The Evolution of Returns to Cognitive Skills across Countries: Evidence on Factor Price Equalization*

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Abstract

Globalization and technological change are constantly changing the demand for skills in national economies. We estimate how returns to cognitive skills have evolved over the past decade in 23 developed countries, finding strong convergence consistent with factor price equalization. The psychometrically linked PIAAC surveys of adult skills in 2012 and 2023 allow consistent international comparisons of skill returns over time. On average across countries, earnings increase by 16.7 percent per standard deviation in numeracy skills in 2023, a decline from 20.3 in 2012. These estimates of returns to cognitive skills are hardly affected by conditioning on non-cognitive skills. But there is substantial cross-country heterogeneity with one third of countries seeing increased returns. Strikingly, much of the cross-country variation in the change in skill returns can be accounted for by convergence, whereas other factors including technological change do not contribute. Consistent with mechanisms of factor price equalization, the speed of convergence is faster in countries with more labor-market flexibility and openness to trade, especially in intangibles.

Keywords: cognitive skills, factor price equalization, education, earnings, labor market, international comparisons

JEL classification: I26, J24, J31, F66

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1. Introduction

Workers around the world are constantly exposed to trends and shocks that alter both the tasks that they are expected to perform and the demand for their skills in the labor market. At the policy level, changing labor-market opportunities have led to an increased focus on how the integration of national economies through globalization of trade affects individual outcomes. International trade theory suggests that factor price equalization across countries would have an impact on each country's labor markets, but the implied general equilibrium effects are difficult to assess within national economies. Evidence on changes in returns to skills (the price of human capital) over time has so far been restricted to individual country settings (e.g., Murnane, Willett, and Levy (1995), Castex and Dechter (2014), Deming (2017), Edin et al. (2022), Izadi and Tuhkuri (2024)). Internationally comparative evidence on the other hand has been restricted to cross-sectional analysis, precluding any investigation of dynamic impacts of changing trade patterns (e.g., Leuven, Oosterbeek, and Ophem (2004), Blau and Kahn (2005), Hanushek et al. (2015)). This paper capitalizes on newly available data to provide consistent international estimates of changes in labor-market returns to cognitive skills over time and to study how these changes relate to forces of factor price equalization and other country differences.

Our analysis has three major components. We first focus on obtaining comparable estimates of recent patterns of returns to cognitive skills across countries. Next, relying on the consistent international measurement of cognitive skills over time, these estimates in turn allow us to construct a picture of the dynamics of labor-market returns across many developed countries. Finally, we investigate the factors lying behind the cross-country differences in the change in returns to cognitive skills over time, focusing on convergence in skill returns and how its speed relates to openness to international trade and freedom of labor markets.

Our analysis of changes in returns to cognitive skills across developed countries is made possible by newly available measures of cognitive skills that allow for consistent comparisons of workers across countries and over time. In 2023, the Organisation for Economic Co-operation and Development (OECD) implemented a second cycle of the innovative survey of the Programme for the International Assessment of Adult Competencies (PIAAC). By psychometric linkage of the cognitive skill tests to its first installment in 2012, PIAAC allows us to consistently estimate returns to cognitive skills over an eleven-year period in 23 developed countries. The survey assesses the numeracy and literacy skills of large representative samples of

roughly 5,000 adults in each country and cycle, which can be linked to labor-market outcomes for individuals. PIAAC is unique in its enormous efforts of test development and test implementation, with each survey taking an average of roughly 1.5 hours to complete.

Our empirical model of wage dynamics follows the human capital tradition. Building on our prior cross-sectional analysis of PIAAC Cycle 1 data (Hanushek et al. (2015)), we estimate a "modified Mincer model" that relates earnings to measures of cognitive skills as direct measures of human capital in each cycle. Focus on changes in estimates of skill returns over time avoids interference from time-invariant biases.

Our analysis contributes five insights into the labor-market returns to skills. First, there are large returns to cognitive skills in 2023 in all countries. On average across the 27 countries participating in PIAAC Cycle 2, each standard deviation (SD) in numeracy skills is associated with 16.7 percent higher earnings. Returns exceed 20 percent in Hungary, Estonia, Singapore, and Germany and exceed 16 percent in 16 countries including the United States (19.0 percent). Even at the lower end, returns are above 8 percent in the Slovak Republic and Sweden. Returns are lower at labor-market entry age, in the public sector, and for part-time workers, but hardly differ by gender, migrant status, and parental background.

Second, accounting for individual differences in non-cognitive skills has little effect on estimates of returns to cognitive skills. Exploiting the newly available measurement of socio-emotional skills in the international data, we show that estimates of the impact of cognitive skills decrease only minimally when controlling for open-mindedness, conscientiousness, extraversion, agreeableness, and emotional stability – the Big Five personality traits – as well as for patience, trust, and volunteering.

Third, returns to cognitive skills have decreased slightly since 2012, but there is substantial cross-country heterogeneity. On average, returns declined from 20.3 to 16.7 percent across the 23 countries that participated in both PIAAC cycles. Still, seven countries saw their skill returns increase, most notably Denmark and the Czech Republic. The largest declines are observed in Singapore, the Slovak Republic, Hungary, and the United States. Drawing on the psychometric linkage of our skill data, we also show that estimates of changes in returns to skills can be quite misleading when assuming that the distribution of skills in the country population does not change over time, a common assumption in the literature.

Fourth, the overwhelming theme that emerges from our estimates is a strong tendency toward factor price equalization. Most of the cross-country variation in changes in returns to cognitive skills can be accounted for by convergence across countries. A one percentage point higher return to cognitive skills in the initial period is associated with a 0.52 percentage point reduction in skill returns over the subsequent 11-year period. This cross-country equalization accounts for over half the cross-country variation in the change in estimated returns to skills. By contrast, the change in returns to skills is not systematically related to measures of technology, changes in the workforce composition, or other country features.

Fifth, the speed of convergence in skill returns across countries is faster in countries with larger openness to international trade and more flexible labor markets. The effect of openness particularly shows for trade in services and intellectual property, indicating the importance of information-based exchanges and knowledge trade for skill returns. These patterns of trade and freedom of factor market adjustments are consistent with mechanisms of factor price equalization.

Our analysis builds on several lines of previous research. Estimation of the returns to skills follows the now-standard models of human capital (Becker (1964), Mincer (1970), Card (2001)) but extends them to include quality differences across school attainment. While most past analyses of skill differences, particularly in international analyses, have by necessity relied on measures of school attainment, it is clear that the amount of learning per year of school differs dramatically (Hanushek and Woessmann (2011)) and that these differences matter for economic outcomes (Hanushek and Woessmann (2008, 2015)).

Cross-sectional analyses of international differences in returns to skills start with the International Adult Literacy Survey (IALS) in 1994-1998 (Leuven, Oosterbeek, and Ophem (2004), Blau and Kahn (2005), Hanushek and Zhang (2009)).[1] Using the PIAAC 2012 data, Hanushek et al. (2015) show substantial underestimation of returns to skills when focusing on early-career workers and find substantial variation in skill returns across countries (see also Hampf, Wiederhold, and Woessmann (2017)). Hanushek et al. (2017) also show that skill returns are larger in rapidly growing economies.

[1] Early studies of returns to skills in the U.S. labor market include Bishop (1989), Murnane, Willett, and Levy (1995), Neal and Johnson (1996), Mulligan (1999), Murnane et al. (2000), and Chetty et al. (2011). For reviews, see Bowles, Gintis, and Osborne (2001), Hanushek and Woessmann (2008), Woessmann (2025), and Deming and Silliman (2025).

Estimates of changes in returns to skills over time have so far been restricted to single country settings. Since the late 1970s, returns to cognitive skills in the United States have first increased (Murnane, Willett, and Levy (1995), Weinberger (2014)) and then decreased (Castex and Dechter (2014), Deming (2017)). Results on changes in returns to cognitive skills over the 1990s and early 2000s in a few European countries are more mixed (see Edin et al. (2022) and Hermo et al. (2022) for Sweden, Izadi and Tuhkuri (2024) for Finland, and Navarini (2023) for Germany). With our new estimates of returns to skills, we focus directly on the pattern of changes in returns to skills across countries.

The linkage to international trade fits into the analysis of factor price equalization. The seminal proof of the factor price equalization theorem holds that under classical assumptions, international trade will lead to an equalization of the prices of factors of production (Samuelson (1948)). While this theorem has not held up well to detailed empirical testing, the basic factor price equalization theorem focuses on a very stylized model with two countries trading according to the Heckscher-Ohlin model. If these two countries have different endowments but observe a common production function in terms of labor and capital, trade in goods acts the same as factor migration to equalize relative prices of inputs. There are many ways in which this model can fail in a world of multiple trading partners (McKenzie (1953), Leamer (1984), Davis and Weinstein (2001), Schott (2004)), with various restrictions on free movement of goods (Trefler (1995), Davis and Weinstein (2001), Debaere (2003)) and of factors both within and across countries (Mundell (1957), Dixit and Norman (1980), Feldstein and Horioka (1980), Helpman, Itskhoki, and Redding (2010)). Three aspects of these analyses call for a new empirical consideration of this theoretical construct. First, global trade has substantially increased over the last few decades with significant changes in the locus of production. Second, this trade has included a substantial component of information-based exchanges that might differ from trade in goods. Third, labor skills have become central to consideration of wage differences but have been poorly assessed across international trading partners.

Section 2 describes the PIAAC data and Section 3 the empirical model. Section 4 reports our results on returns to skills in 2023. Section 5 shows results on dynamics in skill returns across countries. Section 6 provides an analysis of the cross-country variation as related to international trade and freedom of factor markets. Section 7 concludes.

2. Two Cycles of PIAAC Data

The two cycles of the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD provide a unique database for evaluating the returns to skills across developed countries. For the first time it is possible to estimate skill prices using consistent, psychometrically linked measures of cognitive skills over time for a large sample of countries. PIAAC provides standardized testing of numeracy and literacy skills for representative samples of adults. Substantial effort is invested in skill measurement, with respondents spending an average of 50 minutes to complete the cognitive assessment (OECD (2013)). These results are complemented by extensive survey data about the background and characteristics of respondents including detailed information about labor-market outcomes, taking another 30-45 minutes to complete.[2] Importantly, the individuals are sampled across the working age of 16-65, thus providing unique information about economic outcomes across the full work life cycle and avoiding dependency on the highly unstable employment period found at the completion of schooling and labor-market entry.

The recent PIAAC Cycle 2 was conducted in 2022-23. It provides consistent skill and earnings data for 27 developed countries,[3] 23 of which also participated in Cycle 1.[4] Fieldwork in Cycle 1 was conducted over several years, with most countries participating in the first round in 2011-12.[5] Samples are drawn to be representative within each country, and we use sampling weights throughout our analysis. Because the PIAAC tests are psychometrically linked over time, it is possible to study how returns to cognitive skills have changed over the past decade without concerns about the impact of differential skill measurement.

[2] Survey operations remained largely unchanged over the two cycles (OECD (2024a)). Data collection was performed under the supervision of trained interviewers in respondents' homes using a computer-based mode (with an additional paper-based option in Cycle 1), starting with the background questionnaire followed by the skill test.

[3] Of the 31 countries participating in PIAAC Cycle 2 (OECD (2024b)), our analysis drops Poland due to "unusual response patterns" (OECD (2024a), p. 54) as well as Israel and Korea due to flawed collection of earnings data. We further exclude Chile (with a GDP per capita over 20 percent below the next-poorest country) due to our investigation of developed countries, a natural grouping for considering trade patterns, consistent with earlier analyses of factor price equalization (e.g., Leamer (1984), Davis and Weinstein (2001), Schott (2004)).

[4] The four countries participating only in Cycle 2 are Croatia, Latvia, Portugal, and Switzerland. We provide estimates of skill returns in 2023 for them, but they do not enter the analysis of changes in skill returns.

[5] Exceptions are Lithuania, New Zealand, and Singapore, which participated in the 2014-15 round, and Hungary, which participated in the 2017-18 round (OECD (2024b)). Cross-sectional analysis of returns to skills in PIAAC Cycle 1 is provided in Hanushek et al. (2015, 2017) and Hampf, Wiederhold, and Woessmann (2017).

In addition, Cycle 2 for the first time provides consistent measures of non-cognitive skills. Recent attention has focused on the importance of these non-cognitive skills, but there has been no consistent assessment across countries.[6] PIAAC Cycle 2 uniquely incorporates measures of the Big Five personality traits in a cross-country dataset of skills and earnings, allowing for assessment of how consideration of non-cognitive skills affects estimates of returns to cognitive skills.

Our wage measure refers to gross hourly earnings of wage and salary workers. We exclude self-employed workers because PIAAC does not report hourly wages for them. We trim the bottom and top one percent of the wage distribution in each country and cycle to limit any influence of outliers.

In the public-use file of PIAAC Cycle 2, some of the key variables for our analysis are not consistently available across countries. For five countries, most variables are not provided.[7] Hourly earnings information is not available for the Slovak Republic and Switzerland and is reported only in deciles for another 11 countries. We are very grateful to the OECD for allowing detailed analysis of the full earnings data for all countries through providing preparatory code runs on the OECD premises in Paris and subsequent remote code execution services.

Our main analysis focuses on the achievement of numeracy skills, which are generally considered as being most readily comparable across countries. The two measures of cognitive skills – numeracy and literacy skills – are very highly correlated (correlation coefficient of 0.87 in our analysis sample). As a consequence, results for literacy skills (which we report in the appendix) are very similar to the numeracy results. We normalize achievement scores to have mean 0 and standard deviation 1 in our analysis sample (of countries participating in both cycles) in Cycle 1. This allows estimates of returns to cognitive skills to be interpreted in terms of movements within this population.[8]

PIAAC's sampling of workers across the span of work life is an important element of our evaluation of returns to skills. Few data sources incorporate information about both cognitive

[6] For an overview of the structure and testing of different dimensions of non-cognitive skills, see Woessmann (2025). Early analyses of non-cognitive skills such as Heckman, Stixrud, and Urzua (2006) have evolved into analyses of temporal dynamics as in Deming (2017), Edin et al. (2022), and Izadi and Tuhkuri (2024).

[7] This applies to Denmark, Finland, Norway, and Sweden; the Netherlands have not yet released a public-use file.

[8] Throughout, we use the first plausible value of the PIAAC scores in each domain.

skills and earnings. It is most common in panel data sets that sample individuals within schooling periods, but this generally provides labor-market information just for early careers and for a single country. Our prior work, using PIAAC Cycle 1 data, showed that cognitive skill returns are substantially underestimated when studying early-career earnings (Hanushek et al. (2015)). But observed skill returns over time (e.g., Castex and Dechter (2014), Deming (2017)) are usually only able to estimate the path of returns during the very early stages of careers. While this period has considerable movement across early career jobs, it also is prone to misstating returns to human capital because of differential investment patterns at that stage.[9] Furthermore, it takes time for firms to learn the actual skill differences among workers (Altonji and Pierret (2001)), and early-career job matches of skills with employers are often imperfect (Jovanovic (1979)). In our analysis, we thus restrict the analytical sample to prime-age workers (age 35-54). Current earnings in this age range have been shown to be a good proxy for lifetime earnings (Haider and Solon (2006), Böhlmark and Lindquist (2006)).

Additionally, to focus on a relatively homogeneous group of workers with strong labor-force attachment, our baseline estimates are obtained for respondents who are employed full-time at the time of the survey, defining full-time work as at least 30 hours per week.[10] This restriction likely yields a lower bound on the overall association between skills and earnings to the extent that skills also increase employment probabilities. At the same time, it helps isolate estimated returns to cognitive skills from confounding factors that may affect labor supply and observed earnings, such as family responsibilities, health constraints, or other determinants of labor-force attachment. All sample restrictions mirror Hanushek et al. (2015), where we document that returns estimates are robust to alternative earnings measures and sample definitions.

Table 1 provides descriptive statistics referring to PIAAC Cycle 2.[11] The total size of our analysis sample in Cycle 2 is 33,768 observations. The focus on prime-age full-time workers implies that sample sizes are reduced from the original roughly 5,000 observations for each

[9] Mincer (1974) summarized these issues with calculations of "overtaking age" for wages of individuals with different investments. This issue is discussed in a variety of subsequent analyses including Heckman, Lochner, and Todd (2006), Lemieux (2006), and in an international context Lagakos et al. (2018).

[10] For reasons of data availability, full-time status is based on a survey question on full-time work in Austria. For Canada, both full-time and part-time employees are included because working hours and work-status measures are not available.

[11] Due to data access restrictions, a few countries are currently not shown in the table; the table will eventually be updated to the full set of 27 countries in our analytic sample.

country and wave[12] to between 947 observations in the United States and 3,612 in Canada in Cycle 2. Numeracy skills are highest in Japan and lowest in Portugal, with a mean difference of about one standard deviation between the two countries.

3. Empirical Model of Wage Dynamics

Our estimation of returns to skills across countries and over time follows in line with the development of human capital theory and its empirical application. At its heart, earnings (*y*) are seen as being directly related to a worker's productive skills, or human capital (*H*) where *r* is the associated price of human capital:

$$y = rH + \varepsilon \tag{1}$$

The original development of human capital theory by Becker (1964) and Mincer (1970, 1974) spawned a huge literature built on investments of time in school and leading to a standard empirical treatment of school attainment as being synonymous to human capital. The standard empirical approach became estimation of a "Mincer earnings model":

$$\ln y_i = \alpha + rS_i + \gamma_1 E_i + \gamma_1 E_i^2 + \varepsilon_i \tag{2}$$

where y_i is earnings of individual *I*, S_i is years of schooling of individual *I*, E_i is potential experience (*S*-age-6) of individual *I*, and ε_i is a stochastic term. This development along with its interpretation is well developed by Card (1999, 2001). The focus has been on the return to human capital (schooling) of r. But this measurement approach for human capital is particularly problematic in an international context, because a year of schooling can mean very different things in different settings.

A parallel literature of educational production functions is focused largely on issues of differences in school quality and treats assessments of cognitive skills, A_i, as a direct measure of human capital reflecting skills relevant to the labor market.[13] This line of analysis considers how various other factors, in addition to schools, enter into the determination of skills (e.g., Hanushek

[12] Samples in Cycle 2 tend to be somewhat smaller in most countries, falling below 4,000 in Belgium (3,909), Ireland (3,852), Portugal (3,160), Sweden (3,710), and the United States (3,765).

[13] The linkage to the labor market is easiest to see in the discussion of how education improves the ability to adjust to disequilibrium (Nelson and Phelps (1966), Welch (1970), and Schultz (1975)). This adjustment is also seen internationally (Hanushek et al. (2017)).

(2002)). The standard formulation indicates that a range of factors affects skills including family inputs (*F*), the quantity and quality of inputs provided by schools (which we incorporate as the function *Q*(*S*), where *S* is school attainment), individual ability (*G*), and other relevant factors (*X*) that include labor-market experience, health, and so forth. Along with a stochastic term (*v*), assumed uncorrelated with the other determinants of *A*, we can write a linear version of this general model as:

$$A_i = \varphi F_i + \theta Q(S_i) + \delta G_i + \pi X_i + \nu_i \quad (3)$$

Some empirical applications of this production function model have estimated how measures of the various inputs into the educational process affect income. Most often, however, estimation just follows equation (3) where skills (*A*) are measured by achievement tests and are interpreted as direct measures of human capital.

There are two implications of this work for the estimation of labor-market returns to skills. First, it is inappropriate to use just a single input into skills (importantly, such as *S*) as a measure of *H* in equation (1) to estimate the impact of human capital on earnings and to characterize wage differences in the labor market. It is highly unlikely that the stochastic term, ε, is orthogonal to school attainment once it is recognized that it includes the other determinants of skills.

Second, even if we focus just on the impact of schooling, school attainment is a poor measure of learning, especially in an international context. The range of learning per year of schooling even across developed countries is huge (Hanushek and Woessmann (2011)). For example, fifteen-year-olds in the United States were more than one-standard deviation lower than in Singapore in math on the international PISA tests (OECD (2023)). This means that observed skill differences among populations with similar years of schooling can easily amount to the equivalent of 3-4 years of schooling.

Following the estimation in Hanushek et al. (2015), we combine the production function perspective with the labor market earnings model to arrive at an empirical "modified Mincer model":

$$\ln y_i = \alpha + rA_i + \gamma_1 E_i + \gamma_1 E_i^2 + \varepsilon_i \quad (4)$$

where cognitive skills (*A*) enter as the measure of human capital.

In interpreting cross-sectional estimates of *r*, the possibility of omitted variables, reverse causation, and measurement error needs to be taken into account.[14] Two aspects ameliorate concerns of bias in our particular setting. First, Hanushek et al. (2015) provide extensive analysis of causality within this framework that suggests that, if anything, cross-sectional OLS estimates of equation (4) are likely to be biased downwards. In particular, they estimate a series of instrumental-variable models that use school attainment, parental education, or changes in compulsory-schooling laws as instruments for cognitive skills. These IV estimates tend to be larger than OLS estimates.

Furthermore, non-cognitive skills are often considered a prime candidate for an omitted variable in the model that relates earnings to cognitive skills. With the new availability of non-cognitive skill data in PIAAC Cycle 2, we can probe the sensitivity of estimates of cognitive skill returns to the consideration of non-cognitive skills, providing indication of the seriousness of any possible omitted-variable bias. We will return to this in Section 4.3.

Second, the focus of our analysis is comparing the dynamics of returns to skills across countries, which ameliorates the severity of any problems of causality. Perhaps the most significant concern in estimating country-specific returns to skills is that there are important but unmeasured labor-market factors in each country that will bias estimates of the returns to skills. If Z_c is omitted in estimating *r* for country *c*, the expected bias is:

$$E(\hat{r}) = r + \rho_c \beta_c \tag{5}$$

where ρ_c is the correlation of Z_c and *A* in country *c*, and β_c is the impact of Z_c on earnings, *y*.

The dynamics of skill returns in our analysis is characterized by:

$$\Delta\hat{r} = \hat{r}_{2023} - \hat{r}_{2012} \tag{6}$$

[14] Concerns about bias in our model are quite different from those in the standard Mincer model. As noted, the exclusion of all influences on skills other than that from school attainment is particularly important for the Mincer model. Importantly, a major issue with the Mincer model addressed in various forms is selection into further schooling on the basis of ability that potentially biases the estimation of *r*. A frequent approach to this is inclusion of some standard measure of cognitive skills, A_i, which is central to our analysis albeit motivated in the standard Mincer estimation as reflecting fixed abilities (e.g., Card (1999)). For our estimates of the returns to skills, it does not matter whether these skills emerge from fixed abilities, families, schooling, or any other factors of the education production function in equation (3).

The bias of concern thus depends on how $\rho_c\beta_c$ varies over time. If the bias ($\rho_c\beta_c$) does not change within countries over time, the analysis of dynamics does not face concerns about omitted-variable bias. Presumably because of such arguments about differencing out any bias, existing research that focuses on changes in returns to cognitive and non-cognitive skills has not addressed the causality issues (e.g., Castex and Dechter (2014), Deming (2017), Edin et al. (2022), Hermo et al. (2022), Izadi and Tuhkuri (2024)). Furthermore, various international skill tests consistently show that country average achievement, $\bar{A}_c$, is very slow moving, so any bias would be most dependent on how the impact of any country-specific omitted factor changes over time. We consider this when taking various country-specific factors into account in Section 6.1 below.

4. Current Country Variations in Returns to Skills

Before tracing the dynamics of returns to skills over time, we begin by estimating returns to skills across countries in 2023 with the PIAAC Cycle 2 data (Section 4.1). These recent cross-country patterns are of interest in their own right because of their insights into cross-country wage patterns. Section 4.2 looks at heterogeneity of estimates across sociodemographic subgroups. The new PIAAC data also allow us to test the quantitative importance of considering differences in non-cognitive skills when estimating returns to cognitive skills (Section 4.3).

4.1 Current Returns to Skills in Developed Countries around the World

The data of the new PIAAC cycle allow us to study the returns to skills in 27 developed countries around the world in 2023. We start by applying the previously established model to estimate current returns to skills in the countries participating in PIAAC Cycle 2.

Our baseline estimates show that cognitive skills have substantial returns in the labor markets of all participating countries. Figure 1 shows estimates of equation (4) for each of the 27 countries participating in PIAAC Cycle 2; Table 2 provides the details of the underlying models.[15] On average across countries, hourly wages increase by 16.7 percent for each standard deviation (SD) in numeracy skills. But there is substantial variation across the countries. Hungary, Estonia, Singapore, and Germany all have estimated returns to skills that exceed 20

[15] Due to data access restrictions, results for Finland are currently missing throughout this version of the paper; they will be included eventually. In Figure 1 and Table 2, the same applies for the four countries that participated only in Cycle 2.

percent, and Spain, the Netherlands, the United States, and the United Kingdom fall around 19 percent. But at the lower end, the Slovak Republic shows a return of just 9 percent and Sweden of 10 percent.[16]

Returns to literacy skills show a very similar pattern to returns to numeracy skills (Appendix Figure A1 and Table A1). The cross-country correlation between estimated returns to numeracy and literacy skills is 0.95. While numeracy returns (16.7 percent) are slightly higher than literacy returns (15.2 percent) in the pooled sample, countries fall very close to a line parallel to the 45-degree line when plotting numeracy against literacy returns, and the slope is essentially one (Appendix Figure A2).

4.2 Returns by Sociodemographic Subgroups

Estimated returns to skills do vary in predictable ways across sociodemographic subgroups. Figure 2 shows estimates of returns to numeracy skills in various subgroups of the population for the pooled country sample.

Our baseline estimates refer to prime-age workers (age 35-65) whose current earnings are most likely to be a good proxy for lifetime earnings. As expected, estimated returns are lower among entry-age workers (age 25-34) at 15.0 percent because of likely downward lifecycle bias (Hanushek et al. (2015)). By contrast, returns among exit-age workers (age 55-65) are estimated at 18.0 percent, only slightly below those of prime-age workers.[17]

Estimates of returns to skills hardly differ by gender, migrant status, and parental background. Return estimates are only slightly higher for females than for males (19.2 vs.18.2 percent) and for migrants than for natives (19.4 vs. 18.3 percent). There are hardly any differences between individuals whose parents had low, medium, or high education.

There is some heterogeneity in returns between the private and the public sector and between full-time and part-time employees. Returns to skills are higher in the private sector (19.4 percent) than in the public sector (15.6 percent). Full-time workers see higher returns (18.6 percent) than part-time workers (14.5 percent). But overall, all population subgroups see substantial returns, and the variation across subgroups is limited.

[16] For reference, Appendix Figure A3 shows standard Mincer estimates of returns to a year of schooling in the PIAAC Cycle 2 data. The pooled-country estimate is 7.9 percent, ranging from 5.0 percent in Norway to 14.0 percent in Singapore.

[17] The subgroup results currently refer to the countries contained in the public-use file only; they will eventually be updated to the full country sample.

4.3 Accounting for Non-cognitive Skills

Different dimensions of skills, also in non-cognitive areas, have been shown to have payoffs in the labor market (Woessmann (2025)), raising the question to what extent the estimated returns to cognitive skills may partly capture returns to non-cognitive skills. Uniquely among international datasets of skills and earnings, PIAAC Cycle 2 includes a series of measures of non-cognitive skills that allow us to test this question. First, and most importantly, it incorporates standard measurement of the Big Five personality traits which have been shown to relate to labor-market outcomes (Borghans et al. (2008), Almlund et al. (2011)). These include open-mindedness, conscientiousness, extraversion (which has been used to proxy for social skills (Deming (2017))), agreeableness, and emotional stability (which has been shown to mark the same higher-order concept as locus of control and self-esteem (Judge et al. (2002))). Second, PIAAC Cycle 2 includes measures of two dimensions of preferences – patience and social trust – that are relevant for economic outcomes (Falk et al. (2018)). Patience is a key preference parameter for human capital investment decisions (Hanushek et al. (2022), Hanushek et al. (2026)),[18] and trust has been used as a measure of prosociality (Kosse and Tincani (2020)). Third, as the only non-cognitive measure already included in Cycle 1, PIAAC includes a measure of volunteering ("voluntary work, including unpaid work for a charity, political party, trade union or other non-profit organization"), an aspect of social engagement and willingness to cooperate that has been shown to have relevance for labor-market outcomes (Heinz and Schumacher (2017), Baert and Vujić (2018), Piopiunik et al. (2020)).

Controlling for these rich measures of non-cognitive skills barely changes the estimates of returns to cognitive skills. Figure 3 shows how the estimates of returns to numeracy skills evolve when successively controlling for the three sets of non-cognitive skill measures (Appendix Table A2 (currently missing) will eventually provide the underlying estimates). It starts by including volunteering, the only non-cognitive skill measure collected in both PIAAC cycles. This does little to the cognitive-skill estimate in any country (orange bars). Next, we include patience and social trust, which are also available for all countries. This reduces the cognitive-skill estimates somewhat, without changing the overall pattern (red bars). This may partly reflect that patience is an input in the production of cognitive skills (Section 3), in which case it is a bad control.

[18] As such, it is unclear whether it should be controlled for when estimating returns to cognitive skills (see Section 3); we consider the analysis here exploratory for the potential scope of non-cognitive factors.

Finally, we also control for the Big Five personality traits (which were not collected in Japan and the United States). Again, their addition hardly affects the cognitive-skill estimates (gray bars), consistent with the finding that cognitive skills are not strongly associated with personality traits (Rammstedt et al. (2025)).

The imperviousness of the estimates of returns to cognitive skills to accounting for non-cognitive skills has implications for the causal interpretation of the provided estimates. Arguably, non-cognitive skills constitute a leading candidate of labor-market factors related to cognitive skills that often go unmeasured, raising concerns of omitted-variable bias. While the non-cognitive measures available in PIAAC Cycle 2 are far from capturing the universe of potentially relevant non-cognitive skill dimensions, the limited impact of their consideration suggests limits to any potentially remaining bias in the cognitive-skill estimates from this direction.

5. The Dynamics of Returns to Skills

Combining the estimates of returns to skills from the two cycles of PIAAC provides a unique opportunity to trace changes in returns across developed countries for the interesting recent period of 2012-2023. Section 5.1 provides an analysis of the significant changes seen during this period, while Section 5.2 highlights the relevance and interpretation of having psychometrically linked skill measures.

5.1 Changes in Returns to Skills over the Past Decade

The repeated implementation of the psychometrically linked PIAAC test allows us to estimate how returns to cognitive skills have changed between 2012 and 2023. Focusing on the sample of 23 countries that participated in both cycles, we implement exactly the same sample restrictions, variable measurements, and estimation model for Cycle 1 whose results for Cycle 2 are shown in Figure 1.[19]

Panel A of Figure 4 plots the estimated returns to numeracy skills in the two cycles against each other. There clearly is persistence, with countries with high returns in 2012 also tending to have high returns in 2023. But there is also substantial variation in the change in skill returns across countries, with some countries seeing returns increase and others decrease. Panel B

[19] Results of the Cycle 1 model are shown in Appendix Table A3. Slight differences from the estimates shown in Hanushek et al. (2015, 2017) stem from differences in the standardization of test scores (see Section 5.2 below). Returns to literacy skills in Cycle 1 are shown in Appendix Table A4.

depicts the eleven-year change in the return to skills for each country. On average across countries, returns have decreased by 3.6 percentage points (pp), from 20.3 percent per SD in 2012 to 16.7 percent in 2023. Singapore and the Slovak Republic stand out with decreases of more than 10 pp, but from very different levels. Hungary (-5.7 pp), the United States (-5.3 pp), and Ireland (-4.6 pp) also show substantial decreases. Overall, 15 countries show decreasing returns, but seven also show increasing returns. The largest increases are evident in Denmark (3.5 pp) and the Czech Republic (3.2 pp). Changes in returns to literacy skills (depicted in Appendix Figure A4) show broadly similar patterns; the cross-country correlation between changes in literacy and numeracy skills is 0.87.

Comparison to existing alternative estimates of return dynamics for individual countries is not straightforward, as our observation period post-dates all prior analyses. Evidence from the United States suggests increasing returns from the late 1970s to the late 1990s (Murnane, Willett, and Levy (1995), Weinberger (2014)) and decreasing returns from the 1980s to around 2010 (Castex and Dechter (2014), Deming (2017)). Our estimates suggest that this decrease continued during the 2010s into the early 2020s. Prior evidence suggests that in Sweden, returns were rather stable (at 11-13 percent) between 1992 and 2013 (Edin et al. (2022)). Our results indicate that they continued to be stable (at 10-11 percent in our data and specification) between 2012 and 2023.[20]

Consideration of changes in non-cognitive skills does not alter the overall conclusion on changes in cognitive skills. The cross-sectional evidence from Cycle 2 in the previous section suggests that returns to cognitive skills hardly change when taking non-cognitive skills into account. Accordingly, conditioning on the change in volunteering – the only indicator of non-cognitive skills also available in Cycle 1 – hardly affects the estimated changes in returns to cognitive skills at all (Appendix Figure A5).

5.2 Psychometric Linkage and Alternative Normalizations

Raw points on the underlying scores of skill tests do not generally have any meaning, leading to routinely normalizing skill measures to have a mean of 0 and a standard deviation (SD) of 1. With an underlying normal distribution (which is common for these tests based upon

[20] Navarini (2023)'s result of rather constant returns to latent cognitive skills in terms of starting wages in Germany (observed until 2020) between cohorts born around 1990 and 2000 are hard to compare to our model, which suggests a 2.6 pp decline between 2012 and 2023.

Item Response Theory (IRT) scaling), it is then readily possible to translate movements within the population into the economic returns to skills.

In the common circumstance of a single cross-section, it is clear what population distribution is being considered, but interpretations of comparisons across time and countries as we do here require a clear delineation of the relevant population. We express all return estimates in terms of SDs of the first-cycle performance distribution across the 23 countries that participated in both cycles. This standardization facilitates interpretation of the dynamics of returns because the results for all countries refer to a common distribution and because the changes over time incorporate any effects of aggregate changes in the overall distribution. Importantly, other plausible normalizations such as using individual-country standardization or separate standardization by wave of tests can fundamentally change the pattern of returns and the interpretation of the results.

The psychometric scaling of PIAAC allows for comparability across countries and cycles. Because of the common skill measure developed by psychometric linkage across the two cycles,[21] it is possible to compare directly skills observed at the two points in time. In most prior analyses of changes in returns to skills, missing linkage of the underlying test measurements over time leads to standardizing scores within each wave or cohort. This approach effectively implies that estimates of changes in returns to skills rely on the strong implicit assumption that the underlying skill distribution did not change over time (Woessmann (2025)). But recent studies have pointed out that the widening of the pre-market skill distribution and changing skill dynamics during adulthood have important implications for estimates of changes in U.S. skill returns that are likely to be also relevant in other countries (Hellerstein, Luo, and Urzúa (2025), Lochner, Park, and Shin (2025)).

In fact, simply tracing the SDs across the two cycles of PIAAC shows a clear tendency for the dispersion of skills in most developed countries' populations to increase (see Appendix Figure A6). The SD in numeracy skills increased by 11.1 percent in the pooled country sample, with particularly large increases in the Czech Republic, the United States, Estonia, Japan, Austria, and Germany (Appendix Table A5, column 13). Moreover, there is also strong heterogeneity as seen by slightly decreasing SDs in Canada, Lithuania, Norway, and Singapore.

[21] While the tests are not identical, usage of a set of common test items (linking items) allows performance in both test cycles to be expressed on the same scale using standard psychometric methods (OECD (2024a)).

The variation across countries is particularly important for our investigation of the dynamics of returns to skills.

Increased dispersion is consistent with other trends over this period. First, entering young cohorts show larger skill dispersion than older cohorts in many countries. In the United States, this is consistent with recent trends in NAEP scores, where achievement in the bottom percentiles is declining with little change in top percentiles (Hanushek (2025)). Second, as people age, skills of people with low usage of skills (who also tend to have lower skill levels) decline whereas skills of those with high usage increase (Hanushek et al. (2025)). Third, skill dispersion will increase if the size of population groups at the ends of the distribution increases relative to those in the middle. For example, polarization in the labor market due to automation of routine tasks, a phenomenon shown in many developed countries (Autor and Dorn (2013), Goos, Manning, and Salomons (2014), Autor (2019), Acemoglu and Restrepo (2022)), will give rise to a more dispersed skill distribution. Fourth, migration patterns can similarly give rise to increased skill dispersion if the migrant population is more likely to be placed at the ends of the national skill distribution than in the middle.

The PIAAC data allow us to quantify the impact of different normalizations (with their concomitant assumptions of similar and constant skill distributions) on estimates of skill returns and their changes. We consider four different normalizations of our estimated returns to numeracy skills: 1) Cycle 1 international SD – our baseline estimates; 2) international SDs separately for Cycles 1 and 2; 3) individual-country SDs from Cycle 1; and 4) individual-country SDs separately for Cycles 1 and 2.[22] Table 3 presents the country estimates of the change in rates of return between 2012 and 2023 for the four normalizations; the underlying return estimates by country and PIAAC cycle are found in Appendix Table A5.

Ignoring the actual change in the underlying distribution of skills by normalizing with separate SDs for the two cycles leads to underestimation of the decline in returns to skills (Table 3, column 2). In the pooled sample, the decline in the returns to skills by this normalization (1.7 percentage points) would be less than half the actual decline (3.6 percentage points). In the United States, the decline would be 3.2 rather than 5.3 percentage points.

[22] Note that these calculations do not require re-estimation of the country-level rates of return for the two cycles. Since the normalization involves country-level constants, each variant can be calculated with a simple linear transformation.

Ignoring differences in skill distributions across countries and standardizing by the SD within each country implicitly assumes that each country has the same skill distribution in its population, even though the PIAAC data show huge differences in skill distributions. Singapore, for example, has an initial dispersion one quarter larger than in the pooled country sample, while Japan, the Czech Republic, and Estonia are more than 15 percent below the international average SD. Accordingly, returns expressed in terms of SDs of the within-country distribution are biased up in Singapore and down in Japan (column 3). But, as long as the within-country changes in SDs between Cycles 1 and 2 are taken into account, the changes in returns to skills remain similar to those in column 1 even though the levels of country returns change significantly.

Finally, standardizing scores within country and within cycles leads to a significantly different pattern of return dynamics, even changing the sign of changes in a number of countries. In the United States, for example, the decline in returns would be estimated at -1.3 (column 4) instead of -5.3. In several countries, the approach would erroneously suggest an increase in skill returns over time whereas returns actually decreased – e.g., in Austria (2.3 vs. -1.1 percentage points), Germany (1.1 vs. -2.6), and Japan (0.7 vs. -2.8). Importantly, this approach to standardize skill measures within each wave or cohort is common when estimating changes in returns to cognitive or non-cognitive skills for given countries (e.g., Edin et al. (2022), Izadi and Tuhkuri (2024)). Our results show that Sweden is a country where standardization choices do not make much of a difference for the estimated change in returns to cognitive skills over our time period. This is consistent with prior work indicating limited change in the Swedish cognitive-skill distribution over time (see online appendices A1.2 and A3.5 of Edin et al. (2022)). However, our results also show that this imperviousness to standardization choices does not generalize to all countries; it is an exception rather than the rule in international comparison.

In sum, it is very important for these comparisons both over time and across countries to be based on having uniform test scales across countries that are psychometrically linked over time.

6. Factor Price Equalization

In this section, we investigate how the pattern of substantially different changes in skill returns across countries coincides with different existing theoretical and empirical conclusions. We begin by considering the simplest explanation – that cross-country convergence can explain differences in the observed labor-market dynamics (Section 6.1). It can. We then move to test

whether the speed of convergence varies with the extent of international trade flows and internal market restrictions (Section 6.2). It does. Finally, we show that the convergence result is robust to consideration of compositional changes and simple reversion-to-the-mean explanations (Section 6.3).

6.1 Convergence

Why did the returns to cognitive skills increase in some countries but decrease in others? Classical trade theory suggests that under specific assumptions, increased globalization would lead to an equalization of factor prices (Samuelson (1948)). The theory of factor price equalization rested on a series of strong assumptions,[23] and the extensive investigation of factor price equalization largely concluded that the theorem did not hold up well to empirical analysis.

We focus on one consistent issue with the prior testing of the theory. Because of data limitations, this prior testing at best considered crude measures of skill differences in labor and at worst simply looked at average wage differences across countries.[24] Thus, the testing was not truly comparing factor prices for well-defined measures of labor once the human capital aspect of labor is recognized. Moreover, testing generally focused on a time with much less extensive trade flows and concentrated largely just on manufacturing trade. The growth in trade, particularly in intangibles, makes factor price equalization for human capital inputs more relevant and more readily tested. With factor price equalization, we would expect the wage return to skills to decrease in countries with relatively high initial returns and to increase in countries with relatively low initial returns, i.e., a convergence of returns to cognitive skills in our sample of developed countries.

We find very strong convergence in the returns to cognitive skills in our data. Figure 5 shows a scatterplot of the change in skill returns from 2012 to 2023 against the initial level of skill returns in 2012. Countries with initially lower returns very consistently show larger subsequent increases in returns. For each 1 percentage point higher initial return, the change in

[23] The theorem assumes identical technologies across countries, perfect competition in all markets, free trade, constant returns to scale, and more.

[24] The importance and difficulty of measuring labor quality and human capital and returns is discussed in Bhagwati (1964) and in many subsequent studies. For example, Krueger (1968) and Hendricks (2002) introduce schooling levels, Caselli and Coleman (2006) add efficiency measures to schooling, and Schoellman (2012) adjusts schooling for quality with data on immigrants. Freeman and Oostendorp (2001) consider wages by occupation, and Lagakos et al. (2018) add labor-market experience.

returns decreases by 0.52 percentage points. Differences in the initial level of returns account for over half the variance in changes in returns to skills across countries (R^2=0.52).[25]

Consideration of other country characteristics that may plausibly also be related to changes in the demand for and supply of skills shows that the convergence result is robust to alternative explanations and that there is very little evidence that these other factors contribute systematically to the evolution of skill returns. This section looks directly at the overall return dynamics, while the next section focuses on the speed of any changes. Column 1 of Table 4 replicates the association shown in Figure 5. The subsequent columns add various other country factors, included individually to preserve degrees of freedom. While Table 4 considers the various country characteristics in levels at the beginning of the sample period (2011), results do not differ much when considering pre-PIAAC dynamics in these country characteristics instead (see Appendix Table A6).

A plausible driver of differences in the evolution of skill returns is the extent of modern digital technology and other technological changes that alter skill demand in the economy, but there is no indication that it does in fact account for cross-country differences in changes in skill returns. As there is no clear single measure that can fully capture technological differences across countries, we consider a series of alternatives. One measure available in the PIAAC background questionnaire is the frequency with which workers in our data use a computer programming language at work. This measure of digitalization does not enter the model significantly, and it does not affect the estimate of convergence (column 2). The same is true for other measures available in the PIAAC background questionnaire: the share of workers reporting experience with computers at work and how often workers use the internet to obtain work-related information (see Appendix Table A7, columns 1-2). Likewise, the Global Innovation Index, a composite measure provided by the United Nations' World Intellectual Property Organization that summarizes innovation inputs and outputs, does not enter significantly nor change the convergence result (Table 4, column 3). Other broad measures of innovation and technology include expenditure on research and development (R&D), patent applications, the share of information and communication technology exports, and the share of high-technology exports; but again, neither enter significantly nor change the convergence results (see Appendix Table

[25] Without the obvious outlier of the Slovak Republic, the convergence coefficient is essentially unchanged, but the explained variance increases to two thirds (R^2=0.67).

A7, columns 3-6). Similarly, a task-based automatability index, constructed as a standardized latent factor from PIAAC task items with different degrees of susceptibility to automation (Frey and Osborne (2017), Falck et al. (2026)), is unrelated to changes in returns (Table 4, column 4). Finally, the sectoral structure of the economy may be another proxy for exposition to technological changes, but again, the manufacturing share does not enter the model significantly (column 5).

Surprisingly, changes in skill returns are also not systematically related to measures of economic development, skill levels, institutional factors, and trade openness. Columns 6 and 7 of Table 4 add the level of GDP per capita and its growth rate from 1990 to 2011 to the model. While the latter was strongly related to the cross-section of skill returns in the first PIAAC cycle (Hanushek et al. (2017)), it is not related to the change in skill returns over time. Countries with different initial skill levels, indicating differences in the national supply of cognitive skills, also do not see significantly different changes in skill returns (column 8).[26] Our prior evidence in Figure 2 of higher skill returns in the private than the public sector might suggest relevance of the size of the public sector. However, while related to the level of returns, differences in public sector shares do not predict changes in skill returns (column 9). The same is also true for other institutional factors that may compress pay schedules – employment protection and union density – that had been shown in Hanushek et al. (2015) to be associated with the cross-section of skill returns (see Appendix Table A8, columns 3-4). This is also reflected in a combined index of labor-market freedom (Table 4, column 10). The change in returns to skills is also not related to trade openness (the sum of exports and imports over GDP) across countries (column 11).[27]

There is also little indication that changes in skill returns are directly related to the composition of the workforce. In addition to the sectoral structures considered above (manufacturing sector, public sector), neither the share of university graduates nor the share of migrants among workers nor the share of STEM workers are systematically related to the evolution of returns to skills. This finding holds when considering initial levels and when looking at concomitant changes (see Appendix Table A9).

We interpret these findings as reflecting the strong force of external factors on human capital prices through factor price equalization. A key element in past testing of factor price equalization

[26] The same is true for countries with different initial skill dispersions (Appendix Table A8, column 2).

[27] This is also true for other measures of trade openness such as trade freedom, goods trade, services trade, and international property trade (see Table A8, columns 5-8).

has been the challenge of adjusting for labor quality so that the wages observed across countries can be reliably compared. With the measurement of individual skills on a consistent basis across countries, we can extract the pattern of convergence of returns to skills across countries.

6.2 Trade, Labor-Market Flexibility, and the Speed of Convergence

Given the basic factor price equalization results, we can explore the mechanisms of international labor-market forces in greater detail, exploring hypotheses from international trade theory. This investigation is necessarily somewhat speculative because of the limited number of countries that we observe, so we view our descriptive work as an exploratory investigation of key concepts.

Our investigation explores whether the speed of the observed convergence in skill returns varies with various features of the different economies. We begin the study with whether the speed of convergence is related to two factor-price adjustment mechanisms that may be at work to different extents across countries: the exposure to international trade and the flexibility of within-country adjustments. Based on the classical theory of factor price equalization, convergence is expected to be faster the more open a country is to international trade. Given our focus on the cognitive-skill factor, trade patterns related to trade in knowledge and information may be particularly relevant for the adjustment. As posed in prior trade models of skills (e.g., Burstein and Vogel (2017)), changing trade patterns lead workers to move to more efficient firms and firms that can better use their skills. Accordingly, globalization will affect a country's factor prices only to the extent that factor markets are able to adjust. We therefore also look at the flexibility of labor markets across countries. Such general equilibrium effects of globalization are difficult to study just within individual countries.[28]

Our model of convergence speed reflects reactions to changes in market conditions for each country. To reflect uncertainty in how quickly factor prices adjust to the market, we consider two alternative specifications of the adjustments. First, we relate the dynamics of returns over the period 2011-12 to 2022-23 to economic conditions in 2011 (Panel A of Table 5). Alternatively, we consider these dynamics as a function of changes in economic conditions over the prior decade ending in 2011 (Panel B of Table 5). In both cases, we consider the role of labor market

[28] While partial equilibrium effects of various trade and technology shocks have been shown for local labor markets (e.g., Autor, Dorn, and Hanson (2013), Acemoglu and Restrepo (2020, 2022)), it has not been possible to account for the full general equilibrium impacts when nationally integrated factor markets adjust.

flexibility and of various measures of international trade flows for our sample of developed countries. In each model, we condition on the initial level of skill returns and then consider how these returns interact with various measures of the adjustment mechanisms.

Results suggest that the speed of convergence in skill returns is faster in countries with more flexible labor markets. We measure labor-market flexibility by the index of labor freedom provided by the Heritage Foundation. The index comprises six factors – the ratio of the minimum wage to the average value added per worker, the hindrance to hiring additional workers, the rigidity of working hours, the difficulty of firing redundant employees, the legally mandated notice period, and mandatory severance pay. As seen in column 1 of Panel A of Table 5, the speed of convergence is significantly faster in countries with larger labor-market freedom.[29] The Heritage Foundation also provides indices of economic in other dimensions – trade, investment, fiscal, and financial freedom – which allow us to test specific relevance of labor and trade freedom relative to other dimensions of economic freedom more generally. When entered individually, convergence is also faster with greater trade freedom (as well as fiscal freedom and the combined index of economic freedom), but not with investment freedom or financial freedom (see Appendix Table A10). This raises the question whether it is labor or trade freedom in particular (or both) that is the key element. In a horse race (column 7), the coefficient on labor freedom stays large and significant, whereas the coefficient on trade freedom does not, suggesting that it is the flexibility of labor-market adjustments in particular that facilitates the speed of convergence in skill returns.

The speed of convergence in skill returns is also significantly larger in countries that are more open to international trade. We measure trade exposure by the standard measure of trade openness, defined as the sum of exports and imports over GDP. Convergence speed is significantly larger in countries that experienced an increase in trade openness in the decade before our period of skill observation (column 2 of Panel B of Table 5).

When going into the specifics of the trade patterns, convergence in skill returns is related to trade in services rather than goods and in particular to trade in intellectual property. When we

[29] While the labor freedom index combines various aspects of labor-market flexibility, the cross-sectional analysis of skill returns in Hanushek et al. (2015) had looked at three specific institutional factors that operate to reduce wage dispersion: the public sector share, employment protection, and union density. As seen in columns 1-3 of Table A11, the coefficients on each of the three measures also indicate reduced speed of convergence with reduced flexibility, but only the public sector share is statistically significant (and employment protection marginally so).

break down the trade measure into trade in goods and trade in services, only service trade (both in levels and in prior changes) shows an association with the speed of convergence, whereas goods trade does not (columns 3-4 of Table 5). To capture the relevance of knowledge trade, we also measure trade in intellectual property as the sum of charges for the use of intellectual property receipts and payments as a share of GDP. Skill returns do in fact converge faster in countries with a higher level of intellectual property trade (column 5). These results are consistent with a particular relevance of trade in intangibles and knowledge goods, rather than for the formation of market prices for cognitive skills. They also constitute one reason why the existing empirical literature on factor price equalization, which was mostly restricted to manufacturing trade, may have missed relevant equalization forces.

In contrast to labor flexibility and trade openness, other country factors do not seem to have a significant bearing on the speed of convergence in skill returns. This is true for measures of GDP per capita, its growth rate, and the level of skills (see columns 4-6 of Table A11). Likewise, most measures of technology do not interact significantly with how initial levels of skill returns relate to their subsequent change (see Table A12). Of the eight technology measures, only two enter significantly, indicating faster convergence with higher internet use and high-tech export share, consistent with the results on intellectual property trade.

6.3 Robustness of the Convergence Result

A concern with the documented convergence pattern is that it could be mechanically generated by (i) shifts in the composition of the estimation sample between Cycles 1 and 2 or by (ii) measurement error in the country-specific return estimates. We therefore conduct three complementary robustness checks. The first two target compositional change directly. The third corrects for a specific form of mechanical reversion to the mean that can arise when the Cycle 1 return is measured with error and enters both the left-hand side (as part of the change in returns) and the right-hand side (as the initial level). Across all three checks, we continue to find a strong negative cross-country association between the change in returns and the initial return.

6.3.1 Restricting to a Stable Subsample: Native-born Men

Our baseline analysis estimates country-specific returns in each cycle on full-time employees aged 35-54 years. However, the composition of workers differs across cycles in ways that could matter for estimated skill prices – for example, because of immigration patterns or

increases in female labor-force participation. To address this, we re-estimate country-specific returns separately for the subsample of native-born men in each cycle. This group is comparatively stable across waves and avoids the two most salient compositional margins (gender and nativity) that could mechanically influence returns even if underlying skill pricing were unchanged.

Reassuringly, the convergence pattern becomes, if anything, stronger in the restricted sample of native males (Appendix Figure A7). The estimated convergence slope changes from -0.519 in the full sample to -0.751 among native-born men, and the corresponding R^2 increases from 0.52 to 0.61. A formal test, however, cannot reject equality of the convergence slopes between the baseline sample and native-born men ($p = 0.168$).

A useful interpretation is that the convergence result appears to be a broad, country-level phenomenon rather than being specific to demographic groups whose representation may change across survey waves. Of course, this exercise does not rule out compositional shifts along every possible dimension (e.g., occupation). But by holding constant central margins that plausibly evolve over time and differ across countries, it provides a first check that convergence is not a simple aggregation artefact due to shifting group weights.[30]

6.3.2 Reweighting Cycle 2 to the Cycle 1 Composition within Each Country

Next, we implement a formal reweighting strategy that directly aligns the observable composition of the Cycle 2 estimation sample with that of Cycle 1 within each country. The logic is straightforward: if differences in returns across cycles were driven by changes in the distribution of observable worker characteristics, reweighting Cycle 2 to replicate the Cycle 1 covariate distribution should materially alter the estimated Cycle 2 returns and, consequently, the convergence relationship (DiNardo, Fortin, and Lemieux (1996)).

Concretely, within each country we pool individuals from both cycles and estimate a logit model for being observed in Cycle 1 as a function of three covariates: gender, first-generation migrant status, and 10-year age groups (using our full estimation sample and cycle-specific sampling weights). Let $C1_i \in \{0,1\}$ indicate the survey cycle, where $C1_i = 1$ if individual i is

[30] To probe the occupational dimension more directly, we also re-estimate the convergence relationship within broad occupational groups, focusing separately on white-collar and blue-collar workers. Convergence remains clearly visible within both groups (slopes: -0.681 for white-collar; -0.560 for blue-collar, compared to -0.519 in the baseline), suggesting that the cross-country pattern is not mechanically driven by occupational upgrading or shifts in the occupational mix across cycles.

observed in PIAAC Cycle 1 and $C1_i = 0$ if observed in Cycle 2, and let X_i denote the covariate vector. Let $\hat{p}(C1 = 1 \mid X)$ be the fitted probability from this within-country logit. For Cycle 2 observations, we then compute inverse-odds weights

$$\omega(X) = \frac{\hat{p}(C1 = 1 \mid X)}{1 - \hat{p}(C1 = 1 \mid X)},$$

and re-estimate Cycle 2 returns using the product of the PIAAC sampling weights and $\omega(X)$. We normalize $\omega(X)$ within country so that the total weight mass in Cycle 2 is preserved, ensuring that reweighting changes composition rather than effective sample size.

The results are strikingly stable: the reweighted Cycle 2 returns are extremely close to the baseline Cycle 2 returns, and the convergence slope and fitted relationship are essentially unchanged (see Appendix Figure A8). This confirms that the convergence pattern is not driven by shifts in these key demographic characteristics between cycles. Put differently, when the Cycle 2 sample is forced to look like the Cycle 1 sample along these margins, the cross-country convergence in returns remains.

Two clarifications are worth emphasizing. First, we intentionally focus on demographics that are plausibly important for compositional change and comparability across survey waves, while avoiding variables (such as education or occupation) whose distributions may themselves respond to country-level trends in returns and thus risk partialing out channels through which genuine convergence could operate.[31] Second, the reweighting is implemented within country; it does not impose any cross-country harmonization of composition, but tests whether within-country compositional change across cycles can account for the estimated convergence relationship.

[31] As an additional check, we repeat the Cycle-2 reweighting exercise excluding migrant status. While reweighting on migration is a natural way to address compositional change, the migrant share itself could be affected by country-specific changes in labor-market returns (e.g., via selective immigration or emigration), so conditioning on it might partial out part of the adjustment we aim to document. Reweighting Cycle 2 to Cycle 1 using gender and age only yields virtually identical convergence estimates (baseline slope: -0.736, R^2=0.799; reweighted slope: -0.756, R^2=0.814). This closely mirrors the baseline reweighting that also includes migrant status (reweighted slope: -0.732, R^2=0.839) shown in Appendix Figure A8, reinforcing that our conclusions are not sensitive to whether migration is included in the reweighting covariates.

6.3.3 Adjustment for Mechanical Reversion to the Mean in the Convergence Regression

Finally, we assess whether the convergence pattern could be mechanically induced by sampling error in the Cycle 1 return estimates. The key issue is that the dependent variable in the convergence regression is the change in returns, $d = b_2 - b_1$, while the main regressor is the initial return b_1. If b_1 is measured with error, that sampling error enters d with the opposite sign, generating a spurious negative relationship between d and b_1 even in the absence of true convergence. This is the classical reversion-to-the-mean problem when regressing changes on baseline levels measured with error (Barnett, van der Pols, and Dobson (2004)).

Formally, let $b_1 = b_1^* + u_1$, where u_1 denotes sampling error with $\mathrm{Var}(u_1) > 0$. In Appendix A, we derive the implied bias and provide an implementable correction based on the cross-country variance of b_1 and an estimate of $\mathrm{Var}(u_1)$ from the sampling variance of the Cycle 1 return estimates. Applying this adjustment, the bias-corrected convergence slope is -0.482, compared to the baseline estimate of -0.519. The adjustment therefore moves the estimate modestly toward zero – as expected if part of the negative association is mechanical – but leaves the qualitative conclusion intact. In other words, sampling noise and mechanical reversion to the mean can explain only a small portion of the observed convergence pattern.

Overall, these results support the interpretation that the convergence pattern reflects genuine cross-country dynamics in skill prices rather than compositional change or sampling noise. The convergence relationship persists (and even strengthens) in a stable subsample; it is essentially unchanged when Cycle 2 is reweighted to match the Cycle 1 composition within country along key demographic margins; and it remains strongly negative after correcting for mechanical reversion to the mean due to sampling error in initial returns.

7. Conclusions

Understanding how globalization affects labor markets has been difficult to answer clearly in large part because inadequate data on relevant changes in labor-force quality across economies over time. Past analyses of the impacts of trade that incorporate international trade patterns have had limited data on labor-force quality, making it difficult to understand wage patterns for comparable workers across countries. On the other hand, analyses that more adequately measure differences in worker skills have been restricted either to single countries (and often to early-

career workers whose wages do not well reflect lifetime earnings in the labor market) or to cross-sectional international observations.

Novel consistent measurement of the cognitive skills for representative samples of adults across countries and over time allows a unique study of the impact of global integration on the evolution of labor-market returns to human capital. Exploiting the rich skill measures gets much closer to having factor prices for a homogeneous input than the more common measures of school attainment that neglect international differences in education quality. The few studies that have been able to look at changes in these factor prices have been restricted to analysis within individual countries. But the general equilibrium adjustments of national labor markets to global integration cannot be fully captured by looking at one country alone. The new PIAAC data allow us to provide a unique view of how international trade works through the labor markets of different countries.

The main pattern that comes out of the cross-country analysis is one of strong convergence of the price of human capital across developed countries over the past decade. Countries with initially low levels of returns to cognitive skills have seen their returns rise and vice versa. This fact accounts for the majority of the observed international differences in changes in skill returns over time. Consistent with forces of factor price equalization, this convergence in skill returns is faster in countries that are more open to trade and in countries that have institutions that allow factor markets to adjust more flexibly. Trade in services and property rights appears particularly important, while open labor markets appear to be a significant part of the dynamics in returns to skills.

By contrast, we find little evidence that changes in the returns to cognitive skills are related to other features that may trigger changes in the demand for and supply of skills in each national economy. Investigation of a broad series of measures of technology and innovation does not provide strong indication of the relevance of countries' differential exposure to technological change. Our results suggest that trade, rather than technology, is the dominant factor for variations in the evolution of returns to cognitive skills across countries. More broadly, a whole series of factors that might be expected to relate to the demand for or supply of skills such as industry structures, migration, the demographic composition of the workforce, and levels of national skill supplies does not significantly enter the cross-country variation in dynamics of skill returns.

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Appendix A: Adjustment for Reversion to the Mean in the Convergence Regression

Our baseline specification that establishes convergence relates the change in estimated country-level returns to numeracy skills between PIAAC Cycles 1 and 2 to the initial (Cycle 1) return. A potential concern is regression to the mean: when the initial return is measured with sampling error, countries with unusually high (low) estimates in Cycle 1 tend mechanically to show subsequent declines (increases) even if true returns did not change. This issue is well known in repeated-measures settings (e.g., Barnett, van der Pols, and Dobson (2004)).

A.1 Setup

Let c index countries and $t \in \{1,2\}$ index cycles. Denote the true country-level return by $\beta_{c,t}$. We observe an estimated return

$$\hat{\beta}_{c,t} = \beta_{c,t} + u_{c,t},$$

where $u_{c,t}$ captures estimation (sampling) error from the country-specific micro regression.

Define the observed change as:

$$\Delta\hat{\beta}_c = \hat{\beta}_{c,2} - \hat{\beta}_{c,1}.$$

Our baseline convergence regression is:

$$\Delta\hat{\beta}_c = \alpha + \gamma\hat{\beta}_{c,1} + \varepsilon_c. \quad \text{(A1)}$$

A negative γ is typically interpreted as convergence: countries with higher initial returns exhibit larger subsequent declines.

A.2 Downward Bias in the Slope Estimate due to Reversion to the Mean (RTM)

Even if there is no true convergence, i.e., $\beta_{c,2} = \beta_{c,1}$, we still have

$$\Delta\hat{\beta}_c = (\beta_{c,2} - \beta_{c,1}) + (u_{c,2} - u_{c,1}) = u_{c,2} - u_{c,1}.$$

Regressing $u_{c,2} - u_{c,1}$ on $\hat{\beta}_{c,1} = \beta_{c,1} + u_{c,1}$ generates a mechanical negative covariance through the term $-u_{c,1}$ in the dependent variable. Under standard assumptions (errors mean zero;

$u_{c,2}$ independent of $\beta_{c,1}$ and $u_{c,1}$; and $\beta_{c,1}$ independent of $u_{c,1}$), the probability limit of the OLS slope in equation (A1) under "no true change" is:

$$\gamma_{\text{RTM}} = -\frac{\text{Var}(u_{c,1})}{\text{Var}(\beta_{c,1})+\text{Var}(u_{c,1})}. \tag{A2}$$

Thus, even absent any true convergence, the estimated slope is negative whenever $\text{Var}(u_{c,1}) > 0$. This is the standard RTM phenomenon described, e.g., in Barnett, van der Pols, and Dobson (2004).

A.3 Convergence Slope Corrected for RTM

More generally, suppose the true relationship is:

$$\Delta\beta_c \equiv \beta_{c,2} - \beta_{c,1} = \alpha + \gamma\beta_{c,1} + \eta_c,$$

but we estimate equation (A1) using $\hat{\beta}_{c,1}$ and $\Delta\hat{\beta}_c$. Under the same independence conditions as above, the OLS slope in equation (A1) satisfies:

$$\hat{\gamma} \approx \rho\,\gamma - (1-\rho), \tag{A3}$$

where

$$\rho \equiv \frac{\text{Var}(\beta_{c,1})}{\text{Var}(\beta_{c,1})+\text{Var}(u_{c,1})} = 1 - \frac{\text{Var}(u_{c,1})}{\text{Var}(\hat{\beta}_{c,1})}. \tag{A4}$$

is the "reliability ratio" of the Cycle-1 return estimates.

Solving equation (A3) for the RTM-adjusted slope yields:

$$\gamma_{\text{adj}} = \frac{\hat{\gamma}+(1-\rho)}{\rho}. \tag{A5}$$

Interpretation is straightforward: $(1-\rho)$ is the component of the negative slope attributable to RTM; dividing by ρ reverses the attenuation from measurement error in the regressor.

A.4 Implementation

1. Estimate country-level returns and their standard errors in Cycle 1. For each country c, we obtain $\hat{\beta}_{c,1}$ and its standard error $se(\hat{\beta}_{c,1})$ from the micro regression.

2. Approximate the measurement-error variance. We treat sampling error as the primary source of $u_{c,1}$ and approximate:

$$\widehat{\mathrm{Var}}(u_{c,1}) = \frac{1}{C}\sum_{c=1}^{C} se(\hat{\beta}_{c,1})^2.$$

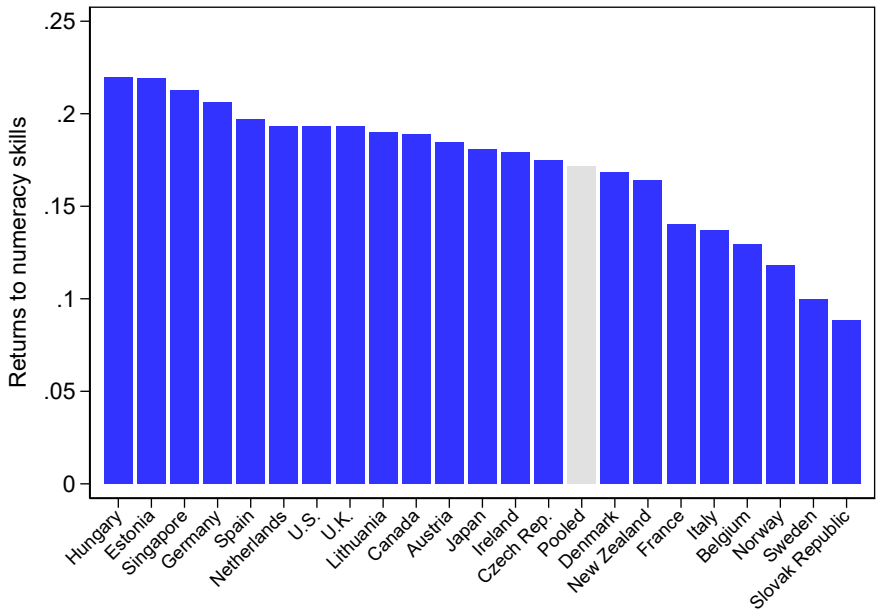
3. Compute the cross-country variance of observed initial returns:

$$\widehat{\mathrm{Var}}(\hat{\beta}_{c,1}) = \text{sample variance of } \{\hat{\beta}_{c,1}\}_{c=1}^{C}.$$

4. Estimate reliability $\hat{\rho}$ using equation (A4) and compute γ_{adj} using equation (A5).

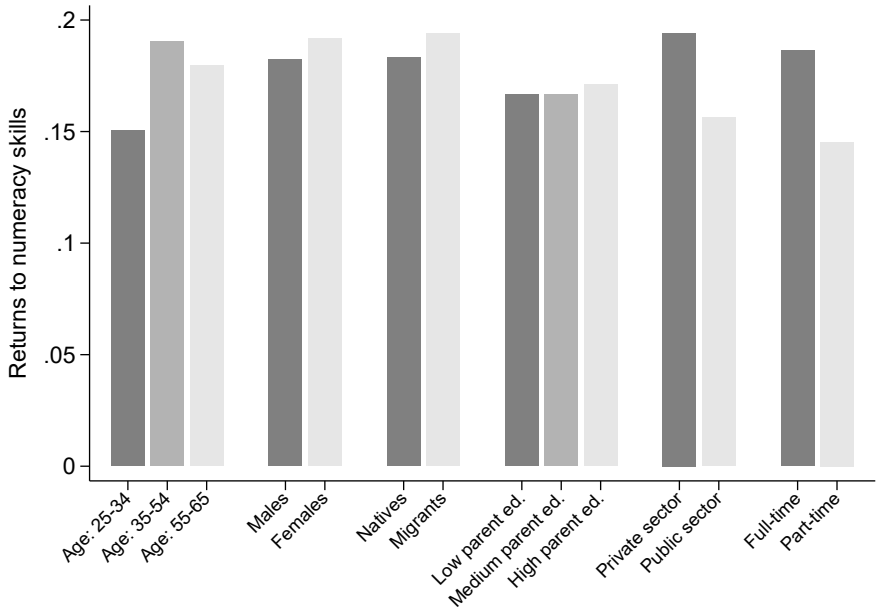
Figures and Tables

Figure 1: Returns to Cognitive Skills around the World, 2023



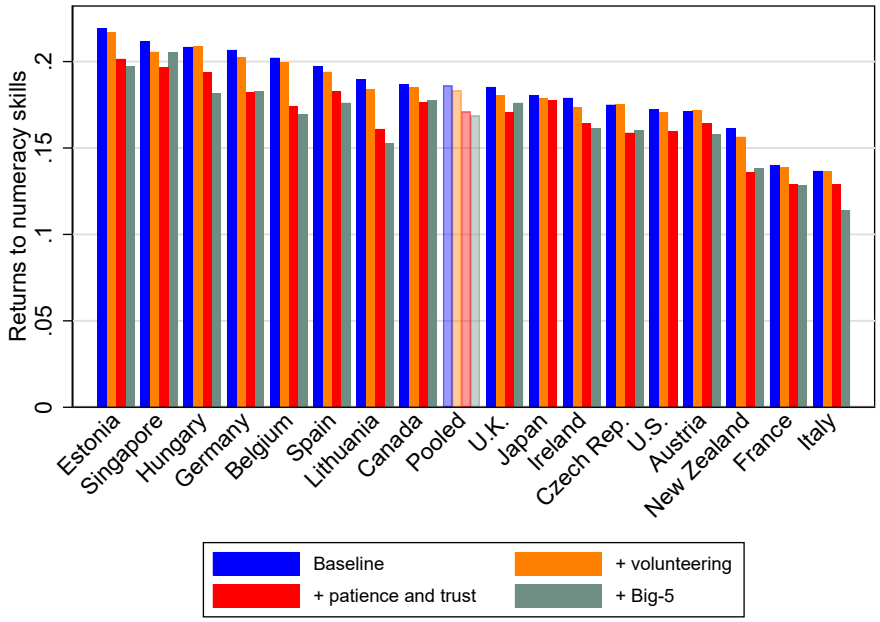
Notes: Coefficient estimates on numeracy score (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on numeracy, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). Replicates baseline model from Table 2. *Data source*: PIAAC Cycle 2.

Figure 2: Returns to Cognitive Skills by Sociodemographic Subgroups

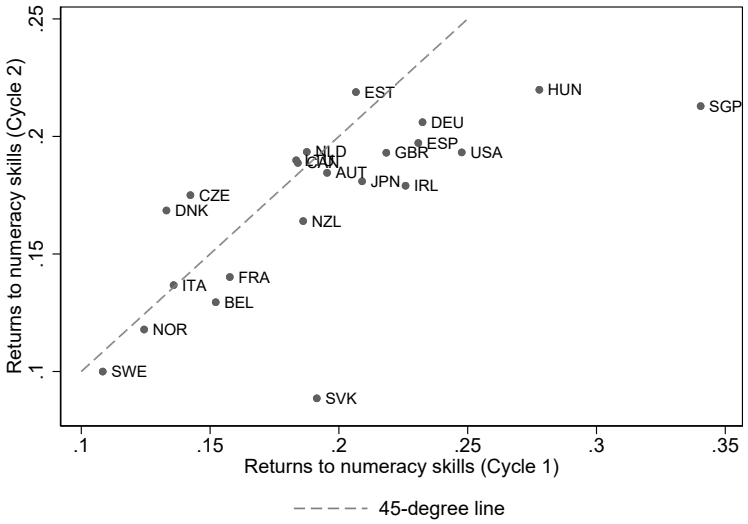


Notes: Coefficient estimates on numeracy score (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) for indicated subgroup in a regression of log gross hourly wage on numeracy, gender, a quadratic polynomial in actual work experience, and country fixed effects, sample of full-time employees (except for full-time/part-time comparison) aged 35-54 (except age-group comparison) pooling all countries. Fully interacted model. The following subgroup differences are statistically significant at the 5 percent level: age 25-34 vs. age 35-54; age 25-34 vs. age 55-65; public sector vs. private sector; full-time vs. part-time. Based on a sample of 17 overlapping countries with earnings information in the PUF of Cycle 2: Austria, Belgium, Canada, Czech Rep., Estonia, France, Germany, Hungary, Ireland, Italy, Japan, Lithuania, New Zealand, Singapore, Spain, U.K., and U.S. *Data source*: PIAAC Cycle 2.

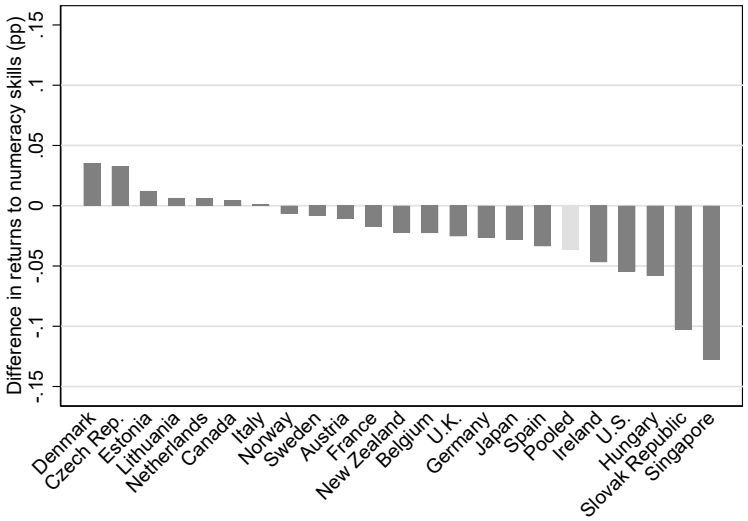
Figure 3: Returns to Cognitive Skills: Accounting for Non-cognitive Skills



Notes: Graph shows returns to numeracy skills for different sets of non-cognitive controls. Four specifications are shown for each country. Blue bars depicts the baseline without controls for non-cognitive skills. Orange bars shows specifications that additionally control for volunteering—the only non-cognitive skill collected in both PIAAC cycles. Red bars show specifications that control for patience and social trust, which were collected in all countries in Cycle 2, alongside volunteering. Teal bars show specifications that account for volunteering, patience, social trust, and the Big Five personality traits; the Big Five were not collected in Japan and the U.S. The bars show coefficient estimates on numeracy score (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on numeracy skills, different sets of non-cognitive skills (see legend), gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). *Data source*: PIAAC Cycle 2.



(a) Returns to Cognitive Skills, 2012 vs. 2023

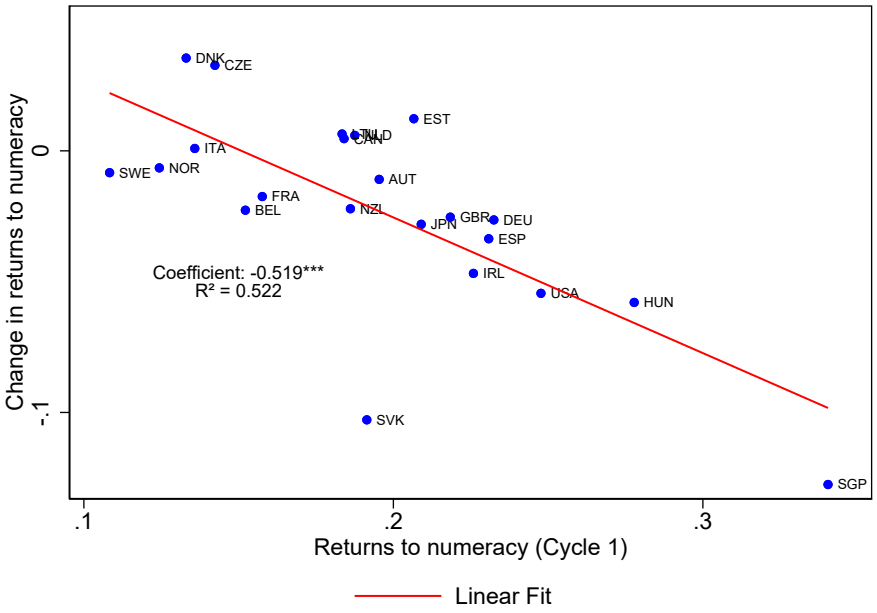


(b) Changes in Returns to Cognitive Skills, 2012–2023

Figure 4: Returns to Cognitive Skills in 2012 and 2023

Notes: Each point/bar corresponds to a country. Country-specific returns are the coefficient on numeracy skills from weighted OLS regressions of log gross hourly earnings on numeracy, a female indicator, and a quadratic in actual work experience, estimated separately by country for full-time employees aged 35–54 (Canada includes part-time employees). Numeracy scores are standardized to have standard deviation one across countries using the Cycle 1, Round 1 distribution. Panel A plots Cycle 2 returns against Cycle 1 returns; Panel B plots the change in returns (Cycle 2 minus Cycle 1) by country. Country labels are ISO-3 codes. *Data source:* PIAAC Cycles 1 and 2.

Figure 5: Convergence in Returns to Cognitive Skills across Countries



Notes: Difference in returns to numeracy between Cycles 1 and 2 vs. returns to numeracy in Cycle 1. Coefficient estimates on numeracy skills (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on numeracy, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). *Data source*: PIAAC Cycles 1 and 2.

Table 1: Descriptive Statistics

Variable	Pooled	Austria	Canada	Chile	Croatia	Czech R.	Estonia	France	Germany	Hungary	Ireland
Numeracy	266.58	275.54	279.03	220.15	260.24	273.92	287.66	268.61	283.65	261.50	269.08
	(57.55)	(58.47)	(54.37)	(59.27)	(50.20)	(56.36)	(51.84)	(57.23)	(61.65)	(53.19)	(51.01)
Literacy	260.20	254.97	279.50	221.19	259.32	264.15	280.82	262.88	272.18	252.97	268.50
	(55.02)	(57.91)	(52.57)	(55.13)	(52.80)	(51.79)	(53.76)	(54.08)	(60.46)	(48.87)	(46.65)
Problem Sol.	250.21	257.05	264.34	219.19	238.45	252.75	266.27	254.80	267.67	243.50	251.99
	(46.79)	(46.95)	(44.47)	(46.97)	(43.66)	(43.38)	(41.58)	(46.67)	(49.74)	(42.77)	(41.83)
Female	0.43	0.32	0.49	0.38	0.49	0.43	0.47	0.43	0.30	0.46	0.38
	(0.49)	(0.47)	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)	(0.50)	(0.46)	(0.50)	(0.49)
Yrs schooling	13.75	.	14.31	13.26	12.89	13.81	.	13.18	14.54	12.92	16.43
	(2.96)	(.)	(2.61)	(3.37)	(2.58)	(2.38)	(.)	(2.80)	(2.48)	(2.65)	(2.65)
Experience	21.86	24.28	21.49	18.06	19.95	22.30	21.64	22.33	22.56	22.83	23.06
	(7.75)	(7.88)	(8.21)	(8.72)	(7.19)	(7.05)	(7.10)	(7.43)	(8.17)	(7.92)	(7.22)
Volunteering	1.54	1.77	1.73	1.53	1.34	1.39	1.49	1.56	1.70	1.49	1.93
	(0.95)	(1.17)	(1.03)	(1.02)	(0.76)	(0.85)	(0.88)	(1.01)	(1.10)	(0.82)	(1.19)
Observations	33768	1089	3612	1042	1348	1622	2241	2070	1116	1663	1329

Variable	Italy	Japan	Latvia	Lithuania	New Z.	Poland	Portugal	Singapore	Spain	U.K.	U.S.
Numeracy	255.84	299.51	270.51	252.12	252.12	245.06	250.73	278.71	259.22	279.27	259.34
	(52.70)	(50.48)	(51.29)	(45.05)	(45.05)	(52.10)	(59.47)	(63.58)	(50.12)	(52.26)	(71.31)
Literacy	253.94	296.08	254.00	242.50	242.50	239.53	242.02	256.83	255.80	278.46	265.97
	(50.67)	(49.22)	(48.98)	(43.39)	(43.39)	(48.28)	(51.65)	(58.76)	(46.87)	(48.89)	(67.07)
Problem Sol.	237.82	281.44	248.26	234.12	234.12	229.57	239.07	253.77	247.33	265.60	253.34
	(39.68)	(39.35)	(42.92)	(35.93)	(35.93)	(41.42)	(42.41)	(49.74)	(42.67)	(43.12)	(57.30)
Female	0.36	0.32	0.50	0.49	0.49	0.48	0.48	0.47	0.43	0.39	0.43
	(0.48)	(0.47)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)	(0.50)
Yrs schooling	12.75	13.58	13.99	14.13	14.13	13.48	12.23	13.87	12.82	14.64	14.52
	(3.67)	(2.30)	(2.49)	(2.36)	(2.36)	(2.69)	(3.57)	(2.95)	(3.22)	(2.45)	(3.07)
Experience	21.06	24.03	21.24	20.52	20.52	20.65	22.75	20.94	20.40	23.60	22.63
	(7.93)	(6.73)	(7.37)	(6.93)	(6.93)	(7.08)	(8.09)	(7.11)	(7.42)	(7.83)	(8.76)
Volunteering	1.35	1.44	1.54	1.24	1.24	1.37	1.47	1.45	1.41	1.55	1.91
	(0.83)	(0.78)	(0.89)	(0.62)	(0.62)	(0.69)	(0.99)	(0.79)	(0.96)	(0.99)	(1.07)
Observations	1050	1622	2097	1762	1762	1791	1123	1698	1860	1418	947

Notes: Means and standard deviations by country. Weighted by sampling weights. Sample: full-time employees aged 35-54 (Canada includes part-time employees). *Data source*: PIAAC Cycle 2.

Table 2: Returns to Cognitive Skills around the World, 2023

	Pooled	Austria	Canada	Chile	Croatia	Czech R.	Estonia	France	Germany	Hungary	Ireland
Numeracy	.187***	.171***	.187***	.345***	.124***	.175***	.219***	.140***	.207***	.208***	.179***
	(.003)	*(.012)*	*(.010)*	*(.024)*	*(.016)*	*(.013)*	*(.011)*	*(.009)*	*(.011)*	*(.014)*	*(.014)*
Experience	.017***	.015	.028***	.017*	.028***	.012	.034***	.014**	.008	.006	.037***
	(.002)	*(.010)*	*(.005)*	*(.010)*	*(.006)*	*(.008)*	*(.007)*	*(.005)*	*(.006)*	*(.009)*	*(.012)*
Experience^2	−.034***	−.027	−.055***	−.037*	−.067***	−.026	−.077***	−.021*	−.007	−.015	−.061**
	(.004)	*(.020)*	*(.012)*	*(.022)*	*(.015)*	*(.017)*	*(.017)*	*(.012)*	*(.013)*	*(.019)*	*(.025)*
Female	−.121***	−.153***	−.058***	−.163***	−.138***	−.168***	−.202***	−.094***	−.079***	−.143***	.070**
	(.006)	*(.028)*	*(.023)*	*(.056)*	*(.025)*	*(.024)*	*(.021)*	*(.017)*	*(.026)*	*(.025)*	*(.029)*
R^2	.198	.298	.244	.323	.152	.264	.259	.202	.309	.210	.145
Observations	27052	825	3609	777	961	1285	1797	1658	932	1326	1069

	Italy	Japan	Latvia	Lithuania	New Z.	Poland	Portugal	Singapore	Spain	U.K.	U.S.
Numeracy	.137***	.180***	.239***	.190***	.161***	.078***	.180***	.212***	.197***	.185***	.172***
	(.015)	*(.012)*	*(.015)*	*(.018)*	*(.026)*	*(.012)*	*(.013)*	*(.012)*	*(.015)*	*(.016)*	*(.020)*
Experience	.017**	.028***	.011	.021**	.005	.015*	.000	.039***	.019***	.011	.027***
	(.008)	*(.009)*	*(.010)*	*(.009)*	*(.010)*	*(.008)*	*(.009)*	*(.013)*	*(.007)*	*(.008)*	*(.009)*
Experience^2	−.030	−.043**	−.019	−.057***	−.010	−.036*	−.005	−.085***	−.041**	−.022	−.049**
	(.019)	*(.018)*	*(.025)*	*(.022)*	*(.019)*	*(.019)*	*(.022)*	*(.030)*	*(.017)*	*(.017)*	*(.019)*
Female	−.060*	−.202***	−.174***	−.191***	−.093**	−.122***	−.079**	−.154***	−.069***	−.086***	−.066
	(.033)	*(.022)*	*(.031)*	*(.029)*	*(.037)*	*(.024)*	*(.033)*	*(.031)*	*(.026)*	*(.029)*	*(.044)*
R^2	.148	.230	.239	.184	.227	.079	.201	.209	.175	.171	.179
Observations	682	1457	1689	1317	981	993	845	1487	1401	1185	776

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

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54 (Canada includes part-time employees). Numeracy score standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1. Experience^2 divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2. Robust standard errors in parentheses. *Data source: Data source*: PIAAC Cycle 2.

Table 3: Alternative Normalizations and Estimated Dynamics of Skill Returns

	Normalization with international SDs		Normalization with national SDs	
	Joint normalization across cycles (1)	Separate normalization within cycles (2)	Joint normalization across cycles (3)	Separate normalization within cycles (4)
Austria	-0.011	0.010	-0.010	0.023
Belgium	-0.022	-0.008	-0.021	-0.002
Canada	0.005	0.026	0.005	0.004
Czech Rep.	0.032	0.052	0.026	0.070
Denmark	0.035	0.054	0.033	0.060
Estonia	0.012	0.037	0.010	0.049
Finland	x	x	x	x
France	-0.017	-0.001	-0.018	-0.002
Germany	-0.026	-0.003	-0.025	0.011
Hungary	-0.057	-0.032	-0.055	-0.036
Ireland	-0.046	-0.026	-0.046	-0.044
Italy	0.001	0.016	0.001	0.014
Japan	-0.028	-0.007	-0.022	0.007
Lithuania	0.006	0.028	0.006	0.003
Netherlands	0.006	0.027	x	x
New Zealand	-0.022	-0.003	-0.022	0.007
Norway	-0.006	0.007	-0.007	-0.007
Singapore	-0.125	-0.101	-0.157	-0.164
Slovak Rep.	-0.101	-0.091	-0.089	-0.088
Spain	-0.033	-0.011	-0.032	-0.028
Sweden	-0.008	0.003	-0.008	-0.003
U.K.	-0.025	-0.003	-0.025	-0.011
U.S.	-0.053	-0.032	-0.057	-0.013
Pooled	-0.036	-0.017	-0.036	-0.017

Notes: Entries report the estimated change in country-specific returns to numeracy skills between PIAAC Cycles 1 and 2 under alternative normalizations of the numeracy score. "International SDs" standardize numeracy using the pooled cross-country standard deviation; "national SDs" standardize using the within-country standard deviation. "Constant SD" uses Cycle 1 standard deviations for both cycles; "changing SD" allows the relevant standard deviation to differ by cycle (i.e., cycle-specific normalization). *Data source:* PIAAC Cycles 1 and 2.

Table 4: Explaining Differences in Changes in Skill Returns: Convergence and Other Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Returns to numeracy skills (C1)	-0.519***	-0.524***	-0.526***	-0.521***	-0.524***	-0.528***	-0.428***	-0.512***	-0.523***	-0.521***	-0.449***
	(0.100)	(0.104)	(0.115)	(0.101)	(0.097)	(0.093)	(0.096)	(0.101)	(0.100)	(0.109)	(0.105)
Computer programming (C1)		-0.061									
		(0.061)									
Innovation index (2011)			0.000								
			(0.001)								
Automatability (C1)				-0.119							
				(0.377)							
Manufacturing share (C1)					0.116						
					(0.163)						
GDP per capita (2011)						-0.003					
						(0.005)					
GDP pc annual growth (1990–2011)							-0.019				
							(0.014)				
Numeracy mean (C1)								0.010			
								(0.034)			
Public sector share (C1)									-0.008		
									(0.080)		
Labor freedom (2011)										0.000	
										(0.000)	
Trade openness (2011)											-0.010
											(0.008)
Countries	22	22	22	22	22	22	22	22	22	22	22
R-sq	0.522	0.531	0.528	0.523	0.532	0.532	0.579	0.523	0.522	0.522	0.549

Notes: Each column reports an OLS regression of the change in country-level returns to numeracy skills between PIAAC Cycles 1 and 2, on the initial country-specific return in Cycle 1, *Returns to numeracy skills (C1)*. Column (1) includes the Cycle 1 returns only. Columns (2)–(11) add one country-level covariate at a time: (i) *Computer programming (C1)*, based on the question about how often respondents use a computer programming language at work; the original 1–5 frequency categories are recoded to range from 0 (never) to 4 (every day), so higher values denote more frequent ICT use at work. (ii) *Innovation index (2011)*, the Global Innovation Index (0–100), a composite measure summarizing innovation inputs and outputs published by INSEAD, Cornell University, and World Intellectual Property Organization (WIPO). (iii) *Automatability (C1)*, the country-level automatability index in Cycle 1: we proxy task-based "automatability" by extracting a single latent factor from PIAAC task items linked to the Frey–Osborne task logic (see Falk et al., 2025). Specifically, we estimate a one-factor SEM on tasks covering manual/dexterity, problem-solving, and social-interaction dimensions and use the standardized predicted factor score as the automation index; we then aggregate it to the country level (weighted by sampling weights); (iv) *Manufacturing share (C1)*, i.e., the share of workers employed in manufacturing industries; (v) *GDP per capita (2011)*, i.e., real GDP per capita in 2011 in constant 2015 US dollars (in units of 10,000); (vi) *GDP per capita growth (1990–2011)*, i.e., the average annual growth rate of real GDP per capita between 1990 and 2011; (vii) *Numeracy mean (C1)*, i.e., country level average numeracy score in Cycle 1, divided by 10; (viii) *Public sector share (C1)*, i.e., the share of workers employed in the public sector in Cycle 1; (ix) *Labor freedom (2011)*, the Heritage Foundation labor-freedom score composed of six quantitative factors: ratio of minimum wage to the average value added per worker, hindrance to hiring additional workers, rigidity of hours, difficulty of firing redundant employees, legally mandated notice period, and mandatory severance pay (0–100, higher values indicating more market-oriented labor-market policies); (x) *Trade openness, 2011*, defined as (imports+exports)/GDP in 2011. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; INSEAD; Cornell University; World Intellectual Property Organization (WIPO); World Bank World Development Indicators; Heritage Foundation (Index of Economic Freedom).

