility rate	−.067	−.070	−.098	−.065
	(.067)	*(.073)*	*(.099)*	*(.105)*
Investment rate	−.066	−.067	−.054	−.038
	(.055)	*(.056)*	*(.081)*	*(.077)*
Openness ratio		−.012		.048
		(.054)		*(.078)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented			X	X
Observations	167	167	165	165
R-squared	.988	.988	.987	.987
Implied long-run elasticity of outcome to literacy	3.31	3.35	3.54	3.56

* p<0.10, ** p<0.05, *** p<0.01

Notes: Regressions are analogous to those presented in Table 2 for the period 1970–2004. Dependent variable: end-of-period labor productivity. All variables are in logarithm. Instruments used in Columns 3 and 4 are initial labor productivity of the previous period and the lagged values of the investment rate, the fertility rate, and openness. Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.

Table A-5: Least Squares Dummy Variable Corrected Model (Arellano-Bond)

	GDP per Capita		Labor Productivity	
	(1)	(2)	(3)	(4)
Literacy	1.050***	.952***	.783***	.771***
	(.328)	*(.321)*	*(.275)*	*(.286)*
Fertility rate	−.124**	−.103**	−.049	−.050
	(.051)	*(.052)*	*(.056)*	*(.056)*
Investment rate	.191***	.186***	.089**	.089**
	(.043)	*(.043)*	*(.038)*	*(.038)*
Openness ratio		.058**		.007
		(.028)		*(.037)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Observations	236	236	229	229
R-squared				
Implied long-run elasticity of outcome to literacy	3.88	3.87	4.42	4.33

* p<0.10, ** p<0.05, *** p<0.01

Notes: Dependent variable: end-of-period GDP per capita (Columns 1–2) and end-of-period labor productivity (Columns 3–4). All variables are in logarithm. Coefficients on lagged-dependent variable omitted. Bootstrapped standard errors (50 repetitions) in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations.