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_Education for people and planet: Creating sustainable futures for all_

**Education, Skills, and Decent Work in Low and Middle Income countries: Trends and Results from an Adult Skills Survey**

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Executive Summary

Education is a central policy tool in uplifting the poor and creating productive societies. Despite gains in recent decades to increase educational attainment, developing countries are beset by the mounting demand for skills in the 21st century. Using the World Bank STEP 2012-2013 surveys, this paper documents the stock and use of skills among the working age population across several low and middle income countries, and investigates the role of education in ensuring equal access to decent employment in today’s labour markets. In least developed countries, large segments of the working population have completed but less than primary schooling. While middle income countries feature a comparatively more educated populace in terms of qualifications, standardized test scores show that the average level of skills in these countries fall well below that of the mean for OECD countries. Moreover for the same level of educational attainment, cross-country gaps in skill proficiency are more pronounced thus suggesting that same level of schooling does not confer the same amount of skills. In an age where jobs that offer the highest returns demand ever higher levels of analytical as well as interpersonal skills, an emphasis on quality in addition to quantity of schooling is thus warranted. The lack of quality assurance mechanisms in many education systems today results to additional investments in quantity with little to no return to the individual. We find that this manifests not only in lower earnings or high incidences of self-reported skill gaps, as in literacy and computers, but also in the prevalence of overqualification, or possessing years of education more than that required by the job. In our sample of developing countries, between 21 and 35 percent of workers report being overqualified for their jobs. Despite more years of education, they exhibit inferior skills than workers with the appropriate qualifications. Apart from ensuring better-matched jobs however, expanding access to quality education are also a potent tool for unlocking decent employment opportunities. For instance, we find that education differences can explain a large part of the differential odds of lower socioeconomic groups, and in some countries the differential odds between women and men, of gaining access to decent work. Furthermore with the prospects of future employment under threat by automation and premature deindustrialization, the pressure to expand the provision of quality education that confers universal basic skills is ever higher.
Introduction

Education has become a central policy tool in uplifting the poor and creating productive societies. Traditional economic thinking stresses educational attainment as a benchmark in light of its strong correlation with economic growth and individual earnings (Mankiw, Romer and Weil, 1993; Bils and Klenow, 2000). Causal evidence of its benefits shows that a year of schooling, on average, raises wages by 6% to 13%. These estimated returns are generally higher in developing countries than in industrialized nations (Kolesnikova, 2010). Furthermore, several studies have also demonstrated that education affords non-pecuniary benefits that reverberate throughout life. In the labor market, more educated workers generally suffer shorter unemployment durations and report higher job satisfaction. Outside this, they also tend to make better decisions about health, marriage, and parenting. In addition apart from private benefits, human capital investment also confers positive externalities on society. Research by Moretti (2004) finds that low-skilled workers enjoy productivity spillovers from working with highly-skilled colleagues, thus resulting in higher earnings. Society also benefits from a more educated populace through reduced criminal activity (Lochner and Moretti, 2004) and improved civic participation (Milligan et al, 2004).

Mounting evidence of the individual and societal gains from education bolsters policy towards investing in affordable quality schooling. To this end, recent decades have seen a dramatic rise in schooling attainment across the world. In advanced economies, average schooling attainment of persons aged 15-64 are now 12 years while in developing countries, average years of education have nearly quadrupled to about 7.8 from their levels in 1950 (See Figure 1) (Barro and Lee, 2013). While this has translated into improved living conditions for large segments of society, the returns to education across countries have not been uniform or guaranteed (Temple, 1999). To explain this, Pritchett (2001) argues that apart from labor demand and institutional factors besetting a country, educational quality could have been so low that additional years in school create no human capital. Thus, both research and policy have begun to shift their attention to issues of quality or how much is learned in the classroom. The availability of locally as well as internationally comparable tests of student achievement such as the Trends in International Mathematics and Science Study (TIMSS) and the Program for International Student Assessment (PISA) has been an invaluable resource for monitoring the state of education systems and human capital.

In their research linking skills with economic growth, Hanushek and Woessmann (2012) find that cognitive skills, as measured through standardized reading, mathematics, and science tests for students, are a stronger determinant of long-term economic growth than the average years of schooling of a country. At the individual level, Hanushek et al (2015) estimate an 18% wage return to an increase of one standard deviation of cognitive skills evaluated among prime-aged wage workers in 23 OECD countries. While the TIMSS and PISA have primarily been concerned with skills possessed by primary and secondary school students, the arrival of the OECD Survey of Adult Skills (PIAAC) and the World Bank Skill Measurement Survey (STEP) has paved the way for the measurement of the stock and use of skills among each country’s working age population¹. This chapter relies primarily on these adult surveys with a focus on the low- and

¹ For STEP, the working age population constitutes those individuals aged 15-64. The relevant population for PIAAC is those at ages 16-65.
middle-income countries covered by STEP. This includes urban labor markets in Armenia, Bolivia, China (Yunnan Province), Colombia, Georgia, Ghana, Kenya, Macedonia, Ukraine, and Vietnam (Hanoi and Ho Chi Minh), as well as urban and rural sectors of Lao PDR and Sri Lanka, during the years of 2012-2013. For consistency and owing to data limitations, majority of the analysis in this paper focuses on the urban subpopulation of the abovementioned countries unless otherwise specified. In select sections of the piece, we refer to 2011-2012 PIAAC data on the United States, Germany, and the Republic of Korea whose samples are representative of the urban and rural populations of their respective countries.

The paper will proceed as follows. The first section compares levels of skills across and within countries as well as measuring skill mismatches and skill gaps which prevent workers from being fully productive. The second section centers on socio-demographic factors affecting skill acquisition, and access to decent work. Finally, drawing from existing literature, the last section delves into the future of jobs in both developed and developing countries and discuss implications for education policy.

**Education, Skills, and Tasks at Work**

*Schooling attainment in STEP and PIAAC countries*

To provide context to the ensuing discussion, we begin by a cross-country comparison of schooling attainments. A useful aide is the UNESCO International Standard Classification of Education which provides an international benchmark for education systems worldwide. For ease of exposition, the highest level of formal education completed by the population is grouped into either primary or less (ISCED 1 and below), lower secondary (ISCED 2), upper secondary (ISCED 3 and 4), and tertiary education (ISCED 5 and above). Shares of the working age population by completed formal education in each country are displayed in Figure 2.

In advanced economies such as the United States, Germany, and the Republic of Korea, we observe that majority of the working age population, or between 65%-70%, have at most upper secondary school qualifications. The share with postsecondary schooling ranges from 29-35% only. In contrast, the patterns of schooling attainments in developing countries vary between having very large groups with tertiary education as in the former Soviet states and having broad segments of those with just primary schooling. Exceeding those of the developed economies, the shares of university or polytechnic graduates in Armenia, Georgia and Ukraine are 51%, 58%, and 45% respectively. Meanwhile, the share of those completing no more than primary education are highest in Colombia, Ghana, Kenya, and Lao PDR at 32%, 35%, 37%, and 43% respectively. Among the STEP survey countries, Macedonia’s distribution of schooling attained is the one that most closely resembles those found in the PIAAC country examples. Against this backdrop, it is imperative for policymakers to take stock of their education investment, the returns it has realized, and those promises it has failed to deliver. The experience of successful education systems demonstrates that while the quantity dimension is crucial, it is hardly a guarantee of the learning required to reap its fruits.

*Cognitive skills and literacy proficiency*

One way in which classroom learning has been measured is through standardized tests in critical subject areas. More than a gauge of factual knowledge, they assess the ability to process information and solve problems systematically. Linked with these are the person’s cognitive skills, which are defined as the ability to understand complex ideas, adapt effectively to one’s environment, to learn from experience, and to
engage in various forms of reasoning (Neisser et al, 1996). These have been traditionally measured in two skill domains, literacy and numeracy, of which the former is shared in common by PIAAC and STEP surveys. That both of these follow comparable 500-point proficiency scales facilitates a cross-country comparison of the functional literacy skills of the potential workforce.

The STEP survey adult skills assessment comprises three sections: a) the core test, b) the reading components booklet, and c) the full literacy evaluation. Not all countries conduct the full battery of exercises. Specifically, China, Lao PDR, Macedonia, and Sri Lanka fail to administer the third module. Nonetheless, common to all countries is an eight-point core test designed to identify respondents with the lowest ability, who are those that are unlikely to succeed in completing the full literacy assessment. This is further supplemented by a reading section designed to provide information about adults with very low levels of proficiency in reading. The reading components include tests on vocabulary, sentence processing, and passage comprehension, which contain 6, 11, 17 items respectively. Performance in this first round of tests typically correlates highly with performance in the full literacy assessment².

In Figure 3, the performance of each country is plotted in descending order of their mean percentage score in the core and reading booklets. Noticeably, there is small cross-national variance of scores among the top seven of the STEP survey countries. Countries where individual mean scores on the core module are at least 85% are able to post near 90% in the reading module. China and Macedonia are in the company of Ukraine, Armenia, Georgia, Vietnam, and Colombia in this group. On the other hand, Sri Lanka, Bolivia, Kenya, Lao PDR, and Ghana perform significantly worse in comparison. To draw a sense of the skill levels in the rural sector, we additionally report core and reading module scores in rural Lao PDR and Sri Lanka in Figure 4. Between the two countries, the urban-rural gap is higher in Lao PDR.

Whereas the mentioned tests aim to describe basic reading skills, the full literacy assessment measures one’s ability to understand, evaluate, and engage with written texts of varying length and complexity. Performance in this test follows a 500-point scale which is divided into proficiency levels defined by a range of score-point values representing a particular level of difficulty in the tasks involved. Table 1, which is from the OECD Skills Outlook of 2013 (OECD, 2013), summarizes the six levels, corresponding score range, and the types of tasks completed successfully at each level of proficiency. In Figure 5, we compare mean scores³ of the working-age population in the seven STEP survey countries and the scores of their counterparts in Germany, the Republic of Korea, and the United States. Average literacy proficiency are highest in the OECD countries, but are not far from those of adults in urban regions of the former Soviet states as well as Vietnam and Colombia. Mean country scores in these countries fall in the range of Level 2 proficiency which requires processing text of medium length, integrating two or more pieces of information therein, and making low-level inferences from the document. It should be noted that these scores fall below the OECD average, with the exception of the Republic of Korea. The worst-performing countries in the literacy assessment are Bolivia, with a score falling in the range of Level 1 proficiency, and the sub-Saharan nations whose average scores rank below Level 1.

² For the STEP survey countries, the Pearson correlation coefficient between the literacy score and the core and total reading components scores fall in the ranges of 0.49 – 0.90 and 0.36 – 0.69, respectively.

³ Statistics are based on the first plausible value of scores.
Beyond averages, Figure 6 displays the percentage of adults scoring below Level 1 and at Level 1, Level 2 and 3, and Level 4 and Level 5 respectively. The more developed economies post the highest proportion of adults with scores at the highest tier, up to as high as 12% for the United States. Despite having shares of the working age population with a tertiary degree exceeding those of the US, Ukraine, Armenia and Georgia have only 5.8%, 1.5%, and 1.4% of their adults with literacy proficiency at this level. Meanwhile, at the other end of the spectrum, large segments of the developing world’s adult populations have skills at or below Level 1. This is most pronounced in Bolivia, Ghana and Kenya where more than half the potential urban workforce are only able to process simple texts, which is Level 1 or below in the literacy proficiency scale. They are followed by Colombia and Vietnam, with adults with Level 1 or below proficiency comprising 30% of the potential workforce. This is twice the proportion reported by OECD countries, wherein on average 83% of adults reach at least Level 2 proficiency. (OECD, 2013).

As Hanushek and Woesmann (2012) emphasize, the entire distribution matters as much as the means. Improving the share of those with basic literacy skills and top performers are separately relevant for growth and require starkly different policy interventions. Their analysis shows that universal basic literacy plausibly enhances growth through institutional and demographic channels, while increasing the share of top performers may accelerate catch-up with more developed nations by facilitating adoption of frontier technologies.

Conditioning on the level of educational attainment, skill proficiency also varies widely across countries. Figure 7 plots the mean scores for each group. Among urban postsecondary graduates, only those from the Republic of Korea, Germany, the United States and Ukraine have mean proficiencies at Level 3. Meanwhile, upper secondary school graduates from Bolivia, Ghana and Kenya exhibit inferior literacy skills than their counterparts in the other countries whose mean scores are at Level 2. Finally, those from these three nations with primary education or less also rank behind the other countries, with the notable exception of similarly educated adults from Vietnam whose mean scores likewise fall below the first level. These figures reinforce the point that the same level of schooling need not necessarily confer similar levels of skills, and in consequence, similar labour market outcomes.

In the labor market, both schooling and skills matter. Skills are important to the extent that they raise productivity in the workplace and are directly used as inputs in production. Traditional Mincer earnings regression estimates of the returns to education implicitly subsume rewards to skills accumulated in school. Cognitive literacy ability, however, is only one dimension of the entire skills spectrum. To estimate the hourly wage gains associated with a standard deviation increase of years of education and literacy proficiency, we follow Hanushek et al (2015) in separately estimating the returns to schooling and skills using the country’s sample of prime-age wage workers⁴.

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⁴ Hanushek et al (2015) show that jointly estimating the returns to cognitive skills and years of schooling may result to an upward bias in the latter’s coefficient. Moreover, if we believe that skills are measured with classical measurement error, the estimate of skill returns in such a regression will be biased towards zero. While no convincing argument of the causal impact of scores can be made here, the analysis aims to document the systematic relationship between earnings and skills, as a component of human capital and economic development. The choice of restricting the sample to prime-age workers is due to the downward lifecycle bias of returns estimated at early ages. Haider and Solon (2006) show that current earnings are a good proxy for lifetime earnings only when observed in the middle of one’s career.
The evidence from that paper on OECD countries is complemented in this study with estimates from a developing country context. Computed returns using a basic Mincer specification are displayed in Figure 8. We find that a standard deviation increase in years of schooling is associated with positive returns to hourly wages ranging from 19%, as in Ukraine, to 53%, as in Kenya. Meanwhile an increase of one standard deviation in literacy is also associated with large positive earnings gains albeit smaller than those of an additional standard deviation of schooling in all countries. The observed returns in literacy are the largest among countries with low average scores and those with high variance in literacy proficiency. Through pooled analysis with log hourly earnings in purchasing power parity (PPP) as the dependent variable in our sample of developing nations, we find that on average a standard deviation increase in literacy skills leads to wage gains of 28%. This is higher than the estimate by Hanushek et al (2015) of 17% for the same subpopulation in the OECD5.

**Non-cognitive skills**

Nevertheless, these achievement test scores capture only functional literacy and fail to account for other skill dimensions, most notably, behaviors and attitudes such as perseverance, self-efficacy, openness to new experiences, tolerance for diverse opinions, and ability to work with peers, which are also valued in the labor market and in society at large. These non-cognitive skills have been found to predict not only performance in school but also various employment and social outcomes such as earnings and involvement in crime (Heckman, Stixrud and Urzua, 2006).

Non-cognitive skills or personality traits are the relatively enduring patterns of thoughts, feelings, and behaviours that reflect the tendency to respond in certain ways under certain circumstances (Roberts, 2009). A well-accepted taxonomy of these character skills is the so-called Big Five. These are openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (emotional stability)6. The STEP survey includes measures of such traits.

In the STEP surveys, these traits are scored on a scale of 1-4 with 4 as the most positive or desirable. We present mean scores of each country in Figure 9. Consistent with evidence from the literature, each trait appears to matter differentially based on outcomes. Conscientiousness, openness to experience, and stability correlate highly with labor force participation; openness and agreeableness are predictive of

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5 Moreover, this observation is consistent with cross-country patterns of schooling returns being higher in low- and middle-income economies than high-income countries.

6 Openness to experience refers to enjoyment of learning. Conscientiousness has been defined as the propensity to be goal directed and follow norms and rules. Agreeableness refers to pro-social orientation with peers, while extraversion relates to sociability. Finally, emotional stability relates to one’s level of disinclination to feel or experience negative emotions. These five comprise the Big Five taxonomy on domains of human personality. Further measures of personality available in STEP are grit, which relates with perseverance for long-term goals; hostile attribution bias, which has been defined as the tendency to interpret others’ behaviors or actions as hostile; and decision-making, which relates to due diligence one takes prior to reaching a decision. The addition of the latter three to the Big Five provides incremental predictive power over measures of professional and educational achievement.
earnings while conscientiousness is positively associated with the likelihood of employment\textsuperscript{7}. We tread carefully in making broad statements using data from STEP given the less-than-ideal reliability of the measures as discussed by Pierre et al (2014) in the STEP survey documentation.

**Skills at work: A task-based perspective**

Certainly, other types of skills (e.g. information and communications technology (ICT), entrepreneurial, financial literacy) also matter. However, basic cognitive and non-cognitive skills are thought to be foundational in that they are pillars of lifelong learning. Whereas skill formation is a life cycle process, investment in these skills at childhood begets higher learning and skill attainment later in life (Cunha and Heckman, 2007). The focus on these skills is also warranted by their increasing relevance to the world of work.

A useful framework for mapping jobs to skills is the lens of occupational tasks. To draw the distinction, a task is a unit of work that produces output while a skill is a worker’s stock of capabilities for performing various tasks. Whereas an occupation may be regarded simply as a bundle of tasks, workers apply their skills to tasks to produce output in return for wages (Autor, 2013). The standard taxonomy of tasks distinguishes between routine and non-routine cognitive and manual tasks. Routine tasks are those that are sufficiently understood such that they can be fully specified as a series of instructions to be executed by a machine. These are characteristic of middle-skilled\textsuperscript{8} cognitive and manual jobs such as bookkeeping, clerical work, repetitive production, and monitoring positions. Manual tasks are those activities that entail physical labor and visual-spatial adaptability. These are common of low-skilled and service-oriented occupations such as drivers, cleaning and maintenance personnel, and security workers. Finally, cognitive tasks are those that require problem-solving, persuasion, and creativity, and are characteristic of workers in professional, technical, managerial, and creative occupations (Acemoglu and Autor, 2011). These cognitive tasks may be further broken down into their analytical and interpersonal components, which highlight where greater cognitive and non-cognitive abilities may be of importance in the workplace.

