A Macroeconomic Analysis of Literacy and Economic Performance*

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Abstract

We pool expanded international data from the PIAAC survey of adult skills across Canadian provinces and other participating countries 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. Our results from panel estimations over the period 1970-2015 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. A closer inspection of the data additionally reveals 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. Our results also suggest that reducing the proportion of low skilled adults yields a positive effect on economic growth. We also find that skills are somewhat less important for economic performance in Canada than in other developed countries; at the same time, low literacy proficiency of the population appears to be less detrimental for economic performance in Canada than elsewhere in the world.

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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).[1] 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

[1] The analysis adjusted for age group, gender, education, one-digit occupation, immigrant status, official language, disability status, urban/rural, and Aboriginal status.

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 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 educational 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 substantial increase in the relative wage premia paid to workers with high literacy skill levels (Canada West Foundation, 2018).

In this report, our aim is 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 across different regions. 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 31 developed countries and 10 Canadian provinces over the period 1970-2015.

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 economic 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 output in the steady state. Using these estimated elasticities, back-of-the-envelope calculations suggest that the skills acquired by an additional year of schooling (8 PIAAC points or 3 percent of mean PIAAC skills) increase output by about 9 percent.

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. These results document the extent to which modern knowledge-based economies value skills.

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 that investment in the human capital of women that precipitates increases in female literacy skills appears to have a much stronger effect on economic performance than investment in the human capital of men. Another potential strategy to boost economic performance is to reduce the share of low literacy achievers (i.e., adults with low literacy proficiency in PIAAC, conventionally Level 1 and 2) in a country.[2] In fact, decreasing the share of low-skilled individuals in Canada by 10 percent (from the average of 46 percent to 42 percent)

[2] 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. See Annex B for a detailed description of the proficiency levels.

would result in a long-run increase of GDI per capita of 770 CAD (using the average Canadian GDI per capita over the sample period as baseline).[3]

When comparing the Canadian provinces to the other countries in our sample, we find that skills are somewhat less important for economic performance in Canada than elsewhere in the world. One potential explanation for this finding is that province-level income growth is more volatile and more prone to other influences compared to country-level growth. At the same time, the negative effect of low literacy proficiency on economic development is attenuated in the Canadian sample. One possible rationale behind this result is that Canadian provinces have a rather small share of individuals with low literacy proficiency. Thus, high-skilled individuals are less scarce than in other developed countries. If there are decreasing returns to skill investment, as traditional neoclassical growth theory (see Section II) would suggest, the economic effects of skill investments will be the lower the higher the skill endowment already is.

The remainder of the report is structured as follows. Section II 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. Section III presents the data, while Section IV provides graphical evidence on the link between literacy skills and economic growth. Section V presents our empirical strategy. The main results, together with robustness checks and heterogeneity analysis, are presented in Section VI. There we also discuss the limitations of our analysis. Section VII concludes with some policy implications of our results.

II. Literature Review

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.

[3] Note that due to data restrictions for the Canadian provinces, we could not investigate the growth effects of increasing the population share with high literacy proficiency (i.e., Level 4 or 5 in the PIAAC assessment).

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.

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 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. 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. Islam's panel analysis yields mainly insignificant results for the human capital variables, which is explained by the fact that they only partially capture actual investment in human capital and do not account for differences in the quality of schooling. Moreover, the used human capital variables show only little over-time variation, which makes the identification of effects in a panel setting difficult.

Another potential estimation problem in such a panel framework is that both the explanatory variables and the outcome of interest are affected by contemporaneous shocks. This would yield the typical endogeneity problem as any relation between the explanatory variable and outcome might simply be driven by the shock. 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.

Empirical research on the importance of human capital for economic growth was also from the beginning dominated by concerns about the measurement of human capital. Such measures play a prominent role in modern cross-country growth regressions (for a detailed review, see Woessmann, 2003). Until fairly recently, the focus of the empirical literature on human capital has been basically limited to quantity-based measures of human capital such as years of schooling 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). More recently, 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 several international tests.[4] 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.[5] 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).

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.[6] 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:

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

[4] 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.

[5] For a description of the methods used to create a common scale see Hanushek and Woessmann (2008).

[6] 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.

where ΔY_{it} represents the growth rate of GDP per capita; Y_{it-1} is the lagged level of GDP per capita 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), 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. Interestingly, no significant effect on GDP growth 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). 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.[7]

As part of this project, we obtained data on the average skill level by age group and gender separately for all Canadian provinces. Since Canada administered the survey to a representative sample in each of its provinces, we can treat Canadian provinces in our analysis in the same way as other participating countries, extending the usable sample with comparable skill data to 42 regions.[8] Since we could not obtain GDP data for the Russian Federation (see below), our estimation sample consists of 41 regions (31 countries and 10 Canadian provinces).

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).[9] 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[10] 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;

[7] 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.

[8] Participating countries in the first round were Australia, Austria, Belgium (Flanders), Canada (Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan), 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.

[9] 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.

[10] The skills assessed in PIAAC are rather general in nature and therefore do not capture occupation-specific knowledge and competencies.

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, and reports the results on a 500-point scale.[11] 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 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 1970–2014 (Canadian provinces: 1971–2015) in five-year intervals.[12] 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.[13] 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).[14] In the case of the 10 Canadian provinces, we construct the synthetic time series of average skills at the province-level based on the province in which participants obtained their high school degree (instead of the province of current residence) as regional mobility might be endogenous to economic condition of provinces.[15]

[11] 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.

[12] We focus on literacy skills to be comparable to the analysis by Coulombe and Tremblay (2006). Results using numeracy skills are qualitatively similar. See Appendix Table A-1. We do not perform the analysis for ICT skills because of the considerably smaller country coverage.

[13] 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.

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

[15] Endogeneity of location choice should not be a major concern in the country sample because between-country mobility is likely much lower than within-country mobility.

We use sampling weights provided in PIAAC when aggregating skills at the region-cohort level to accurately account for the sampling errors.

On average across all time periods, mean literacy skills are 267 points (standard deviation: 23 points). Within Canada, literacy skills range between 274 points (Quebec) and 286 points (Alberta and British Columbia). This suggests that Canadian provinces are among the top performers in literacy worldwide. In our country sample, the range of literacy skills is between 194 points (Indonesia) and 296 points (Japan). Other top performers in literacy are Finland (287), the Netherlands (282), Sweden (278), and Australia (278), while other low performers are Chile (214) and Turkey (221). Average literacy performance in the Unites States (270) is below that in the worst-performing Canadian province.

To measure economic performance in the our sample of 31 countries, we use GDP per capita, obtained through the Penn World Tables 9.0 (see Feenstra, Inklaar, and Timmer, 2015). GDP per capita is expressed in purchasing power parities (PPP), which allow real-quantity comparisons across countries.[16] In our sample of Canadian provinces, GDP data are available only from 1981 onwards, which would severely limit out sample size. We thus use gross domestic income (GDI) per capita to measure economic performance, which has recently become available for all Canadian provinces in our entire period of observation.[17] For expositional purposes, we refer to our measures of economic performance in the estimations simply as *income per capita*.

We follow Coulombe, Tremblay, and Marchand (2004) and Coulombe and Tremblay (2006) in using fertility rate, investment shares, as well as imports and exports as control variables. In the country sample, fertility rates (live births per woman) are from the United Nations' database; the remaining variables are taken from Penn World Tables 9.0. For Canada we obtained province-level data on all variables from Statistics Canada.[18]

IV. Graphical Evidence on the Evolution of Skills and Economic Growth

We plot the evolution of average literacy skills for the population aged 18–27 in the ten Canadian provinces together with income per capita in Figure 1. Both the skill level of entry-age

[16] No GDP data for the Russian Federation are available. For other post-communist countries GDP per capita is only available for periods after 1990.

[17] Results are very similar when we use GDP data for Canadian provinces also, which are available since 1981. See Table A-2.

[18] Note that data on international imports and exports for Canadian provinces are available only since 1981. Our baseline specification will therefore not use openness as control.

workers and income increased over time in all provinces. However, the rate of skills growth varies substantially across provinces and periods; in general, we observe that skill growth tends to attenuate towards the end of the observation period, with some provinces even experiencing a decline in skills of entry-age workers (e.g., Manitoba, Nova Scotia, and Saskatchewan after 2005). In comparison, income per capita grew more smoothly over the sample period, but some differences across periods in the province-specific speed of economic growth are also visible.

Figure 2 plots average literacy skills for the population aged 18–27 as well as GDP per capita in our sample of 31 countries over time. We observe that the evolution of skills is quite different across countries. In some countries, such as Chile, Korea, Singapore, and Spain, we witness steep increases in the skill level of entry-age workers over time, while some other countries show only very modest changes; examples are the United Kingdom and the US. However, in all countries the skill level of entry-age workers increased over time. At the same time, we observe growing GDP per capita in almost all countries over the sample period. Exceptionally high rates of growth are visible in Singapore, Norway, Ireland, and Korea since the mid-1990s.

In sum, Figures 1 and 2 suggest that over the sample period the growth rates of skills and income per capita were positively correlated. The aim of the analysis presented in the next section is to shed more light on the question whether this correlation is merely accidental or whether it reflects a systematic relationship between skills and economic performance.

V. Panel Estimation Framework

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 seminal 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.[19] We prefer the dynamic panel regression model over the "growth-initial level" model for 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.

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

More specifically, our dynamic panel model is given by

$$Y_{it} = \beta_1 Y_{it-1} + \beta_2 h_{it-1} + \beta_3 n_{it} + \beta_4 k_{it} + \beta_5 o_{it} + \tau_t + r_i + \varepsilon_{it} \quad (2)$$

where Y_{it} represents income per capita; Y_{it-1} is the level of income per capita in period t–1; h_{it} measures human capital (i.e., literacy skills) in the beginning of period t;[20] n_{it} is the five-year average fertility rate in period t; k_{it} is the five-year average ratio of investment to aggregate income in period t; o_{it} is the five-year average openness ratio in period t; τ_t is a period fixed effect, c_i is a region fixed effect, and ε_{it} is a stochastic error term. As is standard in the growth literature, all variables in Equation (2) are in logarithm.[21] The inclusion of region fixed effects r_i allows to account for the omitted variable bias arising due unobserved region-specific differences or shocks (see Section II). In particular, r_i pick up all kinds of unobserved region-specific factors that are constant over time. In addition, the period fixed effects τ_t absorb all unobserved effects that similarly affect all regions; for instance, business cycles or changes in global demand and market conditions.

The choice of control variables exactly follows Coulombe and Tremblay (2006). First, we include the fertility rate to capture the long-run rate of population growth (Barro, 2001). Second, the investment rate reflects physical capital accumulation. Openness to international trade is often thought to be conducive to economic growth. Aside from classical comparative-advantage arguments, openness tends to promote competition and, hence, efficiency. Sachs and Warner (1995) have argued empirically that international openness is an important contributor to economic growth. Openness is measured as the ratio of international exports plus imports to GDP (Barro, 2001).[22]

We deal with the potential problem of endogeneity in the explanatory variables by instrumenting all explanatory variables (except for literacy skills) with their lagged values as

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

[21] In education economics, it is more common to specify a log-linear regression when estimating the economic effect of skills. Here, output is in logarithm and skills enter linearly. This specification is derived from a standard Mincerian human-capital model, which is applied to a macroeconomic context (see Hanushek, Ruhose, and Woessmann, 2017, for details). Table A-3 shows that out results are qualitatively similar in a log-linear specification.

[22] 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.

instruments.[23] In particular, instrumenting initial income 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.[24] 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). We therefore decided not to instrument literacy.[25] However, this also means that unobserved variables at the region level which change over time (and are therefore not soaked up by the region fixed effects) may confound the literacy-growth relationship. We are therefore cautious in interpreting the estimated literacy coefficients as causal.[26]

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 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:

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

[23] Using lagged values as instruments effectively reduces our analysis period by one five-year period.

[24] In addition, years-of-schooling data by Canadian province over time are not available.

[25] Results are robust to instrumenting literacy by its lagged value. As expected given the instrument is likely endogenous, estimated literacy coefficients increase as compared to the baseline specification. Results are available on request.

[26] Also see the discussion on further methodological concerns in Section VI for the limits of interpreting our literacy estimates as causal.

VI. Results

Baseline results

Table 1 shows our baseline results using income per capita as dependent variable. In Columns 1 and 3, we estimate OLS regressions with country and period fixed effects; in Columns 2 and 4, we instrument all control variables by their lagged value to alleviate problems of measurement error and, partly, endogeneity (see Section V). Columns 3 and 4 also include the openness ratio, which reduces sample size because data are not available in the Canadian provinces before 1981.

The association between literacy and income 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 around 3.[27] 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 (on the 500-point scale) 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 2.98 in our preferred IV model (Column 2 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.[28] This conclusion is reinforced by Figure 3, which shows our main specification graphically. We observe a clear positive relationship between literacy and economic performance, and there are no apparent outliers which drive this

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

[28] 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 slightly different (50 points in PIAAC and 62 points in IALS, using the full sample in both 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.

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 income.[29] We find annual convergence speeds between 6 percent and 10 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 seven and twelve years to close half of the gap to the new steady state.[30]

The signs of the other control variables are in line with the neoclassical growth framework (i.e., fertility is negative, investment rate is positive but insignificant). In Columns 3 and 4, we add the openness ratio to our panel model ("open economy"). As expected, the estimated effect of openness on economic performance is positive and statistically significant; that is, economies which are more involved in international trade also grow faster. The literacy estimates become somewhat smaller when the openness ratio is added as control, but remain sizeable and highly statistically significant.[31]

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 2 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

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[29] In our set up with end-of-period income 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 income.

[30] These numbers are derived by dividing log(2) by the rate of convergence (in percent). Also see Dalgaard (2007).

[31] In Table A-4, we estimate the models in Columns 1 and 2 using the same sample as those in Columns 3 and 4. Results show that the (moderate) reduction in the magnitude of the literacy coefficient is indeed due to the inclusion of the openness variable and not due the smaller sample size.

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.[32] 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 less elastic.[33]

Percentage of population with low literacy proficiency

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).[34] We define low literacy as a proficiency level of 1 or 2. Note that due data restrictions for the Canadian provinces, we could not obtain the share of the population with high literacy, defined as a proficiency level of 4 or 5. This precludes an analysis of how the growth impact of reducing the share of low literacy achievers differs from the impact of increasing the share of high achievers.

The international average in the share of low performers is 54 percent; this suggests that a considerable share of the population suffers from low literacy skills. However, there is considerable variation in the share of low performers across countries (averaged over all time periods), ranging from 28 percent (Japan) to 95 percent (Indonesia). Other countries with a small share of low performers in literacy are Finland (38 percent), the Netherlands (41 percent), Sweden, Norway, and New Zealand (all 43 percent); in contrast, Turkey (90 percent) and Chile (87 percent) have a substantial share of low performers. The share of low performers in the United States (52

[32] 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.

[33] For instance, Hanushek et al. (2015) and Hampf et al. (2017) have shown that higher PIAAC skills are associated with better employment prospects in all PIAAC countries, However, they have not performed a separate analysis by gender.

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

percent) is close to the international average. Within Canada the share of low performers varies from 37 percent (Alberta) to 57 percent (Newfoundland and Labrador). Thus, in international comparison, the share of low performers in literacy in Canadian provinces is very moderate. Not surprisingly, the share of low performers decreases over time, while the share of high performers increases.

Table 3 reports the results of using the percentage of individuals with low literacy instead of average literacy. A larger population share of low performers in literacy is clearly negatively associated with growth. This suggests that underinvestment in human capital (as indicated by low literacy proficiency) impedes growth. Put differently, decreasing the share of low performers is a viable strategy for a country to foster economic growth. In fact, a one-percent reduction in the share of people with low literacy would increase income per capita by 0.1 percent in the short run and by 0.23 percent in the long run. For Canada, a material reduction in the share of low performers by 10 percent (from the average of 46 percent to 42 percent) would increase income per capita by 330 CAD in the short run and by 770 CAD in the long run. To calculate these numbers, we used the average GDI per capita for all Canadian provinces in our sample period as point of reference (about 33,500 CAD).

Literacy effects in Canadian provinces vs. international mean

Next, we investigate how the relationship between literacy and economic performance differs between Canadian provinces and the remaining countries in our sample. To do so, we augment our baseline specification in Column 2 of Table 1 by an interaction term that estimates a separate skill effect for each Canadian province (and tests it against the cross-country mean).[35] We also estimate these interaction models replacing average literacy by the share of low performers in literacy (as shown in Table 3). Figures 4 and 5 visualize the key findings from these estimations by plotting the estimated coefficients (dot) on the province interactions together with 90 percent confidence intervals (horizontal line). The vertical red line indicates the international average (excluding Canadian provinces), which is normalized at 0. If the confidence interval does not cross the zero vertical line, the interaction is significant at the 10 percent level. Interaction effects are ordered by magnitude.

[35] In each of these estimations, we drop all other Canadian provinces such that the comparison group (i.e., all PIAAC countries) remains the same across specifications.

Figure 4 suggests that in each Canadian province the effect of literacy on income growth is smaller than the international average. The difference is statistically significant in all provinces expect Saskatchewan, New Brunswick, as well as Newfoundland and Labrador. The (negative) difference is most pronounced in Ontario, British Columbia, and Alberta. These results suggest that in most Canadian provinces the literacy effect on economic performance is weaker than elsewhere in the world. Interestingly, Figure 5 shows that the detrimental effect of low literacy on economic performance is *less* pronounced in the Canadian provinces than in other countries. This difference statistically significant in all provinces but Saskatchewan. In terms of magnitude, differences from the average international effect are largest in Newfoundland and Labrador, British Columbia, and Alberta.[36]

Overall, our heterogeneity analysis suggests that skills are somewhat less important for economic performance in Canadian provinces compared to other developed countries. On potential reason for this result is that province-level income growth is more volatile and more prone to other influences compared to country-level growth. At the same time, low literacy proficiency of the population appears to be less detrimental for economic performance in Canada than elsewhere in the world. This may be due to the fact that the share of low performers in literacy is rather low in Canada in international comparison (see above).

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 (this endogeneity concern is to some extent muted in the Canadian data, where we have information on the province of secondary degree). Thus, our results should be seen as largely descriptive in nature. However, considering a range of specifications and alternatives does not change our findings, which suggests that the overall pattern of results is very robust.

Beyond this more general methodical issue, there are a number of remaining design-specific concerns regarding our empirical methodology, which we share with Coulombe and Tremblay

[36] Figures A-1 and A-2 show that results are qualitatively similar, albeit somewhat noisier, when using data on GDP per capita instead of GDI per capita in Canadian provinces to measure economic performance.

(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 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 moving 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).[37] This interpretation is supported by the results of the Upskill project in Canada, a large-scale randomized controlled trial conducted in the food and accommodation industry. Upskill tested the impact of literacy and numeracy on a broad range of firm and individual economic outcomes. The study documented 25 percent first-year rates of return to higher skills for both the individual and firm from monetized benefits.

VII. Conclusions

The availability of new information about growth and skills in a broader set of 31 countries and 10 Canadian provinces 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 economic performance. 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 income per capita with respect to literacy of about 3. In other words, a one-percent increase in literacy skills translates into a three-percent increase in income per capita in the steady state. This suggests that the skills generated by one additional year of schooling (8 PIAAC points or 3 percent

[37] See also Hampf, Wiederhold, and Woessmann (2017) for a detailed discussion of estimating causal effects in the PIAAC data.

of mean PIAAC skills) lead to a nine-percent increase in income 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.

A closer inspection of the data additionally reveals some insights into potential 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. We also investigated the distribution of skills and find that investments in decreasing the share of low achievers in the literacy assessment yields growth benefits. For Canada, the long-run effect of decreasing the share of high achievers by 10 percent is an increase in GDI per capita of 770 CAD.

We also find that skills are somewhat less important for economic performance in Canada compared to other developed countries. A candidate explanation for this finding is that province-level income growth is more volatile and more prone to other influences compared to country-level growth. At the same time, the negative effect of low literacy proficiency on economic development is attenuated in the Canadian sample. One potential rationale behind this result is that Canadian provinces have a rather small share of low achievers in literacy compared to the international average. Thus, high-skilled individuals are less scarce than in many other developed countries. If there are decreasing returns to skill investment, as traditional neoclassical growth theory would suggest, the economic effects of skill investments will be the lower the higher the skill endowment already is.

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 developing highly talented individuals. 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 income per capita.

References

ACCC (2013), Improving Literacy and Essential Skills Instruction in Canada: Results of the ACCC's National Essential Skills Framework Project. Ottawa.

Acemoglu, D. and D.H. Autor (2011), "Skills, Tasks and Technologies: Implications for Employment and Earnings." in O. Ashenfelter and D. Card (eds.), Handbook of Labor Economics, Vol. 4, Amsterdam: Elsevier, pp. 1043-1171.

Aghion, P. and P. Howitt (1992), "A Model of Growth through Creative Destruction", *Econometrica*, Vol. 60, No. 2, pp. 323-351.

AIR (2015), Reconstructing the Evolution of theAmerican Supply of Cognitive Skills: A Synthetic Cohort Analysis. Project report by T.S. Murray, M. Binkley, and R. Shillington.

Autor, D.H., F. Levy, and R.J. Murnane (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, Vol. 118, No. 4, pp. 1279-1333.

AWES (2018), "Skilling Up: Reflections on Instructional Efficiency and Effectiveness." Alberta Workforce Essential Skills Society: DataAngel Policy Research and Skill Plan, Calgary, Ottawa and Burnaby.

Barro, R.J. (1991), "Economic Growth in a Cross Section of Countries", *Quarterly Journal of Economics*, Vol. 106, No. 2, pp. 407-443.

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

Barro, R.J. (2001), "Human Capital and Growth", *American Economic Review*, Vol. 91, No. 2, pp. 12-17.

Barro, R.J. and J.-W. Lee (2001), "International Data on Educational Attainment: Updates and Implications", *Oxford Economic Papers*, Vol. 53, No. 3, pp. 541-563.

Barro, R.J. and J.-W. Lee (2010), A New Data Set of Educational Attainment in the World, 1950–2010, NBER Working Papers No. 15902, National Bureau of Economic Research, Inc., Cambridge, MA.

Becker, G.S. (1973), "A Theory of Marriage: Part I", *Journal of Political Economy*, Vol. 81, No. 4, pp. 813-846.

Bonikowska, A., D.A. Green and W.C. Riddell (2008), Literacy and the Labour Market: Cognitive Skills and Immigrant Earnings, Statistics Canada, Catalogue 89-552-M, No. 020, Ottawa.

Canada West Foundation (2018), First, We Learn to Read: Then, We Read to Learn. Calgary.

Card, D. (1999), "The Causal Effect of Education on Earnings", in O. Ashenfelter and D. Card (eds.), Handbook of Labor Economics, Volume 3a, North Holland, Amsterdam, pp. 1801-1863.

Cascio, E., D. Clark and N. Gordon (2008), "Education and the Age Profile of Literacy into Adulthood", *Journal of Economic Perspectives*, Vol. 22, No. 3, pp. 47-70.

Coulombe, S., J.-F. Tremblay and S. Marchand (2004), Literacy Scores, Human Capital and Growth Across Fourteen OECD Countries, Statistics Canada, Ottawa.

Coulombe, S. and J.-F. Tremblay (2006), “Literacy and Growth”, *B.E. Journals in Macroeconomics: Topics in Macroeconomics*, Vol. 6, No. 2, pp. 1-32.

Dalgaard, C. (2007), “Calculating the Time it Takes to Get Half Way to Steady State in the Solow Model”, http://web.econ.ku.dk/dalgaard/makro2/2007ed/Notermv/note_timetohalve.pdf

DataAngel (2009), Addressing Canada’s Literacy Challenge: A Cost/Benefit Analysis. DataAngel Policy Research, Ottawa

DataAngel (2010), The Economic Benefits of Literacy: Evidence and Implications for Policy. Report by M. McCracken and T.S. Murray, Canadian Language and Literacy Research Network, London

DataAngel (2014), The Efficiency of Essential Skills Markets in Alberta: Summary Report and Implications for Public Policy.

Edin, P.A. and M. Gustavsson (2008), “Time out of Work and Skill Depreciation”, *Industrial and Labor Relations Review*, Vol. 61, No. 2, pp. 163-180.

De la Fuente, A. and R. Doménech (2006), “Human Capital in Growth Regressions: How Much Difference Does Data Quality Make?”, *Journal of the European Economic Association*, Vol. 4, No. 1, pp. 1-36.

Falck, O., A. Heimisch, and S. Wiederhold (2016), “Returns to ICT Skills”, CESifo Working Paper, No. 5720.

Feenstra, R. C., R. Inklaar, and M. P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review,* Vol. 105, No. 10, pp. 3150-82.

Ferrer, A., D.A. Green and W.C. Riddell (2006), “The Effect of Literacy on Immigrant Earnings”, *Journal of Human Resources*, Vol. 41, No. 2, pp. 380-410.