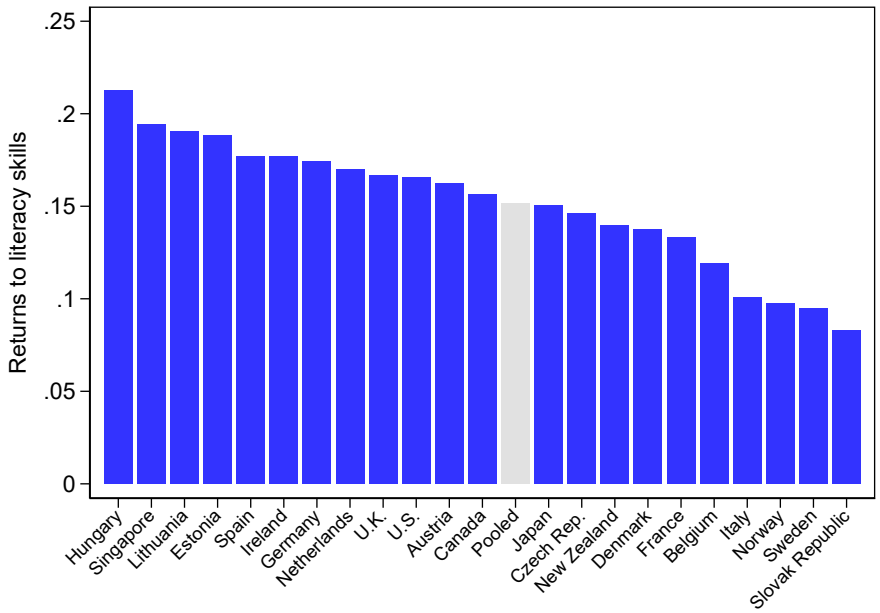
Table 5: Explaining the Speed of Convergence: Labor Freedom and Trade Openness

Panel A: Interactions with levels (2011)					
	(1)	(2)	(3)	(4)	(5)
Initial returns (C1)	-0.438***	-0.419***	-0.429***	-0.429***	-0.472***
	(0.056)	(0.093)	(0.092)	(0.081)	(0.080)
× labor freedom (2011) /100	-1.168***				
	(0.209)				
× trade openness (2011)		-0.109			
		(0.126)			
× goods trade (2011) /100			-0.127		
			(0.123)		
× service trade (2011) /100				-0.760**	
				(0.266)	
× intellectual property trade (2011)					-0.102***
					(0.026)
Main effect of interacted variable	0.005	-0.001	-0.004	0.029	0.002
SE (main effect)	(0.019)	(0.016)	(0.016)	(0.032)	(0.001)
N	22	22	22	22	21
R-sq	0.631	0.570	0.564	0.587	0.587
Panel B: Interactions with changes (pre-PIAAC)					
	(1)	(2)	(3)	(4)	(5)
Initial returns (C1)	-0.572***	-0.477***	-0.517***	-0.433***	-0.534***
	(0.114)	(0.077)	(0.110)	(0.106)	(0.112)
× change labor freedom (2005–2011)	0.012				
	(0.027)				
× change trade openness (2001–2011)		-1.246**			
		(0.502)			
× change goods trade (2001–2011)			-0.002		
			(0.009)		
× change service trade (2001–2011)				-0.023**	
				(0.009)	
× change intellectual property trade (2001–2011)					-0.099
					(0.119)
Main effect of interacted variable	0.002	-0.007	-0.000	0.001	0.007
SE (main effect)	(0.002)	(0.049)	(0.000)	(0.001)	(0.003)
N	22	22	22	19	16
R-sq	0.600	0.572	0.549	0.598	0.536

Notes: Each column reports cross-country OLS estimates relating the change in returns to cognitive skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) to the initial country-specific return in Cycle 1. *Initial returns (C1)* equals the Cycle 1 return minus its sample mean; a negative coefficient therefore indicates convergence (countries with higher initial returns experience larger subsequent declines). All interacted variables are demeaned, so the coefficient on *Initial returns (C1)* captures the convergence slope at the average value of the interacted variable. Panel A interacts *Initial returns (C1)* with level measures (in 2011): *labor freedom* (Heritage Foundation labor-freedom score, composed of six quantitative factors: ratio of minimum wage to the average value added per worker, hindrance to hiring additional workers, rigidity of hours, difficulty of firing redundant employees, legally mandated notice period, and mandatory severance pay; scale of 0–100, higher values indicating more market-oriented labor-market policies); *trade openness (2011)* (defined as (imports+exports)/GDP); *goods trade (2011)* (merchandise exports plus imports as a share of GDP); *service trade (2011)* (services exports plus imports as a share of GDP); and *IP trade (2011)* (charges for the use of intellectual property: receipts plus payments, as a share of GDP). Panel B interacts *Initial returns (C1)* with changes in the variables in Panel A measured prior to Cycle 1. With the exception of *labor freedom*, all changes are measured over 2001–2011; *change labor freedom* is measured over 2005–2011 because 2005 is the first year the index is available. Each specification is estimated on the sample of countries with non-missing values for the interacted variable(s). Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; World Bank World Development Indicators; Heritage Foundation (Index of Economic Freedom).

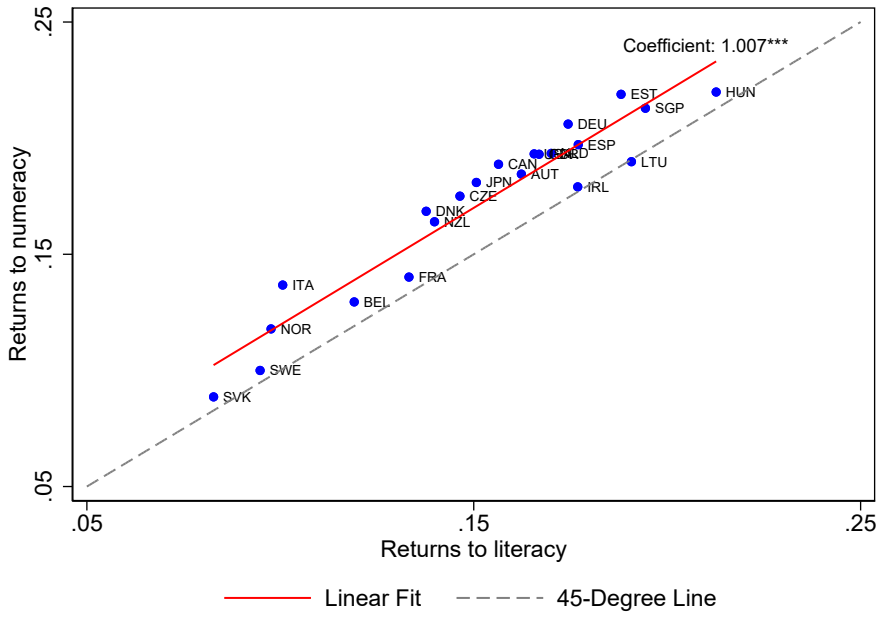
Appendix

Figure A1: Returns to Literacy Skills around the World, 2023



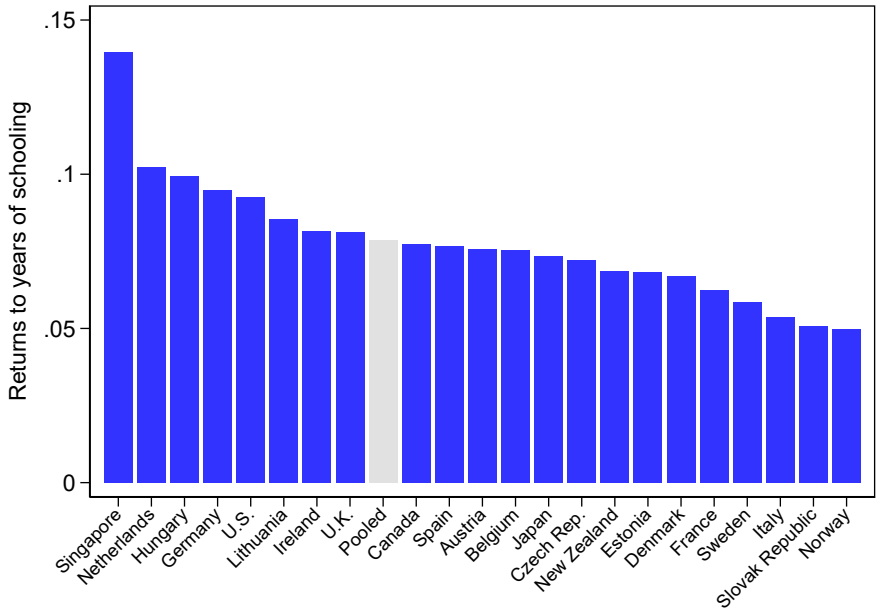
Notes: Coefficient estimates on literacy score (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on literacy, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). Replicates baseline model from Table A1. *Data source*: PIAAC Cycle 2.

Figure A2: Returns to Numeracy and Literacy Skills across Countries

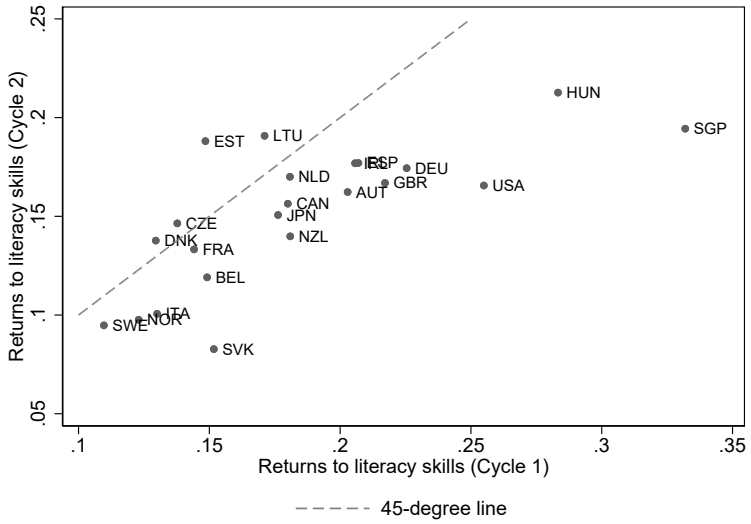


Notes: Graph plots returns to numeracy skills vs. literacy skills. Coefficient estimates on standardized numeracy or literacy score (standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on numeracy or literacy, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). *Data source*: PIAAC Cycle 2.

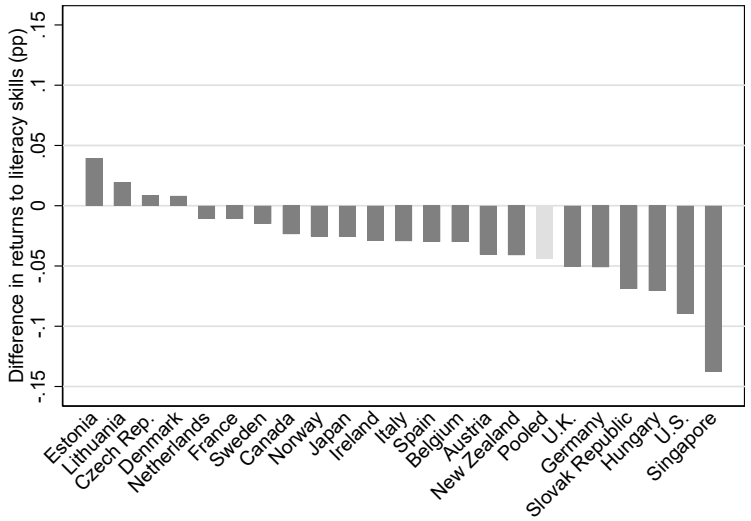
Figure A3: Returns to Years of Schooling: Mincerian Wage Regressions



Notes: Coefficient estimates on years of schooling in a regression of log gross hourly wage on years of schooling, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). *Data source*: PIAAC Cycle 2.



(a) Returns to Literacy Skills, 2012 vs. 2023

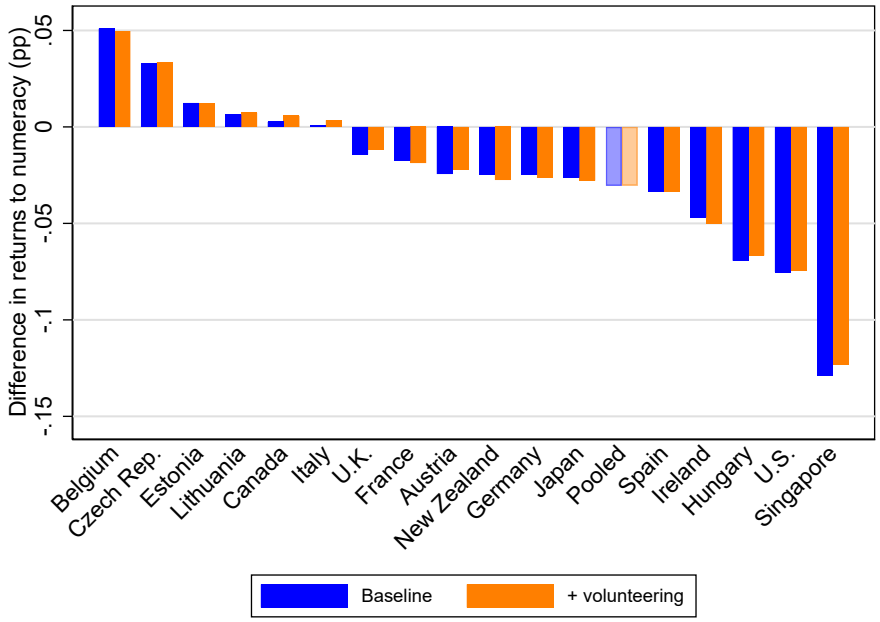


(b) Changes in Returns to Literacy Skills, 2012–2023

Figure A4: Returns to Literacy Skills in 2012 and 2023

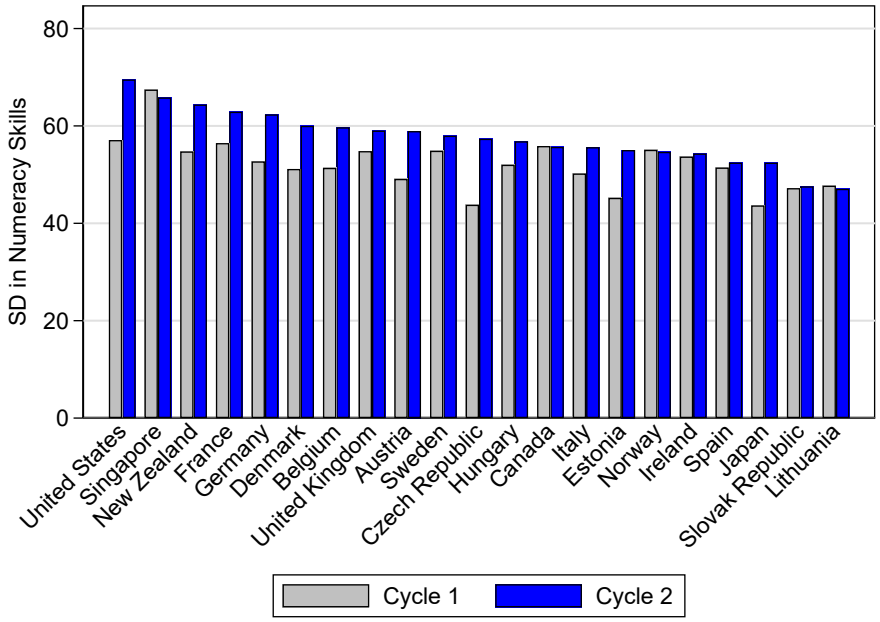
Notes: Each point/bar corresponds to a country. Country-specific returns are the coefficient on literacy skills from weighted OLS regressions of log gross hourly earnings on literacy, a female indicator, and a quadratic in actual work experience, estimated separately by country for full-time employees aged 35–54 (Canada includes part-time employees). Literacy scores are standardized to have standard deviation one across countries using the Cycle 1, Round 1 distribution. Panel A plots Cycle 2 returns against Cycle 1 returns; Panel B plots the change in returns (Cycle 2 minus Cycle 1) by country. Country labels are ISO-3 codes. *Data source:* PIAAC Cycles 1 and 2.

Figure A5: Changes in Returns to Cognitive Skills: Controlling for Volunteering



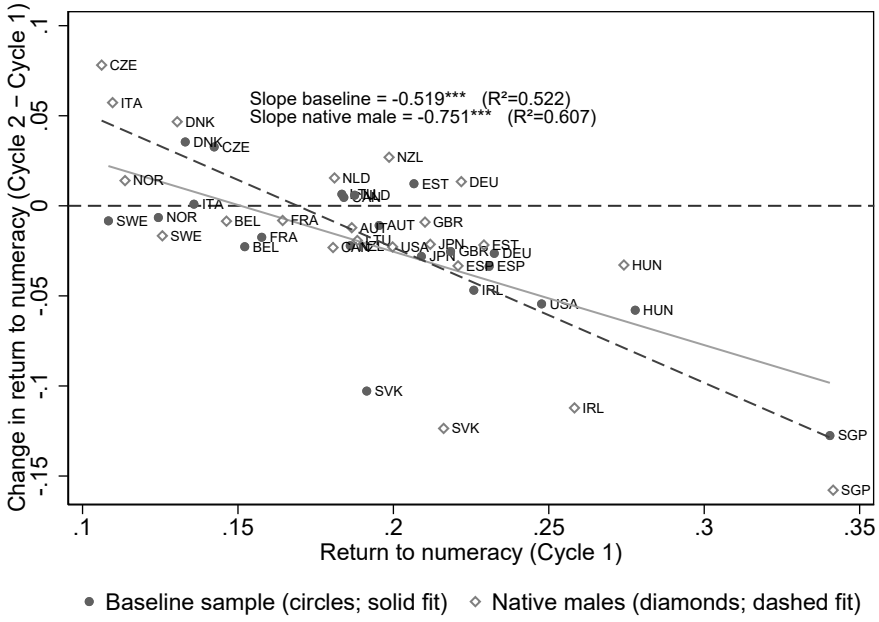
Notes: Graph plots difference in returns to numeracy skills (conditional on volunteering) between Cycle 2 and Cycle 1 by country. Coefficient estimates on standardized numeracy score (standardized to std. dev. 1 across countries; Cycle 2: using std. dev. of Cycle 1, Round 1) in a regression of log gross hourly wage on numeracy skills, volunteering, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54 (Canada includes part-time employees). Volunteering is measured on a 5-point scale, ranging from never (= 1) to every day (= 5). *Data source*: PIAAC Cycles 1 & 2.

Figure A6: Standard Deviation in Cognitive Skills, 2012 and 2023



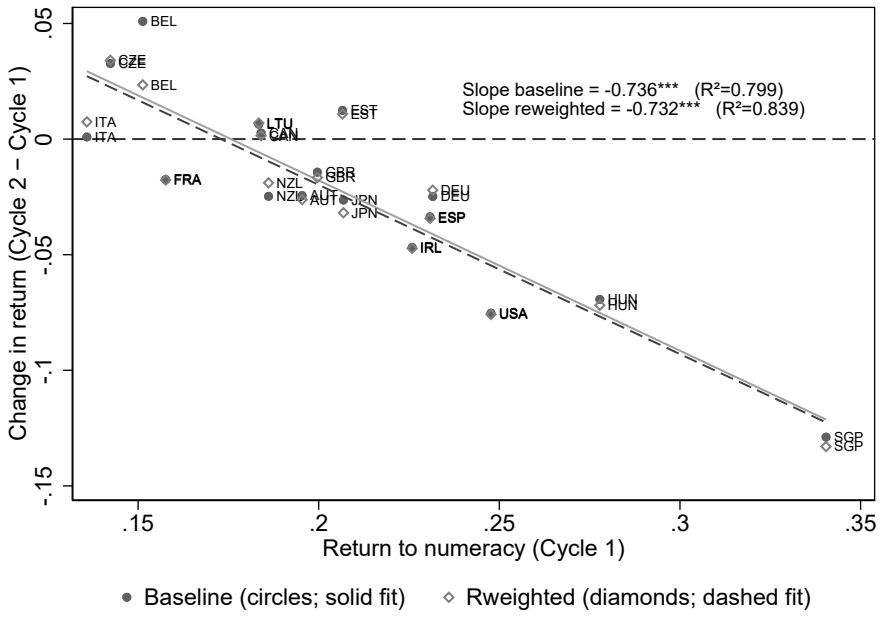
Notes: Graph plots standard deviation in numeracy skills in Cycle 1 and Cycle 2 by country. Full sample, weighted. Graph was generated using the PUF, therefore the Netherlands are missing. *Data source*: PIAAC Cycles 1 & 2.