Whereas the literacy assessment is informative of the cognitive ability of the worker, tasks indicate which other skills may be relevant as inputs for productivity in the labor market. Like the PIAAC, the STEP survey includes detailed questions about the specific tasks performed by workers in their main occupations. These include reading, writing, numeracy, computer use, solving problems, learning, supervising, presenting, and interaction with people outside work, task autonomy, task repetitiveness, and physical labor. Their definitions and scales are reported in Table 2\textsuperscript{9}. Using the Autor and Handel (2013) taxonomy, we group these 12 task indicators into groups that represent interrelated functions on the job. These are the

\textsuperscript{7} These results are from an ordinary least squares regression with log hourly earnings, labor force participation, and employment as the dependent variable and with the Big 5 traits as regressors. I control for dummies of ISCED completed, gender, age, and squared age and include country dummies. Standard errors were clustered by country.

\textsuperscript{8} The use of high-skilled, middle-skilled, and low-skilled terminology in the job task framework and employment polarization literature often refers to the median or mean wage of the occupation in relation with other occupations. This need not, though generally does, map to the level of schooling of those employed in these jobs.

\textsuperscript{9} The STEP survey also includes task indicators of driving, repair, and operating of machines.
analytical, interpersonal, routine, and manual components of work. We compare the intensity of use of these tasks across countries.

Figure 10 presents the means for each task indicator. Among analytical tasks, also known as information-processing skills, China reports the highest mean intensity of reading and writing at work. In terms of numeracy, all countries report mean use of at least the lowest level of complexity, suggesting that a mastery of basic arithmetic is an essential skill. Across countries, there is high variance in the mean frequency of computer use. In all countries but urban Lao PDR and Ghana, more than a fifth of jobs now entail the use of computers in the workplace. The frequency of use is highest among workers in Macedonia and China. In a later subsection, we document skill gaps in computer skills reported by workers in each country. Finally, the frequency of work requiring at least 30 minutes of thinking is highest among Macedonia, Sri Lanka, and Bolivia, while frequency of learning new things is highest in Colombia, Armenia, and Bolivia.

Additionally, we also document interpersonal task intensity in the workplace. China, Colombia and Kenya report the highest average frequency of interaction with people outside of work. Apart from this, the STEP survey also has binary task indicators of whether workers engage in supervising and presenting at their workplace. Over 40% of workers in China, Sri Lanka, and Vietnam report engaging in supervisory tasks suggesting the importance of developing managerial skills in these labor markets. The same countries are also at the top in terms of the proportion of jobs that require skills in presentation.

Furthermore, as a measure of routine and manual task intensity, we draw from the reported degrees of repetitiveness and rigidity of the jobs as well as the amount of physical labor in the workplace. Using indices of the analytical, interpersonal, routine, and manual task intensities derived from a principal components analysis, we characterize each one-digit ISCO occupation category by the tasks involved in each. The scores are graphed in Figure 11\(^\text{10}\).

We find that the highest-paying occupations – managers, professionals, and technicians – generally display the highest intensity of analytical and interpersonal tasks at work. On average the degree of routine intensity is highest among clerical workers but unlike developed country evidence, is not exceptionally high in comparison to non-middle skilled occupations. Finally, manual task intensity is highest among crafts and related trade, plant and machine, and elementary occupation workers.

Comparing across countries using a time series of labor force surveys, Aedo et al (2013) show that as countries develop, they will see a monotonic drop in manual-intensive jobs and a progressive rise in the analytical and interpersonal task content of national production. While it is not possible to study such trends over time using STEP, evidence from the cross-section reveal that indeed higher GDP per capita is associated with higher use of analytical and interpersonal task components. At the individual level, we find that earnings, education, and literacy skills also positively correlate with higher intensity of analytical and interpersonal tasks at work and are negatively associated with the frequency of manual tasks.

\(^{10}\) Sampling weights are used to average scores within countries and equal weights were used to take the means across countries. Military occupations and skilled agricultural workers were dropped due to their small sample sizes in many countries.
**Education needed for the job**

Insofar as the skills used in the workplace are developed in school, a natural measure of the demand for skills in the labor market is the qualifications, that is, the quantity of schooling, needed for the job. This has been measured in the literature in several ways. First, the education required may be assessed by job analysts. A well-known example is the Dictionary of Occupational Titles in the United States. Because this is not widely available across countries, realized matches, which rely on the modal or mean schooling within occupation groups, have been a popular way in which the required qualifications have been measured. In this report, we use two other metrics: a normative (ILO, 2014) measure which uses a fixed qualification for each occupation group, and subjective worker-assessment which asks the worker the education required for the job.

Under the normative measure, the occupational distribution fully determines the education required in the labor market. Managerial, professional and technician jobs require education in the level of ISCED 5 or higher. On the other hand, elementary occupations require ISCED 2 or lower. The rest of the occupation groups require ISCED 3 or 4. We refer to these jobs as high-skilled, low-skilled, and middle-skilled respectively. The shape of employment, or equivalently the distribution of education requirements, is displayed in Figure 12.

Georgia and Armenia have disproportionately high shares of high-skilled employment which exceed those of more developed countries. The United States, like Macedonia and Ukraine, have more even shares of workers in either middle-skilled and high-skilled employment, with a difference in shares of no more than 10%. Despite being advanced economies, German and South Korean labor markets are comprised predominantly by middle-skilled employment possibly owing to their bustling manufacturing sectors. The experience of these countries reveals that the shape of employment is intimately related with the structure of the economy. High-income nations are not necessarily a nation of tertiary graduates or jobs requiring a university degree. For developing countries, the current demand for skills is sure to evolve but the growth in high-skilled, middle-skilled, and low-skilled employment will be contingent in part on the country’s growth strategy. There are thus no hard and fast rules except that of ensuring skill acquisition at each stage of education and linking education policy with foreseen industry demand.

Apart from the normative method, an alternative method in which current skill demand is measured is to use information about the educational requirements of the job provided by the workers themselves. In STEP, survey respondents are asked about the education necessary to satisfactorily carry out her job tasks. In the absence of objective third party assessments, subjective assessment by the worker is the preferred method of measuring education required because it accounts for heterogeneity across jobs within occupations (Leuven and Oosterbeek, 2011). From a cross-national perspective, this method also accounts for factors determining job complexity that is unique to the country such as technology.

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11 The occupation classifications in this paper follow the International Standardized Classification of Occupations or ISCO-08.

