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Abstract

Human capital is widely regarded as a key driver of socioeconomic development. Yet, its measurement, on a global scale and over time, is still unsatisfactory—particularly, regarding its quality dimension (i.e., the skills people actually have). To remedy that, this dissertation places a special focus on the skills dimension of human capital, its measurement and analysis. More specifically, this dissertation project has the following three aims: (i) to understand changes in literacy skills over the life course; (ii) to create a composite indicator of skills-adjusted human capital which is comparable across time and space; and (iii) to analyze among- and within-country differences in skills-adjusted human capital, focusing particularly on population heterogeneity.

Realized in the form of a thesis by publication, this dissertation uses a demographic approach to draw on quantitative methods and analyses of large-scale international adult skills-assessment data. Overall, the results reveal that the massive educational expansion that took place globally in the recent past only partly resulted in a similar rise in literacy skills. These findings challenge the use of existing measures of human capital that exclusively focus on the quantity of education; instead, a novel and more holistic indicator to measure the human capital of the working-age population is suggested. Finally, the results also provide empirical evidence of the large heterogeneity in literacy skills among otherwise similar subpopulations.

This dissertation, which aims to provide a fuller understanding of the level of human capital in populations around the world and over time, makes important contributions to the topics of human capital measurement and skills-adjusted education indicators; it thus has crucial implications not only for scholars working with data on education and human capital but also for policy-makers concerned with development goals and policy evaluations.

Kurzfassung

Bildung und Humanvermögen gelten gemeinhin als entscheidende Faktoren für sozioökonomische Entwicklung. Dennoch ist ihre Messung auf globaler Ebene und im Zeitverlauf immer noch unzufriedenstellend – insbesondere was die Qualitäts-Dimension, d.h. die tatsächlichen Fertigkeiten und Kompetenzen von Personen, betrifft. Um Abhilfe zu schaffen, wird in dieser Dissertation ein besonderer Schwerpunkt auf die Kompetenz-Dimension von Humanvermögen, deren Messung und Analyse gelegt. Konkret verfolgt dieses Dissertationsprojekt drei Ziele: (i) ein besseres Verständnis davon zu haben, wie sich Lesekompetenzen im Laufe des Lebens verändern; (ii) die Entwicklung eines Indikators für Humankapital, der sowohl die quantitative als auch die qualitative Dimension berücksichtigt und über Zeit und Raum hinweg vergleichbar ist; und (iii) Unterschiede im kompetenzbereinigten Humanvermögen in und zwischen Länder zu identifizieren, wobei insbesondere die Heterogenität der Bevölkerungen berücksichtigt wird.

Diese kumulative Dissertation verfolgt einen demografischen Ansatz und stützt sich auf quantitative Methoden und die Analyse internationaler Daten zur Messung der Fähigkeiten von Erwachsenen. Insgesamt zeigen die Ergebnisse, dass die massive Bildungsexpansion, die in der jüngsten Vergangenheit weltweit stattgefunden hat, nur teilweise zu einem ähnlichen Anstieg der Lese-Kompetenzen geführt hat. Diese Ergebnisse stellen die Verwendung bestehender Indikatoren für das Humankapital in Frage, die sich ausschließlich auf die Quantität der Bildung konzentrieren; stattdessen wird ein neuer, ganzheitlicherer Indikator zur Messung des Humanvermögens der Bevölkerung im erwerbsfähigen Alter vorgeschlagen. Schließlich liefern die Ergebnisse auch empirische Evidenz für eine große Heterogenität der Lese-Kompetenzen in ansonsten ähnlichen Bevölkerungsgruppen.

Mit dem Ziel, ein umfassenderes Verständnis des Humanvermögens in Bevölkerungen auf der ganzen Welt zu vermitteln, leistet diese Dissertation einen wichtigen Beitrag zu den Themen Messung von Humanvermögen sowie kompetenzbereinigte Bildungsindikatoren – mit erheblicher Bedeutung nicht nur für Wissenschaftler, sondern auch für politische Entscheidungsträger, die sich mit Entwicklungszielen und Maßnahmen-Evaluierungen befassen.