Figure A7: Convergence in Returns to Cognitive Skills: Sample of Native Males



Notes: Each point is a country. The horizontal axis reports the country-specific return to numeracy in PIAAC Cycle 1; the vertical axis reports the change in the return between Cycle 2 and Cycle 1. Circles refer to the baseline estimation sample; diamonds refer to the subsample of native male workers. Country-specific returns are the coefficient on the numeracy score (Cycle 1: standardized to std. dev. 1 across countries; Cycle 2: using std. dev. of Cycle 1, Round 1) from weighted OLS regressions of log gross hourly earnings on numeracy, a female indicator, and a quadratic in actual work experience, estimated separately by country for full-time employees aged 35–54 (Canada includes part-time employees). Solid and dashed lines show the fitted values from separate OLS regressions of the change in returns (Cycle 2−Cycle 1) on the Cycle 1 return for the baseline sample and native-male sample, respectively. Reported slopes, R^2, and significance stars refer to these bivariate regressions (robust standard errors). The dashed horizontal line marks zero change in returns. Country labels use ISO-3 codes. *Data source:* PIAAC Cycles 1 and 2.

Figure A8: Convergence in Returns to Cognitive Skills: Sociodemographic Reweighting



Notes: Each point is a country. The horizontal axis shows the estimated return to numeracy in PIAAC Cycle 1; the vertical axis shows the change in the return between Cycle 2 and Cycle 1. Returns are the coefficient on numeracy from weighted OLS regressions of log gross hourly earnings on numeracy, a female indicator, and a quadratic in actual work experience, estimated separately by country for full-time employees aged 35–54 (Canada includes part-time employees). The *baseline* series uses the standard PIAAC sampling weights in each cycle. The *reweighted* series reweights Cycle 2 observations *within country* to match the Cycle 1 sample composition along three dimensions: gender, first-generation migrant status, and age group (three categories). Specifically, within each country we estimate a logit model for being observed in Cycle 1 as a function of these covariates and apply inverse-odds weights to Cycle 2 observations; the resulting weights are then normalized to preserve the Cycle 2 country-specific weight totals. Solid (dashed) lines are OLS fits for the baseline (reweighted) series; the estimated slopes and R^2 are reported in the figure (robust standard errors; significance stars refer to the slope estimates). Country labels are ISO-3 codes. *Data source:* PIAAC Cycles 1 and 2.

Table A1: Returns to Literacy Skills around the World, 2023

	Pooled	Austria	Canada	Chile	Croatia	Czech R.	Estonia	France	Germany	Hungary	Ireland
Literacy	.166***	.151***	.155***	.296***	.084***	.146***	.189***	.133***	.178***	.202***	.177***
	(.003)	*(.011)*	*(.010)*	*(.023)*	*(.012)*	*(.013)*	*(.010)*	*(.008)*	*(.010)*	*(.013)*	*(.014)*
Experience	.018***	.013	.026***	.021*	.032***	.010	.039***	.014**	.004	.008	.030**
	(.002)	*(.010)*	*(.006)*	*(.011)*	*(.006)*	*(.008)*	*(.007)*	*(.006)*	*(.006)*	*(.009)*	*(.012)*
Experience^2	−.035***	−.022	−.053***	−.051*	−.075***	−.022	−.084***	−.020*	−.001	−.019	−.047*
	(.004)	*(.020)*	*(.012)*	*(.026)*	*(.015)*	*(.018)*	*(.017)*	*(.012)*	*(.013)*	*(.019)*	*(.024)*
Female	−.161***	−.183***	−.112***	−.230***	−.148***	−.201***	−.279***	−.126***	−.132***	−.186***	.012
	(.007)	*(.028)*	*(.023)*	*(.058)*	*(.025)*	*(.025)*	*(.021)*	*(.017)*	*(.026)*	*(.025)*	*(.030)*
R^2	.179	.286	.206	.273	.123	.227	.253	.197	.275	.205	.142
Observations	27052	825	3609	777	961	1285	1797	1658	932	1326	1069

	Italy	Japan	Latvia	Lithuania	New Z.	Poland	Portugal	Singapore	Spain	U.K.	U.S.
Literacy	.101***	.153***	.208***	.191***	.139***	.069***	.202***	.191***	.177***	.163***	.148***
	(.015)	*(.011)*	*(.016)*	*(.017)*	*(.022)*	*(.012)*	*(.014)*	*(.012)*	*(.014)*	*(.014)*	*(.020)*
Experience	.021***	.028***	.010	.022**	.009	.015*	.000	.040***	.019***	.010	.027***
	(.008)	*(.009)*	*(.011)*	*(.009)*	*(.009)*	*(.008)*	*(.010)*	*(.012)*	*(.007)*	*(.007)*	*(.009)*
Experience^2	−.037*	−.041**	−.017	−.055**	−.019	−.037*	−.001	−.087***	−.041**	−.023	−.052***
	(.020)	*(.019)*	*(.026)*	*(.022)*	*(.018)*	*(.019)*	*(.022)*	*(.030)*	*(.016)*	*(.015)*	*(.020)*
Female	−.067**	−.235***	−.244***	−.232***	−.156***	−.129***	−.111***	−.185***	−.096***	−.134***	−.109**
	(.034)	*(.022)*	*(.031)*	*(.030)*	*(.035)*	*(.024)*	*(.032)*	*(.031)*	*(.027)*	*(.029)*	*(.046)*
R^2	.104	.203	.217	.199	.206	.066	.223	.187	.160	.146	.143
Observations	682	1457	1689	1317	981	993	845	1487	1401	1185	776

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

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54 (Canada includes part-time employees). Literacy score standardized to std. dev. 1 across countries, using std. dev. of Cycle 1, Round 1. Experience^2 divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2. Robust standard errors in parentheses. *Data source: Data source*: PIAAC Cycle 2.

Table A2: Returns to Cognitive Skills: Accounting for Non-cognitive Skills

	Baseline	+ Volunteering	+ Patience & trust	+ Big-5
Pooled	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Estonia	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Singapore	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Hungary	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Germany	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Belgium	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Spain	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Lithuania	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Canada	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
U.K.	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Japan	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Ireland	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Czech Rep.	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
U.S.	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Austria	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
New Zealand	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
France	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])
Italy	[ ]	[ ]	[ ]	[ ]
	([ ])	([ ])	([ ])	([ ])

Notes: Each cell reports the estimated return to numeracy skills for the indicated country and specification (coefficient on the standardized numeracy score), with robust standard errors in parentheses. The *Baseline* specification regresses log gross hourly earnings on numeracy, a female indicator, and a quadratic in actual work experience. The remaining columns add, respectively, an indicator for volunteering, measures of patience and trust, and the Big Five personality traits. All regressions are weighted with PIAAC sampling weights; the pooled specification additionally includes country fixed effects. Sample: full-time employees aged 35–54 (Canada includes part-time employees). *Data source:* PIAAC Cycle 2.

Table A3: Returns to Numeracy Skills around the World, 2012

	Pooled	Austria	Canada	Chile	Czech R.	Estonia	France	Germany	Hungary	Ireland
Numeracy	.224***	.195***	.184***	.306***	.142***	.207***	.158***	.232***	.278***	.226***
	(.004)	*(.011)*	*(.007)*	*(.032)*	*(.019)*	*(.014)*	*(.008)*	*(.013)*	*(.012)*	*(.020)*
Experience	.022***	.009	.021***	.017	.016*	.030***	.018***	.007	.020***	.019
	(.002)	*(.007)*	*(.004)*	*(.015)*	*(.008)*	*(.010)*	*(.005)*	*(.009)*	*(.007)*	*(.012)*
Experience^2	−.041***	−.010	−.033***	−.031	−.039**	−.082***	−.025**	−.000	−.044***	−.025
	(.005)	*(.015)*	*(.008)*	*(.040)*	*(.020)*	*(.021)*	*(.011)*	*(.020)*	*(.015)*	*(.027)*
Female	−.133***	−.126***	−.112***	−.119	−.212***	−.394***	−.085***	−.094***	−.101***	.059*
	(.007)	*(.023)*	*(.014)*	*(.078)*	*(.035)*	*(.025)*	*(.017)*	*(.028)*	*(.025)*	*(.034)*
R^2	.229	.264	.231	.244	.189	.257	.223	.254	.266	.191
Observations	28705	1115	7866	821	1017	1705	1625	1158	1673	1018

	Italy	Japan	Lithuania	New Z.	Poland	Singapore	Spain	U.K.	U.S.
Numeracy	.136***	.207***	.183***	.186***	.195***	.340***	.231***	.200***	.248***
	(.018)	*(.017)*	*(.019)*	*(.011)*	*(.022)*	*(.011)*	*(.018)*	*(.013)*	*(.018)*
Experience	.006	.022**	.017	.026***	.051***	.043***	.025***	.003	.014
	(.009)	*(.009)*	*(.012)*	*(.006)*	*(.009)*	*(.007)*	*(.009)*	*(.009)*	*(.009)*
Experience^2	.004	−.024	−.039	−.045***	−.108***	−.094***	−.042**	−.006	−.027
	(.021)	*(.020)*	*(.026)*	*(.014)*	*(.021)*	*(.018)*	*(.019)*	*(.018)*	*(.018)*
Female	−.082***	−.253***	−.196***	−.104***	−.083**	−.127***	−.027	−.087***	−.151***
	(.031)	*(.030)*	*(.036)*	*(.024)*	*(.035)*	*(.029)*	*(.028)*	*(.026)*	*(.033)*
R^2	.122	.213	.142	.268	.165	.450	.213	.221	.283
Observations	990	1194	1243	1137	811	1432	1133	1735	1032

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

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54 (Canada includes part-time employees). Numeracy score standardized to std. dev. 1 across countries. Experience^2 divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2. Robust standard errors in parentheses. *Data source: Data source*: PIAAC Cycle 1.

Table A4: Returns to Literacy Skills around the World, 2012

	Pooled	Austria	Canada	Chile	Czech R.	Estonia	France	Germany	Hungary	Ireland
Literacy	.212***	.203***	.180***	.271***	.138***	.148***	.144***	.223***	.283***	.206***
	(.004)	*(.011)*	*(.006)*	*(.031)*	*(.019)*	*(.014)*	*(.009)*	*(.013)*	*(.013)*	*(.022)*
Experience	.025***	.011	.022***	.030**	.017**	.033***	.019***	.005	.024***	.019*
	(.002)	*(.008)*	*(.004)*	*(.015)*	*(.008)*	*(.010)*	*(.005)*	*(.009)*	*(.007)*	*(.011)*
Experience^2	−.046***	−.014	−.036***	−.059	−.038**	−.087***	−.028**	.003	−.054***	−.026
	(.005)	*(.015)*	*(.008)*	*(.037)*	*(.019)*	*(.022)*	*(.011)*	*(.020)*	*(.016)*	*(.025)*
Female	−.170***	−.161***	−.152***	−.157*	−.227***	−.428***	−.118***	−.143***	−.132***	.032
	(.007)	*(.023)*	*(.014)*	*(.082)*	*(.035)*	*(.025)*	*(.017)*	*(.028)*	*(.025)*	*(.034)*
R^2	.203	.272	.232	.185	.185	.220	.179	.240	.246	.168
Observations	28705	1115	7866	821	1017	1705	1625	1158	1673	1018

	Italy	Japan	Lithuania	New Z.	Poland	Singapore	Spain	U.K.	U.S.
Literacy	.130***	.171***	.171***	.181***	.208***	.332***	.207***	.200***	.255***
	(.018)	*(.019)*	*(.020)*	*(.012)*	*(.021)*	*(.012)*	*(.016)*	*(.013)*	*(.017)*
Experience	.006	.026***	.019	.025***	.055***	.049***	.030***	.008	.012
	(.009)	*(.009)*	*(.012)*	*(.006)*	*(.008)*	*(.008)*	*(.008)*	*(.009)*	*(.009)*
Experience^2	.005	−.033	−.043	−.045***	−.115***	−.107***	−.050***	−.015	−.021
	(.021)	*(.021)*	*(.027)*	*(.014)*	*(.020)*	*(.019)*	*(.019)*	*(.019)*	*(.019)*
Female	−.099***	−.281***	−.222***	−.148***	−.115***	−.175***	−.055**	−.126***	−.205***
	(.031)	*(.030)*	*(.036)*	*(.024)*	*(.034)*	*(.030)*	*(.028)*	*(.026)*	*(.032)*
R^2	.113	.170	.119	.242	.194	.384	.200	.228	.269
Observations	990	1194	1243	1137	811	1432	1133	1735	1032

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

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54 (Canada includes part-time employees). Literacy score standardized to std. dev. 1 across countries. Experience^2 divided by 100. Pooled specification includes country fixed effects and gives same weight to each country; R^2 refers to within-country R^2. Robust standard errors in parentheses. *Data source: Data source*: PIAAC Cycle 1.

Table A5: Alternative Normalizations and Estimated Dynamics of Skill Returns

	Normalization with international SDs					Normalization with national SDs					Standard deviation (SD)		
	Joint normalization across cycles			Separate normalization within cycles		Joint normalization across cycles			Separate normalization within cycles		Original scale		
	Cycle 1 (1)	Cycle 2 (2)	Δ (3)	Cycle 2 (4)	Δ (5)	Cycle 1 (6)	Cycle 2 (7)	Δ (8)	Cycle 2 (9)	Δ (10)	Cycle 1 (11)	Cycle 2 (12)	% change (13)
Austria	0.192	0.181	-0.011	0.202	0.010	0.176	0.166	-0.010	0.199	0.023	49.12	58.94	20.0%
Belgium	0.149	0.127	-0.022	0.142	-0.008	0.143	0.122	-0.021	0.141	-0.002	51.38	59.72	16.2%
Canada	0.181	0.185	0.005	0.206	0.026	0.188	0.193	0.005	0.192	0.004	55.87	55.69	-0.3%
Czech Rep.	0.140	0.172	0.032	0.191	0.052	0.114	0.140	0.026	0.184	0.070	43.80	57.36	31.0%
Denmark	0.131	0.165	0.035	0.184	0.054	0.124	0.158	0.033	0.185	0.060	51.16	60.01	17.3%
Estonia	0.203	0.215	0.012	0.239	0.037	0.171	0.181	0.010	0.220	0.049	45.23	55.05	21.7%
Finland	x	x	x	x	x	x	x	x	x	x	x	x	x
France	0.155	0.138	-0.017	0.153	-0.001	0.163	0.145	-0.018	0.161	-0.002	56.48	62.91	11.4%
Germany	0.228	0.202	-0.026	0.225	-0.003	0.224	0.199	-0.025	0.235	0.011	52.72	62.37	18.3%
Hungary	0.273	0.216	-0.057	0.240	-0.032	0.264	0.209	-0.055	0.228	-0.036	52.02	56.84	9.3%
Ireland	0.222	0.176	-0.046	0.196	-0.026	0.222	0.176	-0.046	0.178	-0.044	53.71	54.33	1.2%
Italy	0.133	0.134	0.001	0.149	0.016	0.125	0.126	0.001	0.139	0.014	50.23	55.63	10.8%
Japan	0.205	0.177	-0.028	0.198	-0.007	0.167	0.144	-0.022	0.173	0.007	43.67	52.45	20.1%
Lithuania	0.180	0.186	0.006	0.208	0.028	0.160	0.166	0.006	0.163	0.003	47.72	47.07	-1.4%
Netherlands	0.184	0.190	0.006	0.211	0.027	x	x	x	x	x	x	x	x
New Zealand	0.183	0.161	-0.022	0.179	-0.003	0.186	0.164	-0.022	0.193	0.007	54.76	64.39	17.6%
Norway	0.122	0.116	-0.006	0.129	0.007	0.125	0.119	-0.007	0.118	-0.007	55.09	54.67	-0.8%
Singapore	0.334	0.209	-0.125	0.233	-0.101	0.420	0.263	-0.157	0.256	-0.164	67.46	65.85	-2.4%
Slovak Rep.	0.188	0.087	-0.101	0.097	-0.091	0.165	0.077	-0.089	0.077	-0.088	47.23	47.59	0.8%
Spain	0.226	0.193	-0.033	0.216	-0.011	0.217	0.186	-0.032	0.189	-0.028	51.45	52.47	2.0%
Sweden	0.106	0.098	-0.008	0.109	0.003	0.109	0.100	-0.008	0.106	-0.003	54.89	57.98	5.6%
U.K.	0.214	0.189	-0.025	0.211	-0.003	0.219	0.194	-0.025	0.208	-0.011	54.83	59.04	7.7%
U.S.	0.243	0.190	-0.053	0.211	-0.032	0.259	0.202	-0.057	0.246	-0.013	57.10	69.54	21.8%
Pooled	0.203	0.167	-0.036	0.187	-0.017	0.204	0.168	-0.036	0.187	-0.017	53.80	59.79	11.1%

Notes: Columns (1)–(10) report country-specific returns to numeracy skills in Cycles 1 and 2 and the implied change in returns, under alternative normalizations of the numeracy score. "International SDs" standardize numeracy using the pooled cross-country standard deviation; "national SDs" standardize using the within-country standard deviation. "Constant SD" uses Cycle 1 standard deviations for both cycles; "changing SD" allows the relevant standard deviation to differ by cycle (i.e., cycle-specific normalization). Columns (11)–(13) report the standard deviation of numeracy skills on the original PIAAC scale in Cycles 1 and 2 and the percentage change. *Data source:* PIAAC Cycles 1 and 2.