12 On the other hand, PIAAC instruments contain a question asking the respondent the education needed in order to get her job today.
Figure 13 depicts worker-assessed skill demand. The Republic of Korea, United States, and Germany have shares of jobs that reportedly require tertiary education at only 40%, 36%, and 32% respectively. These advanced economies also have large shares of jobs requiring only upper secondary education ranging from 38% to 53% and shares of jobs requiring lower secondary education or lower at between 10 to 21%. In stark contrast, jobs reportedly requiring primary education or less comprise over half of available employment in Ghana and Lao PDR. Together with Kenya, these countries also have the lowest shares of jobs that need tertiary education. Closer in distribution with the developed countries are Ukraine and Macedonia. Exceeding them, however, in terms of the share of jobs purportedly requiring tertiary schooling are Armenia and Georgia. Finally worker assessments in Bolivia, China, Colombia and Sri Lanka have majority of employment that requires up to upper secondary schooling.

Generally, we find that the distribution of education attained by employed workers is to the right of the distribution of education reportedly required by the currently available jobs. This does not imply, however, that there is a surplus of skills much as a deficit in skilled jobs. It is also important to note that these statistics are based on the employed sample. Policymakers should also consider the incidence of unemployment which is high in countries like Armenia and Georgia, and implies that skills may be underutilized. Moreover, as we emphasized, the same qualifications need not reflect the same level of skills so that employers may choose persons who are lacking in terms of schooling but qualified in terms of experience or unobserved ability.

**Qualification mismatch**

At the individual level, the difference between the worker’s educational attainment and that required by his job is called qualification mismatch. This has been well-documented in developed countries (Leuven and Oosterbeek, 2011; OECD, 2013). However, few studies have examined its incidence and causes in the developing country context. Chua and Chun (2015) document mismatches in Asia using the STEP survey. We extend their analysis to the remaining countries.

The concern with mismatches arises not only from wasted resources on unutilized qualifications but also for its adverse effects on welfare and productivity. Notably, studies find that overqualified workers, those with more years of education than needed in their job, often end up in a lower wage trap relative to well-matched peers with similar education (Baert et al, 2013; Clark et al; 2014). Moreover, pervasive under-qualification at the firm level also results in reduced productivity (Kampelmann and Rycx, 2012).

To compute the incidence of mismatch, we take the difference between the ISCED level completed by the worker and the ISCED level they report is required by their jobs. That is, we use the education the worker reports is needed for her job\(^\text{13}\). Surplus levels of acquired schooling denote over-qualification; deficit levels of imply under-qualification; an equality entails an appropriate match. Figure 14 displays the distribution of these worker-job matches. STEP countries report rates of under-qualification that are generally low with the notable exception of Kenya (31%), Bolivia (19%) and Colombia (18%). In these countries, the under-

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\(^{13}\) The main advantage of worker-assessments to statistical and normative measures of job requirements are that the former accounts for the unobserved heterogeneity across jobs within occupation groups. One criticism of the measure however is that workers may lack the self-awareness or competence to appropriately gauge their own abilities or the skills required of their jobs.
qualification is driven predominantly by gaping schooling shortages in jobs requiring at least lower secondary qualifications in the case of Kenya and upper secondary qualifications in the case of Bolivia and Colombia. Meanwhile, over-qualification typically ranges from 21% in Ukraine to 35% in Vietnam which is close to the range observed in the more developed economies with United States at the lower end and the Republic of Korea on the upper end.

High incidences of over-qualification should be cause for concern as overqualified workers may be investing in education for which they are earning inferior returns. On the surface, rampant over-qualification suggests that the supply of educated workers has outpaced demand. However, mere schooling attainments mask heterogeneity in individual skills and abilities. A leading explanation for mismatch is human capital compensation (Korpi and Tahlin, 2009). That is, overqualified candidates often make up for dearth in actual skills and experience by investing in greater years of schooling than necessary while underqualified workers demonstrate to employers their capacity to perform the job tasks at a level beyond the workers’ level of schooling. To test this, we compare average literacy proficiencies of workers who are overqualified and underqualified with the scores of well-matched workers, controlling for the ISCED completed, gender, age, and squared age. The score difference is shown in Figure 15. Consistent with the above hypothesis, we find that workers self-reporting being overqualified for their jobs tend to have lower literacy proficiency than well-matched counterparts. This relationship is statistically significant across all STEP countries except Armenia and Colombia. Moreover, the mean literacy proficiency of underqualified individuals are statistically higher than the well-matched in Georgia, Kenya, and Viet Nam.

**Literacy Skill mismatch**

Apart from mismatches in education qualifications, the STEP and PIAAC survey also allows for an examination of mismatches in particular skill dimensions. Several methods have been proposed namely by Allen et al (2013), Pellizari and Fichen (2013), and Perry et al (2014). Owing to data constraints, we adopt the Perry et al (2014) methodology which uses only the information on literacy scores. Looking at persons in the same occupation group of each country, workers within 1.5 standard deviations above or below the mean literacy score in the same occupation are considered well-matched in terms of skills. Those with literacy proficiency that falls short of this range are considered under-skilled while those with literacy proficiency that exceeds this range are considered over-skilled. Because of the smaller sample size of STEP, we use reduced occupation categories by grouping together high-skilled occupations, clerical and sales and service workers, workers in either skilled agricultural work, crafts and related trade, and plant and assembly, and finally those from elementary occupations. Another difference with the Perry et al (2014) paper is the use of just the first plausible value of literacy.

Using this method, we find that about 90% of workers are well-matched in terms of cognitive literacy skills (See Figure 16). Moreover, under-skilling is more common than over-skilling. In more developed economies such as the United States, Germany and the Republic of Korea, under-skilling is comprised mainly of low literacy workers in high-skilled professions. The same is true of Armenia, Georgia, Ukraine, and to a lesser extent Vietnam. Furthermore, a simple cross-tabulation of mean reading and writing scores with type of skill match reveals that well-matched workers generally perform reading and writing tasks at similar or higher intensity than overskilled, while underskilled workers consistently report the least intensity of literacy tasks at work.
The hallmark of a good education system, and more broadly, a well-functioning labor market does not stop at the effective delivery of skills, but more than this, ensures equitable access to learning opportunities and decent work for all. This section examines socio-demographic aspects explaining disparities in literacy proficiency, odds of employment in the formal vis-à-vis the informal sector, as well as the risk of working poverty. The motivation goes beyond one of equity. From an economic perspective, education helps ensure that workers are able to nurture their innate talents and pursue their comparative advantages. In the case of the United States, Hsieh et al. (2014) estimate that between 15 to 20 percent of growth in aggregate output per worker between 1960 and 2008 can be attributed to institutional and technological developments during this period that allowed broad segments of society, notably women and blacks, to acquire further education and participate in occupations of their choosing.
Specifically, we look at gender, socioeconomic status and ethnolinguistic backgrounds as among the factors likely to affect skill acquisition. In terms of gender, inequities in educational attainment between women and men in some parts of the world are a leading driver of the differences in skills. We plot in Figure 20(a) the mean literacy score by gender using results from the STEP and PIAAC surveys. We notice that the gap in scores is most pronounced in the sub-Saharan African countries of Ghana and Kenya. Conditioning on having the same level of educational attainment as men, we find that women still systematically score lower in Ghana, Kenya, Bolivia, Colombia, and Viet Nam, even as we control for other demographic characteristics as shown in Figure 20(b). Possibly explaining these differences are persistent cultural norms that induce families to invest less in other facets of women’s human capital, such as their health.