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1. Introduction

1.1. Motivation

Over the last decades, many countries have made impressive progress in terms of child school enrollment, hence improving the educational attainment of their populations. While in 1950, only roughly one-fifth of the world's population aged 15 years or older had completed lower secondary or higher education, this proportion had more than tripled to 67% in 2020, or, in absolute terms, increased by more than 3.5 billion people. During the same period, the share of people aged 15+ who had never been in school diminished from almost half of the world's population (45.6%) to only 12.6% in 2020 (Wittgenstein Centre for Demography and Global Human Capital, 2018).

There is wide consensus that such progress is beneficial for global development. Education is associated with learning essential skills that help realize humanity's most important aspirations, including health and avoidance of premature death (Caldwell, 1979; Caselli et al., 2014; Cutler et al., 2006; Fuchs et al., 2010; Gakidou et al., 2010; Lleras-Muney, 2005; Lutz & Kebede, 2018; Mechanic, 2007; Ross & Mirowsky, 2010; Smith, 2007), ending poverty and hunger (Awan et al., 2011; Hofmarcher, 2021; Lutz et al., 2008; van der Berg, 2008), improving institutions and participation in society (Lipset, 1959; Lutz et al., 2010), fostering economic growth (Hanushek & Woessmann, 2012; Lutz et al., 2008, 2019), and even enhancing adaptive capacity to already unavoidable climate change (Butz et al., 2014; Lutz et al., 2014). A student's mere physical presence in a classroom, however, or their attainment of a certain level of education do not necessarily guarantee that essential educational skills are acquired. In fact, evidence suggests that this is often not the case. A recent study by The United Nations Educational, Scientific and Cultural Organization (UNESCO) even estimates that, globally, six out of ten adolescents do not meet basic proficiency levels in mathematics and reading—despite the years of steady growth in enrollment rates (UNESCO, 2017). In countries of the Global South, in particular, there is a serious gap between schooling and learning (Angrist et al., 2021; World Bank, 2018).

Such findings reveal a substantial gap in the formation of human capital: students are in school, but are not learning enough. Yet, most existing measures of human capital exclusively focus on the quantity of education (i.e., the duration of schooling or highest educational level attained) and disregard the actual skills people have. As societies transform into knowledge societies and advanced skills of all kinds become increasingly important, this one-sided view of human capital becomes particularly problematic. This dissertation therefore takes a more comprehensive approach, by analyzing human capital together with an explicit consideration of the level of skills in a population. By adding a qualitative (or skills) dimension to the measurement of human capital, previously hidden differences in (skills-adjusted) human capital can be brought to light among countries and over time, as can important gender and generational gaps. The research thus aims not only to contribute to the literature but also to provide relevant insights for progress towards development goals.

Finally, an improved measure of human capital will also benefit future research on the impact of human capital on society. Existing studies have shown that educational attainment is an essential prerequisite for fundamental aspects of human well-being, such as health and survival, or the voluntary choice of family size (see Lutz and Reiter (2021) for a comprehensive summary on how education has served human well-being). There is every reason to expect that the causal mechanisms underlying these associations are at least partly related to cognitive skills (i.e., higher-educated people having greater cognitive capacity, better access to information, and wider future orientation). In terms of economic development, recent empirical findings show that the cognitive skills of a population—rather than just school attainment—do indeed have powerful effects on individual earnings, the distribution of income, and economic growth (Altinok & Aydemir, 2017; Angrist et al., 2021; Hanushek & Woessmann, 2008, 2012; Pritchett, 2001). The advent of more comprehensive measures of human capital that are consistent over time and among countries may thus help us to further clarify and better understand the innumerable effects of human capital on our lives beyond the sphere of economic development.

1.2. Research Subject: Defining Human Capital and Skills

To stress the importance of skills in addition to educational attainment, I use the term *human capital* rather than education throughout this dissertation when referring to the "cognitive capacity" of a population. But what exactly is meant by the term "human capital"? Given its ambiguous meaning, and also the variety of meanings given to it by different disciplines, it is important to specify right from the start how the notion of human capital is understood within this dissertation.[1] Narrowly defined, human capital is "the economic value of a worker's experience and skills [...]" (Kenton, 2020). However, this largely economic interpretation does not reflect the linguistic roots of the term, nor does it cover the broader understanding of the notion beyond the monetary value it implies. The word capital is derived from the Latin *caput* (genitive: *capitis*) meaning head. Human capital thus literally means "human heads," and this is exactly the meaning that will be used in this dissertation—with heads referring not only to the number of heads but also to the brain power within them. This is very much in line with modern demographic usage such as human capital formation and depletion through fertility, mortality, and migration, and will be used consistently in this dissertation project.