Goldin, C. and L. F. Katz (2008), The Race between Education and Technology, Harvard University Press, Cambridge, MA.

Green, D.A. and W.C. Riddell (2003), “Literacy and Earnings: An Investigation of the Interaction of Cognitive and Unobserved Skills in Earnings Generation”, *Labour Economics*, Vol. 10, No. 2, pp. 165-84.

Hanushek, E.A. and D.D. Kimko (2000), “Schooling, Labor-Force Quality, and the Growth of Nations”, *American Economic Review*, Vol. 90, No. 5, pp. 1184-1208.

Hanushek, E. A., G. Schwerdt, S. Wiederhold, and L. Woessmann (2015), “Returns to Skills around the World: Evidence from PIAAC”, *European Economic Review*, Vol. 73(C), pp. 103-130.

Hanushek, E. A., G. Schwerdt, S. Wiederhold, and L. Woessmann (2017), “Coping with change: International differences in the returns to skills”, *Economics Letters*, Vol. 153, pp. 15-19.

Hanushek, E.A. and L. Woessmann (2008), “The Role of Cognitive Skills in Economic Development”, *Journal of Economic Literature*, Vol. 46, No. 3, pp. 607-668.

Hanushek, E. A., and L. Woessmann (2011), “The Economics of International Differences in Educational Achievement”, *Handbook of the Economics of Education, Vol. 3,* edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann. Amsterdam: North Holland, pp. 89-200.

Hanushek, E. A., and L. Woessmann (2012), “Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation.” *Journal of Economic Growth*, Vol. 17, No. 4, pp. 267-321.

Hanushek, E. A., and L. Woessmann (2015), “The Knowledge Capital of Nations: Education and the Economics of Growth”, MIT Press, Cambridge, MA.

Hanushek, E.A. and L. Zhang (2009), “Quality-Consistent Estimates of International Schooling and Skill Gradients”, *Journal of Human Capital*, Vol. 3, No. 2, pp. 107-143.

Hanushek, E.A., J. Ruhose, and L. Woessmann (2017), “Knowledge Capital and Aggregate Income Differences: Development Accounting for US States”. American Economic Journal: Macroeconomics 2017, 9(4): 184–224.

Hampf, F. S. Wiederhold, and L. Woessmann (2017), “Skills, earnings, and employment: exploring causality in the estimation of returns to skills”, *Large Scale Assessments in Education*, Vol. 5, No. 12.

Heckman, J. J., L. J. Lochner, and P. E. Todd (2006), “Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond.” in E.A. Hanushek and F. Welch (eds.), Handbook of the Economics of Education, Vol. 1. Amsterdam: North Holland, pp. 307-458.

IRPP (Institute for Research on Public Policy) (2017), The Peril and Promise of Canada’s Essential Skills Problem. Montreal.

Islam N. (1995), “Growth Empirics: A Panel Data Approach”, *Quarterly Journal of Economics*, Vol. 110, No. 4, pp. 1127-70.

Kahn, L. (2004), “Immigration, Skills and the Labor Market: International Evidence”, *Journal of Population Economics*, Vol.17, No. 3, pp. 501-534.

Lucas, R.E. (1988), “On the Mechanics of Economic Development”, *Journal of Monetary Economics*, Vol. 22, No. 1, pp. 3-42.

Mankiw, N.G., D. Romer and D.N. Weil (1992), “A Contribution to the Empirics of Economic Growth”, *Quarterly Journal of Economics*, Vol. 107, No. 2, pp. 407-437.

McCracken, M. and Murray, T.S. (2009), The Economic Benefits of Literacy: Evidence and Implications for Policy, Canadian Language and Literacy Research Network, London.

Mincer, J. (1974), Schooling, Experience, and Earnings, National Bureau of Economic Research, New York.

Nickell, S. (1981), “Biases in Dynamic Models with Fixed Effects”, *Econometrica*, Vol. 49, pp. 1417–1426.

OECD (Organization for Economic Co-operation and Development) (2013), OECD Skills Outlook 2013. First Results from the Survey of Adult Skills, OECD, Paris.

Perry, A., S. Wiederhold, and D. Ackermann-Piek (2014), “How Can Skill Mismatch be Measured? New Approaches with PIAAC”, *Methods, Data, Analyses: A Journal for Quantitative Methods and Survey Methodology*, Vol. 8, No. 2, pp. 137-174.

Romer, P.M. (1986), "Increasing Returns and Long-run Growth", *Journal of Political Economy*, Vol. 94, No. 5, pp. 1002-1037.

Romer, P.M. (1987), "Growth Based on Increasing Returns Due to Specialization", *American Economic Review*, Vol. 77, No. 2, pp. 56-62.

Romer, P.M. (1990), "Endogenous Technological Change", *Journal of Political Economy*, Vol. 98, No. 5, pp. 71-102.

Sachs, J.D., and A. Warner (1995), "Economic Reform and the Process of Global Integration" *Brookings Papers on Economic Activity*, Vol. 1, pp. 1-95.

Sala-i-Martin, X., G. Doppelhofer and R.I. Miller (2004), "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach", *American Economic Review*, Vol. 94, No. 4, pp. 813-835.

Schwerdt, G. (2018), "Returns to Quality-Adjusted Schooling: New Evidence from PIAAC" In Kirsch, I., Gonzalez, E., von Davier, M., Yamamoto, K. (Eds.) The Importance of Skills and How to Assess Them - Results from PIAAC, Springer (forthcoming).

Solow, R.M. (1956), "A Contribution to the Theory of Economic Growth", *Quarterly Journal of Economics*, Vol. 70, No. 1, pp. 65-94.

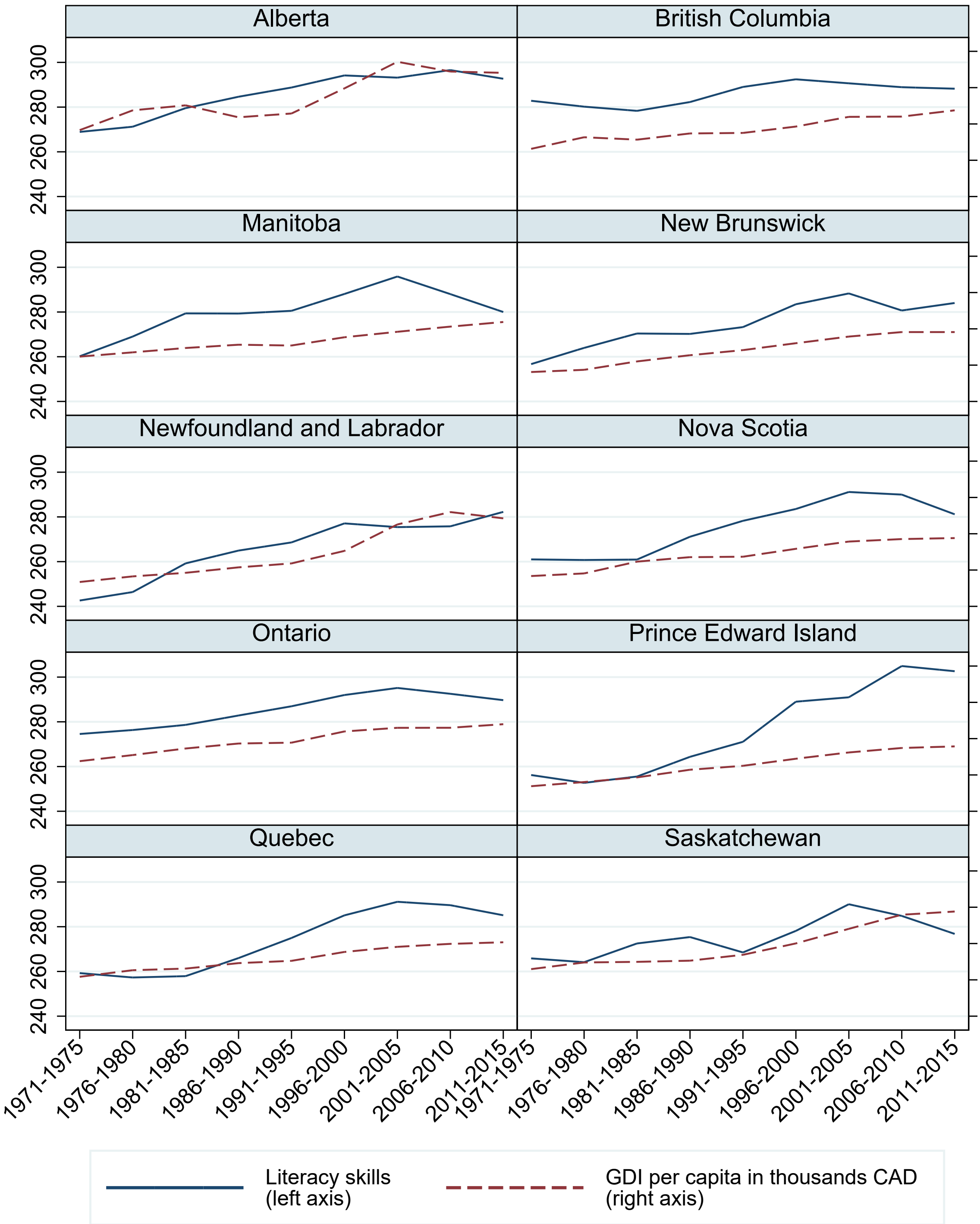
SRDC (2014), Upskill: A Credible Test of Workplace Literacy and Essential Skills Upgrading. Ottawa.