Likewise being born into a low income family is associated with underinvestment in skills. Poorer, credit-constrained households have been found to make fewer such investments especially in early life (Dahl and Lochner, 2012; Lochner and Monge-Naranjo, 2012). Low income status is also related with inferior health (Currie, 2009) and family environments (Carneiro et al, 2012) which affect not only performance in school but later life outcomes as well. In Figure 21(a), we graph mean proficiencies in literacy by the individual’s reported socioeconomic status when s/he was 15 years of age. We find that the former Soviet states’ mean scores are more compressed along this dimension. Moreover, while there is no substantial difference in achievement between persons from high and middle income backgrounds, those from low income families consistently post the worst average scores. The score difference between people from high income backgrounds and low income backgrounds diminish when controlling for education, gender, and other socioeconomic characteristics (See Figure 21(b)).

A more objective way in which to assess the role of early life conditions would be to use the parents’ level of education in lieu of self-reported socioeconomic status. More educated parents are likely to provide better not only in terms of addressing their child’s material needs but also offering a supportive home environment. Using this measure, we observe a larger variation in mean scores depending on whether the highest education attained by either parent is primary or less, secondary, or postsecondary. As shown in Figure 22, children of highly educated parents outperform children of parents with only primary schooling or less in the literacy assessment by as much as 77 points, unadjusted, or 36 points when accounting for schooling and other demographic factors.

While affordable quality education has proven necessary in bridging these disparities, they are unlikely to be sufficient in the presence of other channels that disadvantage children from poorer backgrounds. Apart from resources at home, recent research also finds that poorer households disproportionately suffer from misinformation with respect to the opportunities available to them. They tend to underestimate the returns to further schooling (Jensen, 2010), overestimate the cost of education (Dinkelman and Martinez, 2014), and are less informed about school quality (Hastings and Weinstein, 2008) and thus they are unable to make sound education investment decisions.

Finally, we also find that people from migrant or minority backgrounds are also among the most disadvantaged when it comes to skills. Evidence from PISA reveals that students from immigrant backgrounds consistently perform worse than locals in subject tests. While the STEP survey has no direct measure of the immigrant status of the individual, we rely on survey questions about the respondent’s mother tongue. We consider the difference in scores between those whose mother tongue is purely the
predominant language and those with a mother tongue that is a minority language or spoken by less than 33% of the population. Bolivia, Georgia, Kenya, and Ukraine are countries in which one’s ethnolinguistic background negatively associates with skills even after controlling for the level of education and other demographic factors (see Figure 23). From a policy standpoint, it is important to identify the degree of integration of these subpopulations with the rest of the community. If these groups live in relative isolation, then perhaps the quality of teaching institutions available to them, cultural norms, or neighborhood factors explain their inferior skill achievement. On the other hand, if these groups are well integrated with the greater community, disadvantage in terms of mastery of the dominant language may be hampering their performance, and schools should take measures to bring them up to par with the rest, for instance through the provision of remedial classes. To the extent that the above social and demographic factors systematically lead to private underinvestment in human capital, the public sector plays a key role in ensuring these gaps are closed.

**Education matters to bridging disparities in decent work access**
Whereas education and skills are a means to secure employment, persistent inequities in human capital investment can also be linked with differences in access to decent work. In this section, we explore how much of the variation in decent work access between men and women, as well as between individuals from low versus middle or high socioeconomic status at age 15, can be explained by the gaps in skills and educational attainment.

The International Labour Organization defines decent employment as productive work in which rights are protected, which generates adequate income, and which provides social protection. Following this definition, we use two indicators of decent work namely working in the formal sector, and earning weekly income above the working poverty threshold.

Characteristic of many developing countries, the informal sector largely comprises small firms that are low in productivity and run by poorly educated entrepreneurs (La Porta and Schleifer, 2014). Apart from reaping lower returns to skills, informal workers also typically suffer from poorer working conditions and the lack of a written contract and social security benefits. In the STEP data, informal sector workers are defined as either wage workers without social security or benefits, unpaid family workers, or self-employed workers working in an establishment with only one employee. Using a similar definition for the PIAAC surveys, we document the proportion of employment belonging to the informal sector. These are displayed in Figure 24. Of the STEP survey countries, only Armenia, Macedonia and Ukraine have formal sector shares comparable to those of the industrialized economies. In addition, whereas more advanced countries feature a comparatively large share of wage workers as opposed to self-employment or unpaid family work, in countries such as Bolivia, Colombia, Ghana, Lao PDR, Sri Lanka and Vietnam, self-employment comprises more than 40% of total employment and is almost entirely in the informal sector.

Given persistent inequities in educational attainment and skills acquisition along gender and socioeconomic lines, decent work access is spread unevenly across these groups. In terms of gender, we find that among employed workers, women are more likely than men to be in the informal sector in countries such as Bolivia, Colombia, Ghana, and Kenya. On the other hand, the reverse is true in Armenia, Georgia, and Ukraine where it is men that are more likely to be working in the informal sector. Meanwhile in terms of socioeconomic status, individuals from disadvantaged socioeconomic backgrounds
are also found to be less likely to be employed in the formal sector. The question is how much of these gaps can be explained by differences in education and skills. To answer this, we employ the Oaxaca-Blinder method (Oaxaca, 1973; Blinder, 1973) for decomposing mean differences in outcomes between two groups based on a linear regression model. The outcome differential is divided into an explained component or the part that can be attributed to group differences in endowments (e.g. education, experience) and a residual or unexplained component which cannot be accounted for by the determinants of the model. The latter is usually attributed to discrimination; however it also captures the potential effects of differences in unobserved variables (Jann, 2008).