In empirical terms, human capital is mainly measured in terms of mean years of schooling of a population or its distribution by highest educational attainment level, both referring to the *quantitative* dimension of human capital. In this dissertation, I argue that this *quantitative* dimension needs to be complemented by a *qualitative* dimension (i.e., the skills that people have) which is likely to matter equally for many of the benefits that come with increased human capital. To avoid any misunderstanding, I would like to clarify from the start that the use of the terms *quantitative* and *qualitative* dimensions of human capital must not be confused with questions related to the research design. As will be discussed in more detail at a later stage, this dissertation takes a purely quantitative research approach (i.e., even when talking about the *qualitative* dimension of human capital, I refer to a quantitative measure of skills).

Finally, and before moving on to the more specific research problem, objectives, and questions, it is important to define the notion of skills as they should be understood within the context of this dissertation project. Classical ability theory usually differentiates between fluid and crystallized skills (Carroll, 1993; Cattell, 1963). Fluid skills, which are not based on prior knowledge and are therefore largely independent of learning, experience, and education, are used to draw inferences or identify relations, and are required, for example, to solve novel problems, to think abstractly, or to provide reasoning. Crystallized skills, on the other hand, are rooted in experiences and refer to acquired and learned knowledge as well

[1] The remaining part of this paragraph partly draws on a recently published working paper: Reiter et al. (2020).

as the application of that knowledge. This type of skill is usually linked more to education and practice, and can be measured when specific knowledge needs to be applied (Engelhardt et al., 2021).

A somewhat different approach is taken to the notion of skills within this project, following the definition of the Organization for Economic Co-operation and Development (OECD) in its "Programme for the International Assessment of Adult Competencies" (PIAAC),[2] which contains both crystallized aspects (as skills are assumed to be learnable) and also important fluid skills (e.g. working memory or drawing inferences). Rather than focusing on the mastery of certain content (e.g., vocabulary or arithmetical operations), this concept of skills builds on the ability to draw on content to successfully perform information-processing tasks. To be more precise, the definition of skills used within this dissertation is based on the following requirements, as stated by the OECD in the PIAAC framework:

- Skills must be preconditions for successful integration and participation in the labor market, in education and training, as well as in social and civic life.
- They must be relevant to all adults, regardless of cultural or socioeconomic background.
- They must be highly transferable (i.e., be relevant to multiple social fields and work situations).
- They must be "learnable" and therefore able to be influenced by policy-makers (OECD, 2016).

As the main focus of this dissertation, literacy skills are thus conceived as extending well beyond the mere ability to read (and/or write) as this is commonly understood. Rather, literacy in PIAAC is conceived as a skill that involves "constructing meaning, and evaluating and using texts to achieve a range of possible goals in a variety of contexts" (OECD, 2019, p. 21) and is defined as "the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (OECD, 2013, p. 20). Since a dichotomous scale (i.e., being literate vs. being

[2] The PIAAC Survey of Adult Skills is an international assessment measuring adults' proficiency in three key information-processing skills: literacy, numeracy, and problem-solving in technology-rich environments. It serves as a key data source for empirical analyses within this dissertation; a detailed description can be found in the individual papers.

illiterate) would be inadequate in terms of measuring this concept of literacy, literacy skills in PIAAC (and other adult skills assessments used in this dissertation) are conceptualized along a continuous scale ranging from 0 to 500, where scores increase along with greater proficiency (OECD, 2019).