Willms, D. and T.S. Murray (2007), "Gaining and Losing Literacy Skills over the Lifecourse". Statistics Canada, Ottawa.

Woessmann, L. (2003), "Specifying Human Capital", *Journal of Economic Surveys*, Vol. 17, No. 3, pp. 239-270

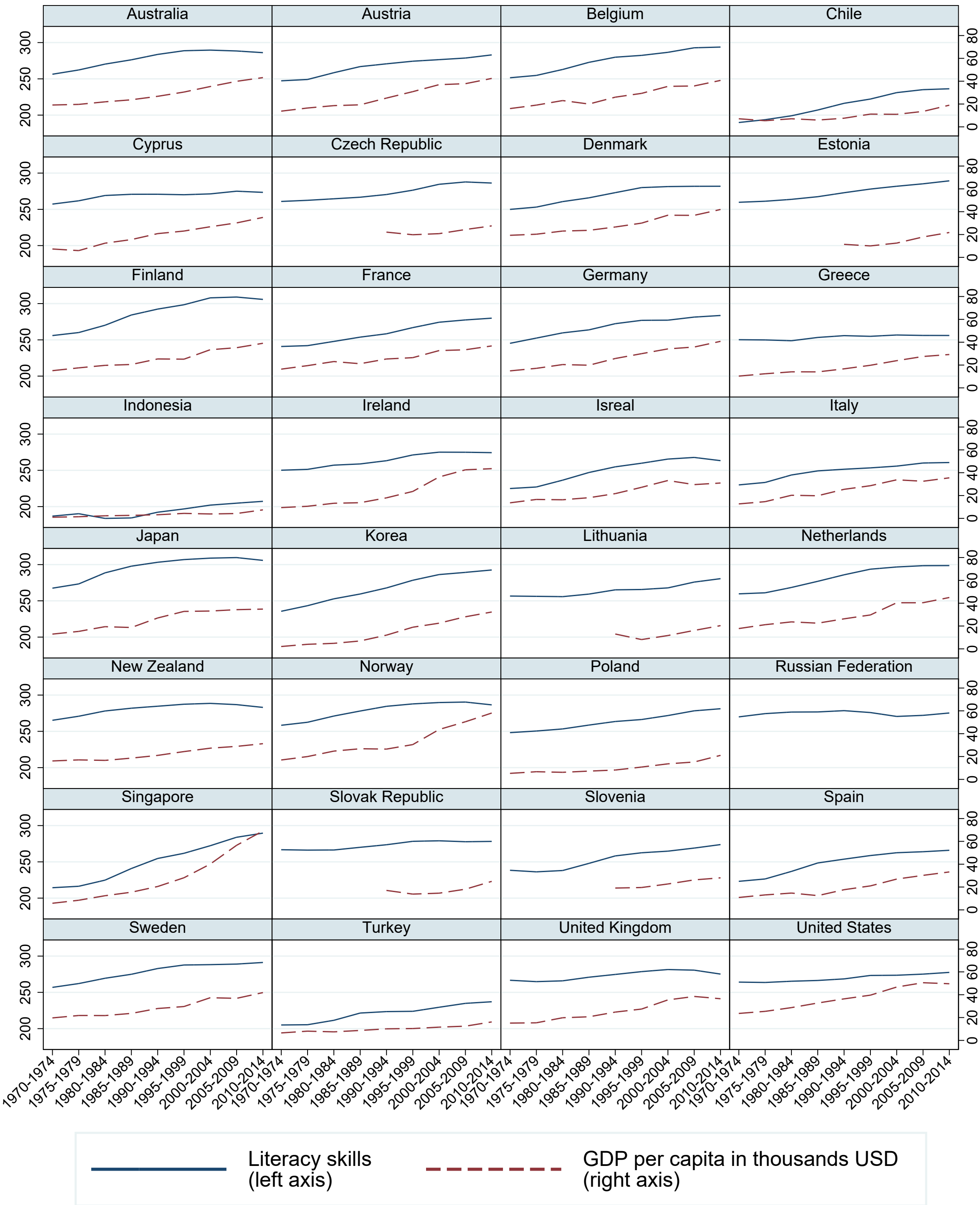
Woessmann, L. (2016), "The Economic Case for Education." *Education Economics*,Vol. 24, No. 1, pp. 3-32.

Figure 1: Literacy Skills and Economic Performance: Canadian Provinces



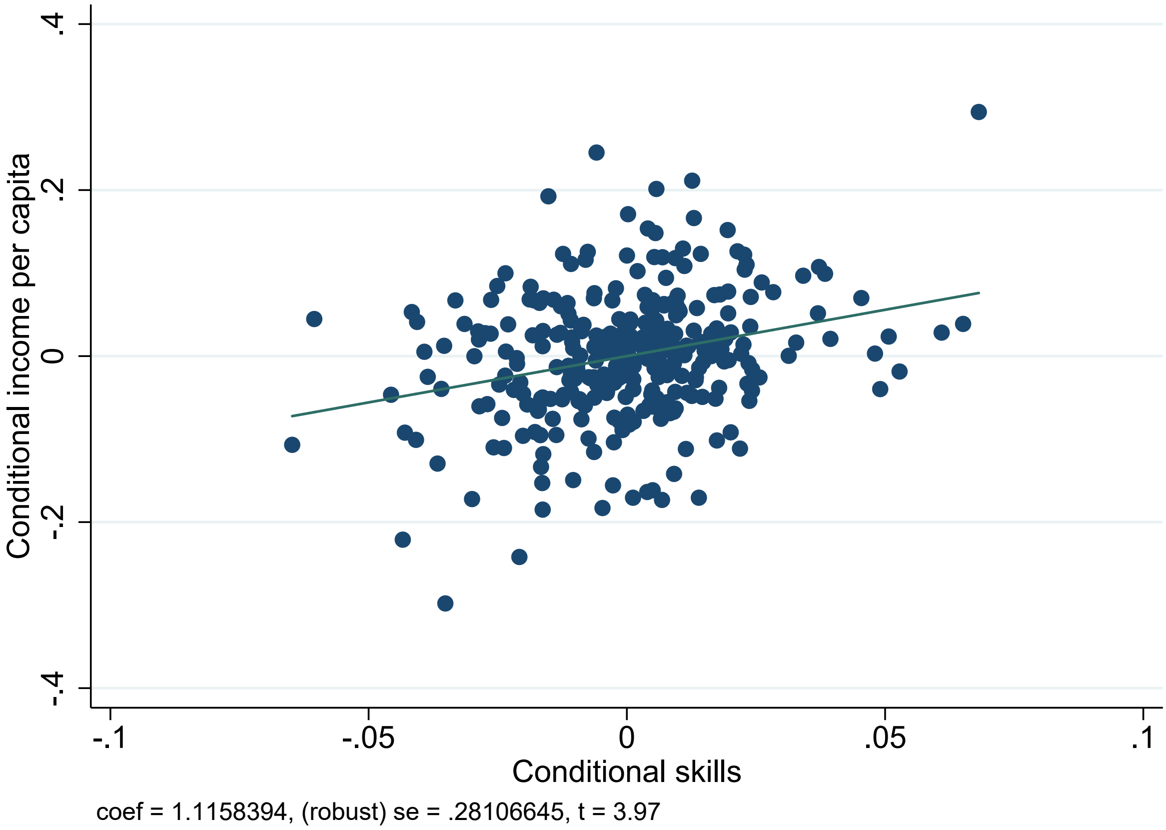
Notes: Graph shows average literacy skills of the population aged 18 to 27 years in five-year periods from 1971 to 2015 (left axis) as well as average Gross Domestic Income (GDI) for all ten Canadian provinces. *Data sources:* PIAAC, Statistics Canada.