Gender differences in the likelihood of working in the informal sector are statistically significant in all countries we examine but Vietnam. In Armenia, Georgia, and Ukraine, men are between 6 and 10 percentage points more likely than women to be in the informal sector, while the reverse holds for women in the rest of the countries by as much as 18 percentage points. Moreover, we find that across countries the unexplained component generally dominates endowment effects except in Ghana where group differences in years of education completed can explain 51% of the gap between men and women and skills a further 11%. On the other hand, differences between individuals from low versus middle or high socioeconomic status are also statistically significant except in Bolivia, Georgia, and Ukraine. Where the gap is significant, the incidence differential between groups ranges between 6 and 12 percentage points, and endowment effects account for majority of this with educational attainment nearly fully explaining the component; differences in measured skills only matter marginally. Using a pooled sample of all employed individuals, we find that on average across countries differences in educational attainment account for 37% of the gap between low SES and middle or high SES workers and skills a further 6%.

Apart from informality, another indicator of decent work opportunities in the labor market is the incidence of working poverty. We take the OECD (2009) definition which sets the threshold at half of the median earnings. Individuals with weekly earnings falling below this threshold are considered as working poor. Among the STEP survey countries, Ukraine and Macedonia post the lowest incidence of working poor. Meanwhile, Ghana, Bolivia, and Kenya have the highest proportion of workers earning below half the median weekly salary at 28%, 22% and 21% respectively.

Across all countries, women are more likely to be classified as working poor than men. The gender gap is largest in Armenia, Colombia and Ghana with the incidence of working poverty among women being 20 percentage points greater than men and lowest in Ukraine and Vietnam at only 3 and 5 percentage points respectively. In all cases, the unexplained component accounts for majority of the difference in probabilities of being working poor. In terms of socioeconomic background, we only find a statistically significant

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14 The methodology is often employed in the labor economics literature to decompose earnings differentials. The results from which our analysis is based originates from a logistic model of our binary dependent variable, decent employment, with years of education, literacy skills, age, squared age, gender, and socioeconomic status at age 15 as the explanatory variables. For pooled sample regressions, we add country fixed effects and cluster standard errors at the country level.

15 Without controlling for education, skills account for 16% of the gap.

16 The threshold is computed as half the median earnings of the sample of employed working at least 30 hours in a given week.
difference in the likelihood of being working poor between low and middle or high SES individuals in Ghana (9 percentage points), Kenya (12 percentage points), and Vietnam (4 percentage points). In these countries, educational attainment accounts almost entirely for the difference in odds of being working poor. A pooled sample regression reveals that on average across countries 39% of the observed gaps between the two socioeconomic groups can be attributed to differences in educational attainment, and a further 4% can be linked with skills differences, albeit the latter is not statistically significant. This is similar with results using formal sector employment as a measure of decent work; we obtain similar results from using a linear probability model rather than a logit.

In summary, these results demonstrate that expanding access to education is vital to bridging disparities not only skills but also in decent employment. Education, and to a lesser extent skills, enable individuals to overcome at least their socioeconomic disadvantages. The results above also show however that gaps in educational attainment have poor explanatory power over outcome differentials between men and women. This suggests that other factors may be driving the gap and for which policy levers other than education may be more appropriate.
Future of the World of Work and Implications for Education Policy

The world of work has undergone rapid and dramatic changes over the course of the last few decades. The force of structural change has lifted masses of workers out of low-productivity agriculture to modern economic activities. Likewise developing countries have become more integrated with the world economy since the 1990s, thus increasing not only trade in goods and services but also movement of labor and offshoring of jobs. Amid all of this, technological progress has provided an enabling environment for the release of the immense potential energy of the world economy by increasing per capita productivity.

The impact of these forces has nowhere been better documented than in the advanced economies. Since the 1970s, scholars have predicted a continued rise in the demand for skills owing to rapid scientific advances of the times – hence the metaphorical race between education and technology (Tinbergen, 1975). This so-called skill bias of technology has led to high enough shifts in demand that highly educated workers enjoyed much higher growth in earnings over this period even as supply had risen in response. The increase in employment and wages, however, has not been monotonic across the skill distribution. Technological progress has not only been skill-biased but routine-biased as well (Goos, Manning, and Salomons, 2014). Though computers and robots complement the activities of high-skilled workers, they also have disproportionately displaced human labor in such occupations as clerical work and plant operations, which are traditionally considered middle-skilled. This substitution of labor with machines in occupations whose tasks are repetitive and routinized have led to the polarization of employment or the rise of high-skilled and low-skilled jobs and the relative demise of opportunities in middling occupations (Goos and Manning, 2007; Autor and Dorn, 2013). Compounding the effects of technology in advanced economies is the increased trade between high-income and low-income nations. While there is no consensus on the net effect of trade on employment in these countries (Gorg, 2011), there are indications that this expands high-skilled employment while displacing low-skilled workers whose jobs are offshored or outsourced where labor is cheaper. Because of the relative inelasticity of the supply of highly-skilled, such trends have put a marked premium for workers that can execute non-routine analytical and interpersonal tasks. In such economies, the future of jobs is in high-skilled employment or in low-skilled occupations that require human interaction. Nevertheless, if the wage patterns since the 1990s are any indication, jobs falling in the latter group will face a ceiling on wage growth, with the prospects for upward mobility concentrated in the former. Acemoglu and Autor (2012) suggest that while many jobs, middle-skilled or otherwise, are susceptible to automation, employment is likely to respond by a rearrangement of the required tasks, which will draw from across the skill spectrum. In terms of the skill requirements of the future, Goldin and Katz (2007) stress the importance of increasing the supply and quality of human capital as a way of ensuring rapid and equitable growth. The predominance of high-skilled occupations does not imply that middle skill education will be rendered futile. Rather, it will be even more important in ensuring that students are prepared to master higher order skills, and that they are able to adapt and learn in a rapidly changing labor market.