Table A6: Explaining Differences in Changes in Skill Returns: Change in Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Returns to numeracy skills (C1)	-0.519***	-0.515***	-0.517***	-0.514***	-0.496***	-0.516***	-0.514***	-0.561***	-0.520***
	(0.100)	(0.111)	(0.103)	(0.105)	(0.110)	(0.103)	(0.109)	(0.096)	(0.110)
Change computer programming (C2–C1)		-0.001							
		(0.022)							
Change automatability (C2–C1)			0.056						
			(0.340)						
Change manufacturing share (C2–C1)				-0.043					
				(0.070)					
Annual GDP per capita growth (2001–2011)					-0.003				
					(0.006)				
Change numeracy mean (C2–C1)						0.000			
						(0.001)			
Change public sector share (C2–C1)							-0.247		
							(0.306)		
Change labor freedom (2005–2011)								0.001*	
								(0.001)	
Change trade openness (2001-2011)									0.002
									(0.049)
Countries	22	22	22	22	22	22	22	22	22
R-sq	0.522	0.542	0.543	0.545	0.534	0.542	0.563	0.592	0.522

Notes: Each column reports an OLS regression of the change in country-level returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) on the initial country-specific return in Cycle 1, *Returns to numeracy skills (C1)*. Column (1) includes Cycle 1 returns only. Columns (2)–(9) add one country-level change measure at a time: (i) *Change computer programming (C2–C1)*, the change in average computer-programming frequency at work (PIAAC 1–5 categories recoded to 0–4); (ii) *Change automatability (C2–C1)*, the change in the country-level task-based automatability index; (iii) *Change manufacturing share (C2–C1)*, the change in the share of workers employed in manufacturing; (iv) *Annual GDP per capita growth (2001–2011)*, the average annual growth rate of real GDP per capita between 2001 and 2011; (v) *Change numeracy mean (C2–C1)*, the change in the country's mean numeracy score (divided by 10); (vi) *Change public sector share (C2–C1)*, the change in the share of workers employed in the public sector; (vii) *Change labor freedom (2005–2011)*, the change in the Heritage Foundation labor-freedom score from 2005 to 2011 (0–100, higher values indicating more market-oriented labor-market policies); and (viii) *Change trade openness (2001–2011)*, the change in (imports+exports)/GDP from 2001 to 2011. See Table **??** for details on the control variables. Data on the innovation index are unavailable prior to 2011; we therefore do not include a corresponding change measure. The change variables have one missing observation each for *change computer programming*, *change automatability*, *change manufacturing share*, *change numeracy mean*, and *change public sector share*; the remaining change variables have no missing observations. Missing values in control variables are imputed with the sample mean, and an indicator for imputed observations is included. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; World Bank World Development Indicators; Heritage Foundation (Index of Economic Freedom).

Table A7: Explaining Differences in Changes in Skill Returns: Technology Measures

Panel A: Levels (2011)						
	(1)	(2)	(3)	(4)	(5)	(6)
Returns to numeracy skills (C1)	-0.519***	-0.557***	-0.511***	-0.513***	-0.418**	-0.552***
	(0.104)	(0.107)	(0.112)	(0.115)	(0.147)	(0.124)
Computer use (C1)	-0.001					
	(0.071)					
Internet use (C1)		0.031				
		(0.026)				
R&D/GDP (2011)			0.007			
			(0.011)			
Patents/worker (2011)				-0.000		
				(0.000)		
IT exports share (2011)					-0.001	
					(0.001)	
High-tech exports share (2011)						0.001
						(0.001)
Countries	22	22	22	22	22	22
R-sq	0.522	0.539	0.540	0.524	0.558	0.527
Panel B: Changes (pre-PIAAC)						
	(1)	(2)	(3)	(4)	(5)	(6)
Returns to numeracy skills (C1)	-0.526***	-0.524***	-0.567***	-0.521***	-0.555***	-0.482***
	(0.099)	(0.107)	(0.060)	(0.108)	(0.145)	(0.105)
Change computer use (C2–C1)	0.140					
	(0.181)					
Change internet use (C2–C1)		-0.005				
		(0.028)				
Change R&D/GDP (2001–2011)			0.034***			
			(0.008)			
Change patents/worker (2001–2011)				-0.000		
				(0.000)		
Change IT exports share (2001–2011)					-0.000	
					(0.001)	
Change high-tech exports share (2007–2011)						0.002
						(0.002)
Countries	22	22	22	22	22	22
R-sq	0.554	0.543	0.657	0.526	0.529	0.539

Notes: Each column reports a cross-country OLS regression of the change in country-level returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) on the initial country-specific return in Cycle 1, *Returns to numeracy skills (C1)*, adding one innovation/technology indicator at a time. Panel A uses the initial *levels* of the indicators; Panel B uses the corresponding pre-PIAAC *changes*. A negative coefficient on *Returns to numeracy skills (C1)* indicates convergence (countries with higher initial returns experience larger subsequent declines). *Computer use (C1)* is the share of workers reporting experience with computers at work. *Internet use (C1)* is based on how often respondents use the internet to obtain work-related information; the original 1–5 frequency categories are recoded to range from 0 (never) to 4 (every day), so higher values denote more frequent ICT use at work. *R&D/GDP (2011)* is gross domestic expenditure on research and development as a share of GDP (percent). *Patents/worker (2011)* is resident patent applications divided by the number of employees (number of employees taken from PIAAC Cycle 1). *IT exports share (2011)* is information and communication technology goods exports as a share of total goods exports (percent). *High-tech exports share (2011)* is high-technology exports as a share of all exports (percent). "Change" variables are defined as Cycle 2 minus Cycle 1 for the ICT indicators, as 2011 minus 2001 for R&D/GDP, IT exports, and patents/worker, and as 2011 minus 2007 for high-tech exports (data on high-tech exports available only since 2007). Patents/worker (2011) is unavailable for Ireland; changes in computer and internet use are unavailable for the Netherlands (no public-use file in Cycle 2); and the change in patents/worker is unavailable for Ireland and Italy. Missing values are imputed with the sample mean, and an indicator for imputed observations is included. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; The Global Economy; World Bank World Development Indicators.

Table A8: Explaining Differences in Changes in Skill Returns: Further Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Returns to numeracy skills (C1)	-0.519***	-0.446***	-0.430***	-0.482***	-0.518***	-0.474***	-0.503***	-0.514***
	(0.100)	(0.079)	(0.117)	(0.126)	(0.102)	(0.102)	(0.098)	(0.110)
Numeracy SD (C1)		-0.184						
		(0.126)						
Employment protection (2011)			-0.005					
			(0.011)					
Union density (2011)				-0.029				
				(0.049)				
Trade freedom (2011)					-0.012			
					(0.217)			
Goods trade (2011)						-0.009		
						(0.011)		
Service trade (2011)							-0.009	
							(0.021)	
Intellectual property trade (2011)								-0.045
								(0.105)
Countries	22	22	22	22	22	22	22	22
R-sq	0.522	0.573	0.573	0.576	0.522	0.541	0.524	0.525

Notes: Each column reports a cross-country OLS regression in which the dependent variable is the change in the country-level return to numeracy skills between PIAAC Cycles 2 and 1 (Cycle 2 minus Cycle 1). The regressor of interest is the initial return in Cycle 1, *Returns to numeracy skills (C1)*; a negative coefficient indicates convergence (countries with higher initial returns experienced larger subsequent declines). Columns (2)–(10) add one country characteristic at a time. Country-specific returns are the coefficient on the standardized numeracy score from weighted OLS regressions of log gross hourly earnings on numeracy, a female indicator, and a quadratic in actual work experience, estimated separately by country for full-time employees aged 35–54 (Canada includes part-time employees). *Numeracy SD (C1)* is the within-country standard deviation of numeracy skills in Cycle 1 (sampling-weighted). *Employment protection (2011)* is the employment-protection index for individual/collective dismissals (higher values indicate stricter regulation). *Union density (2011)* is the share of wage and salary earners who are members of a trade union. *Trade freedom (2011)* is the Heritage Foundation trade-freedom index (0–100, higher values indicating fewer trade restrictions). The Trade freedom index is based on two indicators: the trade-weighted average tariff rate and non-tariff barriers (including quantity, price, regulatory, customs and investment restrictions, and direct government intervention). *Goods trade (2011)* and *Service trade (2011)* are goods/services exports plus imports as a share of GDP. *IP trade (2011)* is charges for the use of intellectual property (receipts plus payments) as a share of GDP. Employment protection and union density are missing in Singapore; missing values are imputed with the sample mean, and an indicator for imputed observations is included. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; World Bank World Development Indicators; Heritage Foundation (Index of Economic Freedom).

Table A9: Explaining Differences in Changes in Skill Returns: Workforce Composition

Panel A: Workforce composition (levels)			
	(1)	(2)	(3)
Returns to numeracy skills (C1)	-0.540***	-0.531***	-0.554***
	(0.115)	(0.108)	(0.109)
University grad share (C1)	0.035		
	(0.078)		
Migrant share (C1)		0.015	
		(0.052)	
Share STEM workers (C1)			-0.058
			(0.092)
Countries	22	22	22
R-sq	0.528	0.524	0.548
Panel B: Workforce composition (changes)			
	(1)	(2)	(3)
Returns to numeracy skills (C1)	-0.491***	-0.516***	-0.666***
	(0.108)	(0.091)	(0.151)
Change uni share (C2–C1)	-0.047		
	(0.110)		
Change migrant share (C2–C1)		0.090	
		(0.052)	
Change STEM share (C2–C1)			0.223
			(0.167)
Countries	22	22	22
R-sq	0.571	0.565	0.595

Notes: Each column reports cross-country OLS estimates relating the change in returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) to the initial country-specific return in Cycle 1. *Returns to numeracy skills (C1)* equals the Cycle 1 return minus its sample mean; a negative coefficient therefore indicates convergence (countries with higher initial returns experience larger subsequent declines). Panel A adds workforce-composition measures in levels (Cycle 1): *University grad share (C1)* is the share of workers with a university degree; *Migrant share (C1)* is the share of foreign-born workers; and *Share STEM workers (C1)* is the share of workers in STEM fields of study (Information and Communication Technology; Natural Sciences; Mathematics and Statistics; Engineering and Manufacturing; Construction) in all workers. Panel B uses the corresponding changes between Cycles 2 and 1 (C2–C1). All change variables are missing in Denmark and the Netherlands; additionally, changes in migrant and STEM shares are missing in Norway, and the change in STEM share is missing in Sweden (in each case because the underlying country-level variable is suppressed in the PUF). Each specification includes a missing-value indicator for the added covariate(s). Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2.

Table A10: Explaining the Speed of Convergence: Alternative Freedom Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial returns (C1)	-0.438***	-0.439***	-0.518***	-0.433***	-0.435***	-0.489***	-0.438***
	(0.056)	(0.092)	(0.100)	(0.112)	(0.094)	(0.080)	(0.067)
× labor freedom (2011) /100	-1.168***						-1.176***
	(0.209)						(0.257)
× trade freedom (2011) /100		-7.904*					-0.407
		(3.821)					(1.790)
× investment freedom (2011) /100			0.917				
			(1.439)				
× fiscal freedom (2011) /100				-1.147***			
				(0.267)			
× financial freedom (2011) /100					0.532		
					(0.934)		
× economic freedom, overall index (2011) /100						-2.242***	
						(0.640)	
Main effect of interacted variable	0.005	0.011	0.098	-0.020	0.122	0.078	.
SE (main effect)	(0.019)	(0.170)	(0.053)	(0.064)	(0.055)	(0.076)	(.)
N	22	22	22	22	22	22	22
R-sq	0.631	0.545	0.573	0.602	0.603	0.596	0.633

Notes: Each column reports cross-country OLS estimates relating the change in returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) to the initial country-specific return in Cycle 1. *Initial returns (C1)* equals the Cycle 1 return minus its sample mean across countries; a negative coefficient therefore indicates convergence (countries with higher initial returns experience larger subsequent declines). Columns (1)–(5) include an interaction between *Initial returns (C1)* and one centered Heritage Foundation sub-index of economic freedom in 2011—*labor freedom*, *trade freedom*, *investment freedom*, *fiscal freedom*, and *financial freedom*. The Labor freedom index is composed of six quantitative factors: ratio of minimum wage to the average value added per worker, hindrance to hiring additional workers, rigidity of hours, difficulty of firing redundant employees, legally mandated notice period, and mandatory severance pay. The Trade freedom index is based on two indicators: the trade-weighted average tariff rate and non-tariff barriers (including quantity, price, regulatory, customs and investment restrictions, and direct government intervention). The Investment freedom index evaluates a variety of investment restrictions (burdensome bureaucracy, restrictions on land ownership, expropriation of investments without fair compensation, foreign exchange controls, capital control, security problems, a lack of basic investment infrastructure, etc.). The Fiscal freedom index measures the tax burden imposed by government. It is composed of three quantitative factors: the top marginal tax rate on individual income, the top marginal tax rate on corporate income, and the total tax burden as a percentage of GDP. The Financial freedom index evaluates: the extent of government regulation of financial services, the degree of state intervention in banks and other financial firms through direct and indirect ownership, the extent of financial and capital market development, government influence on the allocation of credit and openness to foreign competition. Higher index values denote banking efficiency and independence from government control and interference in the financial sector. Column (6) includes an interaction with the composite index, *economic freedom, overall index*, in 2011. The overall index of economic freedom has ten components grouped into four broad categories: Rule of Law; Limited Government; Regulatory Efficiency and Open Markets. Column (7) adds a horse race between the interaction terms with labor freedom and trade freedom, respectively. All freedom indices are scaled 0–100; higher values indicate more market-oriented policies); indices are demeaned, so the coefficient on *Initial returns (C1)* captures the convergence slope at the average level of the respective index. The bottom row reports the estimated main effect of the interacted freedom index (evaluated at average initial returns). Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; Heritage Foundation (Index of Economic Freedom).

Table A11: Explaining the Speed of Convergence: Other Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Initial returns (C1)	-0.486***	-0.444***	-0.470***	-0.525***	-0.412***	-0.481***
	(0.072)	(0.107)	(0.138)	(0.090)	(0.091)	(0.092)
× public sector share (C1)	2.560**					
	(1.149)					
× employment protection (2011)		0.201				
		(0.140)				
× union density (2011)			0.199			
			(0.652)			
× GDP per capita (2011) / 10,000				-0.006		
				(0.038)		
× GDP growth (1990–2011)					-0.085	
					(0.167)	
× numeracy mean (C1)						0.097
						(0.081)
Main effect of interacted variable	0.054	-0.006	-0.018	-0.003	-0.015	0.002
SE (main effect)	(0.078)	(0.010)	(0.064)	(0.005)	(0.021)	(0.004)
N	22	21	21	22	22	22
R-sq	0.568	0.353	0.334	0.533	0.585	0.542

Notes: Each column reports cross-country OLS estimates relating the change in country-level returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) to the initial country-specific return in Cycle 1. *Initial returns (C1)* equals the Cycle 1 return minus its sample mean across countries; a negative coefficient therefore indicates convergence (countries with higher initial returns experience larger subsequent declines). In each column, *Initial returns (C1)* is interacted with one centered country characteristic (levels), so the coefficient on *Initial returns (C1)* captures the convergence slope at the sample-average value of that characteristic; the interaction coefficient shows how the convergence slope varies with the characteristic. The interacted variables are: *Public sector share (C1)*, the share of workers employed in the public sector in Cycle 1; *Employment protection (2011)*, an index of employment protection for individual and collective dismissals; *Union density (2011)*, the share of employees who are union members; *GDP per capita (2011)*, real GDP per capita in 2011 in constant 2015 US dollars (in units of 10,000); *GDP growth (1990–2011)*, the compound annual growth rate of real GDP per capita between 1990 and 2011; and *Numeracy mean (C1)*, the country-level average numeracy score in Cycle 1 (divided by 10). The row "Main effect of interacted variable" reports the coefficient on the (centered) interacted variable. Employment protection legislation and union density are missing in Singapore; each specification is estimated on the set of countries with non-missing values for the interacted variable. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; World Bank World Development Indicators; OECD Employment Protection Indicators.

Table A12: Explaining the Speed of Convergence: Other Country Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial returns (C1)	-0.518***	-0.495***	-0.517***	-0.460***	-0.520***	-0.518***	-0.369***	-0.458***
	(0.085)	(0.093)	(0.091)	(0.068)	(0.111)	(0.102)	(0.116)	(0.114)
× computer programming (C1)	-3.630							
	(2.259)							
× innovation index (2011)		-0.008						
		(0.016)						
× computer use (C1)			-0.055					
			(0.876)					
× internet use (C1)				-0.963***				
				(0.182)				
× R&D/GDP (2011)					0.077			
					(0.157)			
× patents/worker (2011)						-0.001		
						(0.003)		
× IT exports share (2011)							-0.011	
							(0.013)	
× high-tech exports share (2011)								-0.025***
								(0.008)
Main effect of interacted variable	-0.147	0.000	-0.002	0.039	0.008	0.000	-0.001	0.001
SE (main effect)	(0.088)	(0.002)	(0.077)	(0.021)	(0.011)	(0.000)	(0.002)	(0.001)
Countries	22	22	22	22	22	21	22	22
R-sq	0.567	0.532	0.522	0.619	0.545	0.515	0.579	0.584

Notes: Each column reports cross-country OLS estimates relating the change in country-level returns to numeracy skills between PIAAC Cycles 1 and 2 (Cycle 2 minus Cycle 1) to the initial country-specific return in Cycle 1. In each column, *Initial returns (C1)* is interacted with one centered innovation/technology indicator. The coefficient on *Initial returns (C1)* captures the convergence slope at the sample-average value of the interacted indicator; the interaction coefficient shows how the convergence slope varies with the indicator. The row "Main effect of interacted variable" reports the coefficient on the (centered) interacted indicator. The interacted variables are: *Computer programming (C1)*, based on the question about how often respondents use a computer programming language at work; the original 1–5 frequency categories are recoded to range from 0 (never) to 4 (every day), so higher values denote more frequent ICT use at work. *Innovation index (2011)* is the Global Innovation Index (0–100), a composite measure summarizing innovation inputs and outputs published by INSEAD, Cornell University, and the World Intellectual Property Organization (WIPO). *Computer use (C1)* is the share of workers reporting experience with computers at work. *Internet use (C1)* is based on how often respondents use the internet to obtain work-related information; the original 1–5 frequency categories are recoded to range from 0 (never) to 4 (every day), so higher values denote more frequent ICT use at work. *R&D/GDP (2011)* is gross domestic expenditure on research and development as a share of GDP (percent). *Patents/worker (2011)* is resident patent applications divided by the number of employees (number of employees taken from PIAAC Cycle 1). *IT exports share (2011)* is information and communication technology goods exports as a share of total goods exports (percent). *High-tech exports share (2011)* is high-technology exports as a share of all exports (percent). Each specification is estimated on the set of countries with non-missing values for the interacted variable; patents/worker (2011) is unavailable for Ireland. Robust standard errors are reported in parentheses. Significance levels: * $p < .10$, ** $p < .05$, *** $p < .01$. *Data sources:* PIAAC Cycles 1 and 2; INSEAD; Cornell University; World Intellectual Property Organization (WIPO); World Bank World Development Indicators.