Figure 2: Literacy Skills and Economic Performance: PIAAC Countries



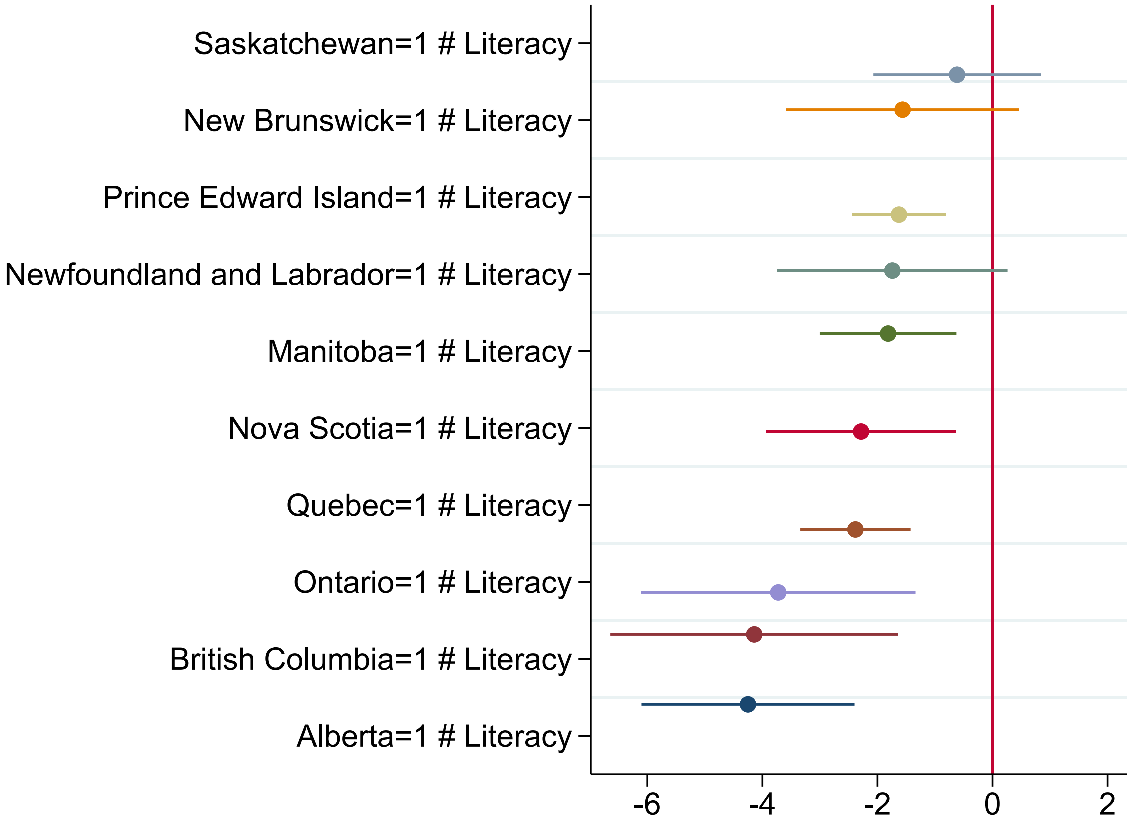
Notes: Graph shows average literacy skills of the population aged 18 to 27 years in five-year periods from 1970 to 2014 (left axis) as well as average Gross Domestic Product (GDP) for PIAAC countries. *Data sources:* PIAAC, Penn World Tables.

Figure 3: Literacy Skills and Income Growth



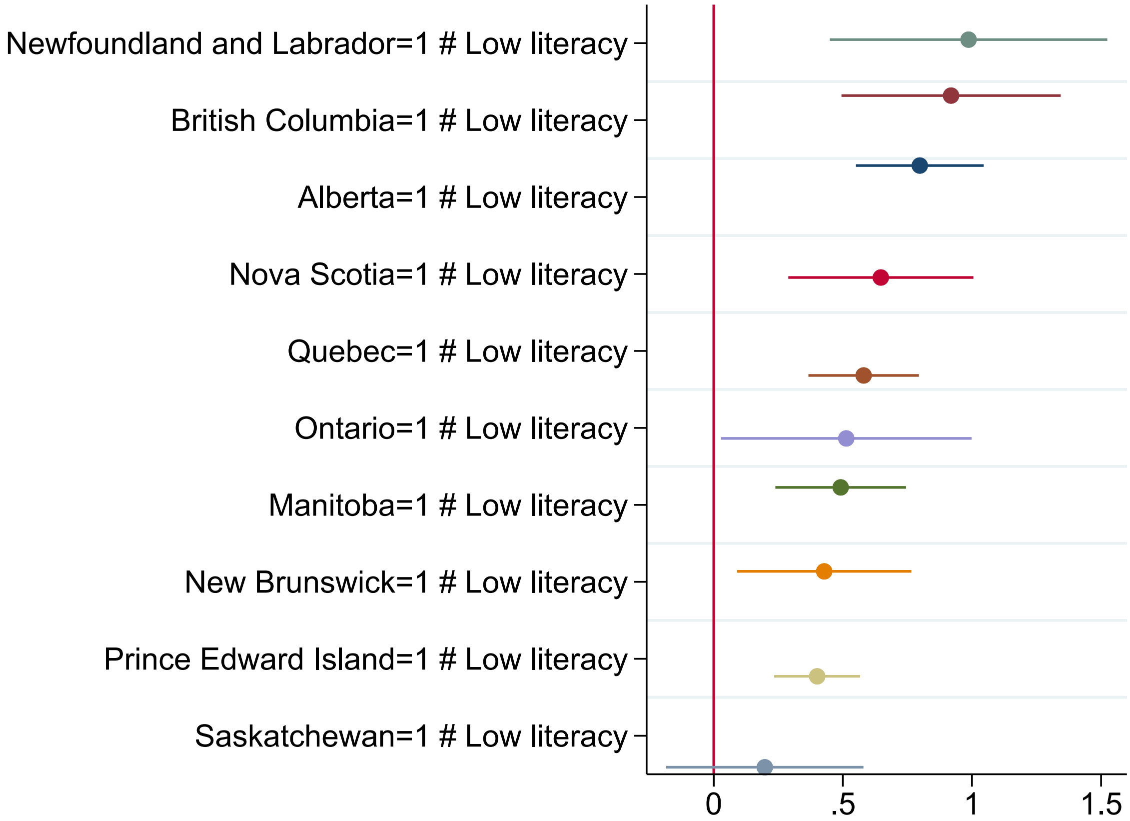
Notes: Added-variable plot of literacy skills in a regression of end-of-period income on initial income, fertility rate, investment rate, and literacy skills. All variables are in logarithm. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations, Statistics Canada.

Figure 4: Literacy Effects in Canadian Provinces vs. International Mean



Notes: Interaction effects of literacy skills and Canadian province (augmented specification based on the regression model reported in Column 2 of Table 1), showing the coefficient (dot) and the 90% confidence interval (line). Interaction effects are ordered by magnitude. Red vertical line indicates international average literacy effect. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations, Statistics Canada.

Figure 5: Literacy Effects in Canadian Provinces vs. International Mean:
Low Literacy Proficiency



Notes: Interaction effects of low literacy indicator (proficiency levels 1 and 2) and Canadian province (augmented specification based on the regression model reported in Column 1 of Table 3), showing the coefficient (dot) and the 90% confidence interval (line). Interaction effects are ordered by magnitude. Red vertical line indicates international average effect of low literacy on economic performance. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations, Statistics Canada.