For developing countries, we have shown that widespread skill gaps and mismatch plague labor markets. Their future prospects will depend on their respective growth strategies and development phase. On the one hand, the classical structural change story of diversification from traditional sectors has generated more productive employment in modern industries. Their cost advantage in labor-intensive industries has allowed them to be the beneficiary of offshoring of operations and outsourcing of personnel by high-
income trade partners. While this model of economic development has been largely successful in many East Asian countries, its promise has come under threat with the increasing affordability of labor-replacing technology. Felipe et al (2014) find that developing countries are now increasingly unable to sustain high manufacturing employment shares, which have been historically necessary in transitioning into high income status. With the premature destruction of such jobs relative to the country’s development phase, Rodrik (2015) finds that workers are often displaced towards even lower-productivity activities in the informal sector rather than equally productive sectors as evinced by Latin American and sub-Saharan African examples. He additionally finds that the adverse effects of deindustrialization on employment have been disproportionately borne by low-skilled workers. Under such an environment, the pressure to expand educational provision is ever higher.

The good news is that most developing countries have made great strides in this regard. The bad news, at least for policymakers, is that great may not necessarily be enough. As we have shown, wide disparities in skills still exist among individuals with the same level of educational attainment. Quality assurance mechanisms such as audits or other accountability measures are hardly in place to ensure that education institutions are delivering within acceptable standards of quality. Widespread informational market failures such as on school quality and education returns are also an area of policy which many developing countries have thus far ignored. In addition, paucity of efforts to curb severe inequities in access to education, either due to socioeconomic background or cultural norms, continue to haunt systems worldwide. In the long term, countries hoping to unlock their full productive potential will undoubtedly need to invest in developing a labor force with universal basic skills and high enough shares with top end abilities. Brick-and-mortar policy has hitherto succeeded in raising schooling quantities, but now is the time for quality-centered reforms and interventions that allow individuals to acquire the skills necessary to be employable and productive in today's rapidly changing labour market.
### Tables

**Table 1:** Description of proficiency levels in literacy  
(See p. 64 of OECD Skills Outlook 2013)  
(Alternatively, see p. 83 of the STEP documentation)

**Table 2:** Indicators of tasks at work

<table>
<thead>
<tr>
<th>Task</th>
<th>Description and interpretation</th>
<th>Score range</th>
</tr>
</thead>
</table>
| **Analytical** | **Reading**  
Number of pages normally read as part of work; a score of zero means skill is not used at work; a score of one involves reading ten or less pages of text, while a score of two indicates reading between 11 to 25 pages, and a score of three means reading text of more than 25 pages in length | 0-3         |
| **Writing**  | Number of pages normally written as part of work; a score of zero means skill is not used at work; a score of one involves writing ten or less pages of text, while a score of two indicates writing between 11 to 25 pages, and a score of three means writing text of more than 25 pages in length | 0-3         |
| **Numeracy** | Complexity of math used at work; a score of zero means skill is not used at work while a score of one refers to tasks involving measurement of sizes and weights or calculation prices and performing basic arithmetic; a score of three refers to use of advanced math such as algebra at work | 0-3         |
| **Computer** | Frequency of computer use at work; a score of zero means a computer is not used as part of the job and a score of three means the use of computers everyday as part of the job | 0-3         |
| **Thinking** | Frequency of performing tasks that require at least thirty minutes of thinking such as making a lesson plan, creating a menu, or budgeting; a score of zero means never while a score of three means everyday | 0-3         |
| **Learning** | Frequency of work involving learning new things; a score of zero means rarely or never while a score of three means everyday | 0-3         |
| **Interpersonal** | **Interaction**  
Frequency of contact with persons outside of colleagues and the length of interaction with these persons; a score of zero means no contact with people other than colleagues while a score of three means work involving meeting or interacting for at least 10-15 minutes at a time with a customer, client, student, or public | 0-3         |
|              | **Supervise**  
Indicator whether the individual directs and checks the work of co-workers | 0-1         |
|              | **Present**  
Indicator as to whether the individual makes presentations to clients or colleagues to provide information or persuade | 0-1         |
Routine
Repetitive  Frequency of work involving carrying out short, repetitive tasks; recoded to range from least to most repetitive  0-3
Autonomy  Degree of freedom one has to go about one’s tasks; recoded to range from least to most structured  0-3
Manual
Physical  Degree of how physically demanding is the work; from least to most physically demanding  0-3

Figures
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Average Years of Schooling: Advanced vs Developing Economies

Source: Barro and Lee (2013)
Figure 2 Educational Attainment of the Working-age Population

Source: STEP and PIAAC; Sample of working age population
Figure 3 Percentage Score in Core and Reading Components Assessments: Urban Working Age Population

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Percentage score in core and reading components assessments

Source: STEP; Sample of working age population
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Source: STEP and PIAAC, Sample of working age population
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Source: STEP and PIAAC; Sample of working age population
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Mean literacy score by education attained

Source: STEP and PIAAC; Sample of working age population
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Note: Estimates from separate OLS regressions of log hourly earnings on years of schooling (standardized) and literacy skills (standardized), controlling for gender, age, squared age, and using the subsample of prime-age workers (35-54 years old).
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Mean literacy score by gender

Literacy proficiency gaps by gender

Note: Literacy proficiency score gaps (male minus female) are obtained from an OLS regression of literacy proficiency on dummies of educational attainment, gender, age, squared age, and indicators of socioeconomic status at age 15 and ethnolinguistic background.
Figure 21a and 21b: Literacy Proficiency Gaps by Socioeconomic Status at Age 15

Note: Literacy proficiency score gaps (high SES minus low SES) are obtained from an OLS regression of literacy proficiency on dummies of educational attainment, gender, age, squared age, and indicators of socioeconomic status at age 15 and ethnolinguistic background.
Figure 22a and 22b Literacy Proficiency Gaps by Parents’ Highest Educational Attainment

Note: Literacy proficiency score gaps (at least one parent finished ISCED 4 or higher minus both parents finished ISCED 1 or less) are obtained from an OLS regression of literacy proficiency on dummies of educational attainment, gender, age, squared age, and indicators of socioeconomic status at age 15 and ethnolinguistic background.
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Note: Literacy proficiency score gaps (those whose mother tongue purely in major language minus those with at mother tongue in a minority language) are obtained from an OLS regression of literacy proficiency on dummies of educational attainment, gender, age, squared age, and indicators of socioeconomic status at age 15 and ethnolinguistic background.
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Source: STEP and PIAAC; author's computations
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References

(n.d.).