Table 1: The Relationship between Literacy Skills and Economic Performance

	(1)	(2)	(3)	(4)
Literacy	1.116***	1.374***	.948***	1.011***
	(.281)	*(.283)*	*(.285)*	*(.280)*
Initial income per capita	.694***	.538***	.698***	.647***
	(.045)	*(.072)*	*(.046)*	*(.073)*
Fertility rate	−.078*	−.273***	−.071	−.148*
	(.045)	*(.084)*	*(.047)*	*(.083)*
Investment rate	.009	−.082*	.050	.001
	(.031)	*(.043)*	*(.040)*	*(.048)*
Openness ratio			.083**	.105**
			(.034)	*(.050)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented		X		X
Observations	308	308	288	288
R-squared	.982	.980	.984	.984
Implied long-run elasticity of outcome to literacy	3.65	2.98	3.14	2.87

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

Notes: Dependent variable: end-of-period income per capita. All variables are in logarithm. Instruments used in Column 2 are lagged values of initial income per capita, investment rate, and fertility rate (in Column 4, the set of instruments also includes the openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Table 2: Female Versus Male Literacy

	(1)	(2)	(3)
Female literacy	1.343***		1.179***
	(.252)		*(.303)*
Male literacy		1.049***	.229
		(.269)	*(.321)*
Initial income per capita	.549***	.548***	.544***
	(.070)	*(.072)*	*(.071)*
Fertility rate	−.255***	−.289***	−.259***
	(.083)	*(.086)*	*(.083)*
Investment rate	−.077*	−.086**	−.078*
	(.042)	*(.044)*	*(.042)*
Country fixed effects	X	X	X
Period fixed effects	X	X	X
Controls instrumented	X	X	X
Observations	308	308	308
R-squared	.980	.979	.980
Implied long-run elasticity of outcome to female literacy	2.98		2.58
Implied long-run elasticity of outcome to male literacy		2.32	

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

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

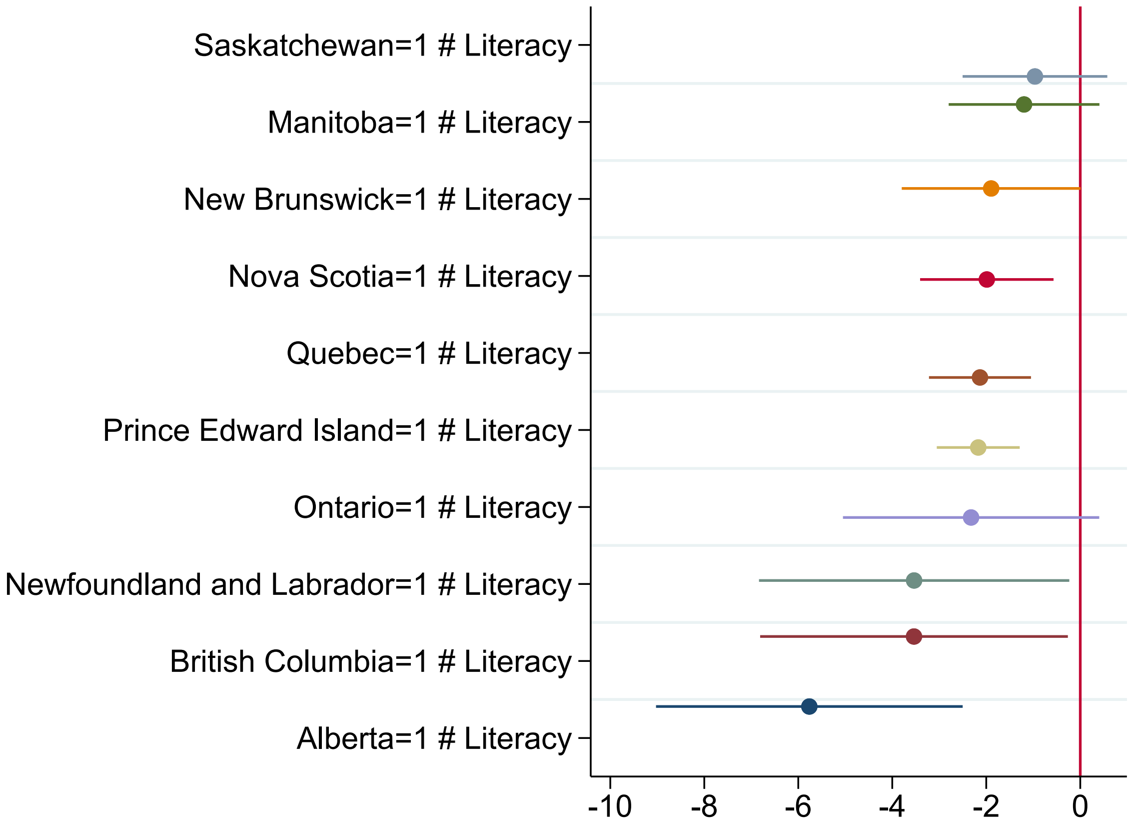
Table 3: The Relationship between Low Literacy Proficiency and Economic Performance

	(1)	(2)
Low literacy	−.099**	−.077*
	(.048)	*(.043)*
Initial income per capita	.575***	.699***
	(.073)	*(.068)*
Fertility rate	−.324***	−.150*
	(.090)	*(.086)*
Investment rate	−.092**	.018
	(.046)	*(.049)*
Openness ratio		.132***
		(.047)
Country fixed effects	X	X
Period fixed effects	X	X
Controls instrumented	X	X
Observations	308	288
R-squared	.978	.983
Implied long-run elasticity of outcome to literacy	−.23	−.26

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

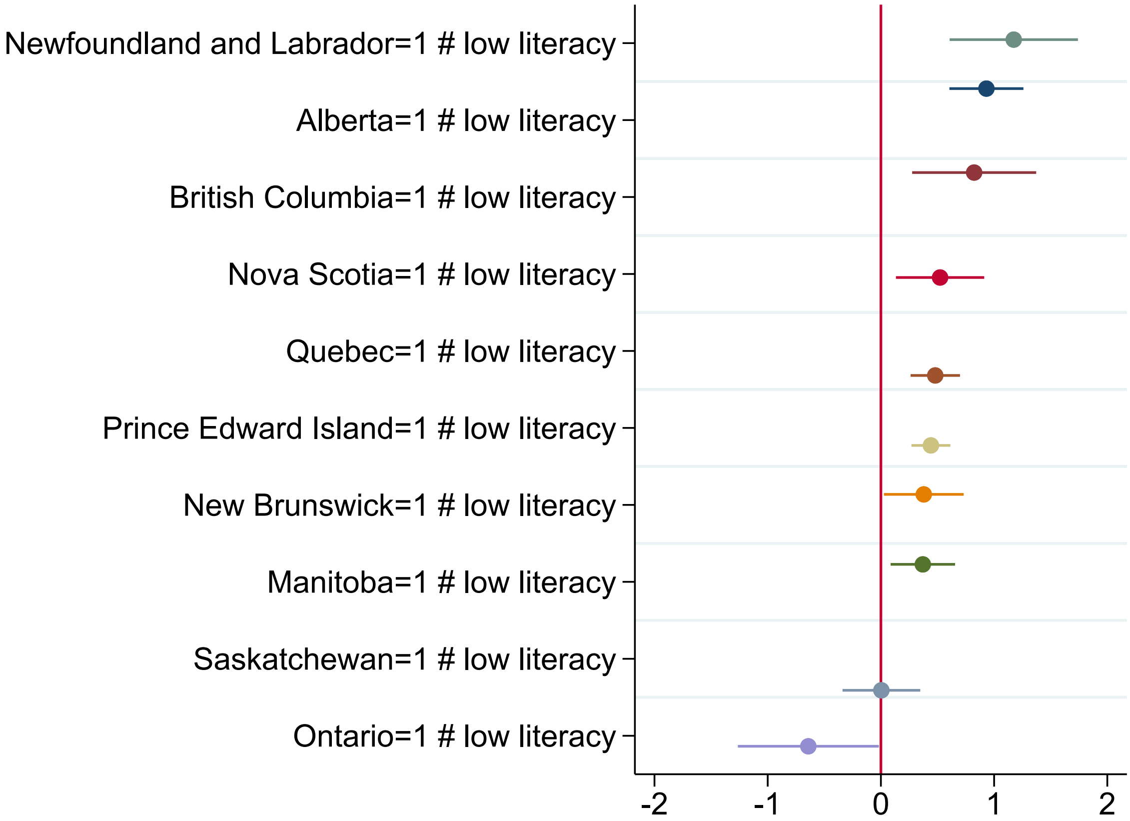
Notes: Dependent variable: end-of-period income per capita. "Low literacy" is defined as the share of the population with proficiency levels 1 and 2 in PIAAC (i.e., below 276 points). All variables are in logarithm. Instruments used in Column 1 are lagged values of initial income per capita, investment rate, and fertility rate (in Column 2, the set of instruments also includes the openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Figure A-1: Literacy Effects on GDP Per Capita in Canadian Provinces vs. International Mean



Notes: Figure replicates Figure 4 using GDP per capita instead of GDI per capita in Canadian provinces. Number of observations decreases from 308 to 288 because GDP data in Canadian provinces are available only from 1981 onwards. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations, Statistics Canada.

Figure A-2: Literacy Effects on GDP Per Capita in Canadian Provinces vs. International Mean: Low Literacy Proficiency



Notes: Figure replicates Figure 5 using GDP per capita instead of GDI per capita in Canadian provinces. Number of observations decreases from 308 to 288 because GDP data in Canadian provinces are available only from 1981 onwards. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, United Nations, Statistics Canada.

Table A-1: The Relationship between Numeracy Skills and Economic Performance

	(1)	(2)	(3)	(4)
Numeracy	.965***	1.161***	.801***	.838***
	(.269)	*(.287)*	*(.287)*	*(.303)*
Initial income per capita	.692***	.542***	.697***	.653***
	(.047)	*(.077)*	*(.049)*	*(.078)*
Fertility rate	−.046	−.231***	−.043	−.117
	(.047)	*(.085)*	*(.048)*	*(.082)*
Investment rate	−.000	−.094**	.042	−.010
	(.031)	*(.044)*	*(.040)*	*(.048)*
Openness ratio			.087**	.109**
			(.035)	*(.051)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented		X		X
Observations	308	308	288	288
R-squared	.982	.979	.984	.984
Implied long-run elasticity of outcome to numeracy	3.13	2.53	2.65	2.42

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

Notes: Dependent variable: end-of-period income per capita. All variables are in logarithm. Instruments used in Column 2 are lagged values of initial income per capita, investment rate, and fertility rate (in Column 4, the set of instruments also includes the openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Table A-2: Robustness: Using Gross Domestic Product (GDP) in Canadian Provinces

	(1)	(2)	(3)	(4)
Literacy	1.100***	1.270***	.910***	.958***
	(.285)	*(.264)*	*(.291)*	*(.287)*
Initial GDP per capita	.690***	.608***	.722***	.691***
	(.045)	*(.067)*	*(.047)*	*(.072)*
Fertility rate	−.078*	−.177**	−.055	−.106
	(.046)	*(.075)*	*(.046)*	*(.080)*
Investment rate	.053	−.006	.054	−.004
	(.037)	*(.048)*	*(.037)*	*(.048)*
Openness ratio			.088***	.107**
			(.034)	*(.048)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented		X		X
Observations	288	288	288	288
R-squared	.986	.985	.986	.986
Implied long-run elasticity of outcome to literacy	3.55	3.24	3.27	3.10

* 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 Column 2 are lagged values of initial GDP per capita, investment rate, and fertility rate (in Column 4, the set of instruments also includes openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Table A-3: The Relationship between Literacy Skills and Economic Performance: Log-Linear Specification

	(1)	(2)	(3)	(4)
Literacy skills (standardized)	.091***	.117***	.081***	.088***
	(.025)	*(.026)*	*(.025)*	*(.024)*
Initial income per capita	.700***	.536***	.700***	.648***
	(.046)	*(.072)*	*(.046)*	*(.072)*
Fertility rate	–.087*	–.295***	–.079*	–.159*
	(.046)	*(.085)*	*(.047)*	*(.083)*
Investment rate	.010	–.086**	.054	.007
	(.032)	*(.043)*	*(.040)*	*(.048)*
Openness ratio			.086**	.104**
			(.034)	*(.050)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented		X		X
Observations	308	308	288	288
R-squared	.982	.979	.984	.984

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

Notes: Dependent variable: end-of-period income per capita. Literacy skills are standardized with mean zero and standard deviation 1 across regions. All other variables are in logarithm. Instruments used in Column 2 are lagged values of initial income per capita, investment rate, and fertility rate (in Column 4, the set of instruments also includes the openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Table A-4: Robustness: Same Number of Observations in Each Specification

	(1)	(2)	(3)	(4)
Literacy	1.122***	1.306***	.948***	1.011***
	(.277)	*(.259)*	*(.285)*	*(.280)*
Initial income per capita	.667***	.564***	.698***	.647***
	(.044)	*(.068)*	*(.046)*	*(.073)*
Fertility rate	–.092**	–.220***	–.071	–.148*
	(.047)	*(.077)*	*(.047)*	*(.083)*
Investment rate	.051	.004	.050	.001
	(.039)	*(.048)*	*(.040)*	*(.048)*
Openness ratio			.083**	.105**
			(.034)	*(.050)*
Country fixed effects	X	X	X	X
Period fixed effects	X	X	X	X
Controls instrumented		X		X
Observations	288	288	288	288
R-squared	.984	.983	.984	.984
Implied long-run elasticity of outcome to literacy	3.37	3.00	3.14	2.87

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

Notes: Dependent variable: end-of-period income per capita. All variables are in logarithm. Instruments used in Column 2 are lagged values of initial income per capita, investment rate, and fertility rate (in Column 4, the set of instruments also includes the openness ratio). Robust standard errors in parentheses. *Data sources:* International Monetary Fund, Penn World Tables, PIAAC, Statistics Canada, United Nations.

Annex B: Description of Proficiency Levels in Literacy

Level	Score range	Percentage of adults scoring at each level (average)	Types of tasks completed successfully at each level of proficiency
Below Level 1	Below 176 points	3.3%	The tasks at this level require the respondent to read brief texts on familiar topics to locate a single piece of specific information. There is seldom any competing information in the text and the requested information is identical in form to information in the question or directive. The respondent may be required to locate information in short continuous texts. However, in this case, the information can be located as if the text were non-continuous in format. Only basic vocabulary knowledge is required, and the reader is not required to understand the structure of sentences or paragraphs or make use of other text features. Tasks below Level 1 do not make use of any features specific to digital texts.
1	176 to less than 226 points	12.2%	Most of the tasks at this level require the respondent to read relatively short digital or print continuous, non-continuous, or mixed texts to locate a single piece of information that is identical to or synonymous with the information given in the question or directive. Some tasks, such as those involving non-continuous texts, may require the respondent to enter personal information onto a document. Little, if any, competing information is present. Some tasks may require simple cycling through more than one piece of information. Knowledge and skill in recognising basic vocabulary determining the meaning of sentences, and reading paragraphs of text is expected.
2	226 to less than 276 points	33.3%	At this level, the medium of texts may be digital or printed, and texts may comprise continuous, non-continuous, or mixed types. Tasks at this level require respondents to make matches between the text and information, and may require paraphrasing or low-level inferences. Some competing pieces of information may be present. Some tasks require the respondent to ▪ cycle through or integrate two or more pieces of information based on criteria; ▪ compare and contrast or reason about information requested in the question; or ▪ navigate within digital texts to access and identify information from various parts of a document.
3	276 to less than 326 points	38.2%	Texts at this level are often dense or lengthy, and include continuous, non-continuous, mixed, or multiple pages of text. Understanding text and rhetorical structures become more central to successfully completing tasks, especially navigating complex digital texts. Tasks require the respondent to identify, interpret, or evaluate one or more pieces of information, and often require varying levels of inference. Many tasks require the respondent to construct meaning across larger chunks of text or perform multi-step operations in order to identify and formulate responses. Often tasks also demand that the respondent disregard irrelevant or inappropriate content to answer accurately. Competing information is often present, but it is not more prominent than the correct information.
4	326 to less than 376 points	11.1%	Tasks at this level often require respondents to perform multiple-step operations to integrate, interpret, or synthesise information from complex or lengthy continuous, non-continuous, mixed, or multiple type texts. Complex inferences and application of background knowledge may be needed to perform the task successfully. Many tasks require identifying and understanding one or more specific, non-central idea(s) in the text in order to interpret or evaluate subtle evidence-claim or persuasive discourse relationships. Conditional information is frequently present in tasks at this level and must be taken into consideration by the respondent. Competing information is present and sometimes seemingly as prominent as correct information.
5	Equal to or higher than 376 points	0.7%	At this level, tasks may require the respondent to search for and integrate information across multiple, dense texts; construct syntheses of similar and contrasting ideas or points of view; or evaluate evidence based arguments. Application and evaluation of logical and conceptual models of ideas may be required to accomplish tasks. Evaluating reliability of evidentiary sources and selecting key information is frequently a requirement. Tasks often require respondents to be aware of subtle, rhetorical cues and to make high-level inferences or use specialised background knowledge.

Notes: The percentage of adults scoring at different levels of proficiency adds up to 100% when the 1.2% of literacy-related non-respondents across countries are taken into account. Adults in this category were not able to complete the background questionnaire due to language difficulties or learning and mental disabilities (see section on literacy-related non-response). *Source:* OECD (2013), p. 64.