I focus on literacy skills for two main reasons. Firstly—and mainly for pragmatic reasons—the availability of high-quality longitudinal and cross-country data is larger for literacy skills than for any other skill domain. This enables me to include a diverse set of countries in my analysis and to use data from different points of time. Second, and more substantially, literacy is strongly related to crucial dimensions of human well-being, social entitlement, and socioeconomic development (Vézina & Bélanger, 2020). Following Sen and Nussbaum in their capability approach, literacy is even identified as a necessary condition of well-being and human development that has a major impact on people's achieved *functioning* (what people are actually "able to do and be") and their future capabilities (Nussbaum, 2000a, 2000b; Sen, 1999). Without adequate literacy skills, individuals cannot meaningfully participate in society or engage in political discourse, and they thus struggle to process basic day-to-day information relevant in a society, such as law enforcement or tax return. With the advent of the "knowledge-based economy", literacy skills are becoming even more essential to enable individuals to thrive in contemporary societies (Vézina & Bélanger, 2020). As jobs requiring information-processing and communication competencies increasingly replace manufacturing jobs, literacy skills are more and more becoming a prerequisite for obtaining stable and lucrative employment (Levy, 2010). Moreover, a growing body of research is showing empirically the overwhelming social and economic importance of literacy skills, both on the individual and aggregate level (Falzon, 2019; Green & Riddell, 2003; Hanushek et al., 2015; Kakarmath et al., 2018; Schwerdt & Wiederhold, 2018; Smith-Greenaway, 2015). This will be highlighted throughout this dissertation. Finally, literacy skills can also provide a good proxy for the overall cognitive skill level in the population, as sensitivity analyses have shown literacy to be closely correlated with other skill domains such as numeracy or problem-solving skills (see Figure A1 in Paper 1).

1.3. Problem Statement and Research Gap

Many studies have highlighted the importance of considering skills when assessing the state of human capital in a population (Angrist et al., 2021; Barro & Lee, 2001; Behrman & Birdsall, 1983; Lutz et al., 2008, 2018; Vera-Toscano et al., 2017). However, given the lack of consistent data between countries and over time, human capital analyses are mainly limited to information on educational attainment or only narrowly study the skills of the school-age population. The inadequacy of existing measures of human capital is problematic for two main reasons:

i. Focusing merely on the quantitative dimension of human capital clouds analysis, primarily because educational attainment and years of schooling do not necessarily guarantee learning (Angrist et al., 2021; Spaull & Taylor, 2015), and they are unable to account for changes in skills beyond the age at which formal education is usually attained.

ii. Indicators that do consider actual skills are, for the most part, demographically inconsistent, as they apply the skills of the young cohorts in school to simultaneously represent the skills of the working-age population. In the case of rapidly expanding school systems, this assumption is untenable and may lead to biased conclusions.

Previous literature explores this issue[3]; however, most of it focuses only on a limited number of countries and/or bases estimates solely on student assessments. Michaelowa (2001), for example, conducted a study using student assessment data and net enrollment rates from the Programme for the Analysis of Education Systems (PASEC) to measure educational success for francophone sub-Saharan Africa. Hanushek and Woessmann (2008) linked educational attainment data with student achievement test outcomes to provide a holistic depiction of the educational system for 14 developing countries. Hanushek and Zhang (2009) combined quality-adjusted measures of schooling and international literacy test information to estimate skill gradients for 13 countries. Spaull and Taylor (2015) formalized a method of combining school access and learning indicators and applied their "Access to Learning" indicator to 11 sub-Saharan African countries. More recently, Filmer et al. (2020) constructed a dataset called the "Learning Adjusted Years of Schooling" (LAYS) by

[3] The remaining part of this paragraph partly draws on a recently published working paper: Reiter et al. (2020).

combining 8th grade mathematics assessment data from the 2015 Trends in International Mathematics and Science Study (TIMMS) with mean years of schooling by country. In this way, LAYS by gender for a total of 157 countries were calculated. Finally, in a recent paper, Angrist et al. (2021) presented a globally comparable database including harmonized learning data for 164 countries from 2000 to 2017.

While these are all important contributions, there is still a lack of understanding of the role of adult skills in human capital formation. Whereas student assessment data are a good indicator of current education quality and may predict a population's human capital of the future, skills assessed in schools were found to be a poor measure of the concurrent level of human capital in the working-age population (Breton, 2013). Consequently, and particularly in the light of rapidly expanding or changing school systems, applying outcomes of student assessments to estimate the skills of the working-age population is demographically inconsistent and can lead to flawed and error-prone conclusions. To remedy this, the present research differs from existing approaches by drawing largely on adult skills data as a qualitative dimension of human capital.

Finally, this dissertation also stands out from existing research in this field by offering a distinct perspective: namely, it takes a demographic approach to studying the role of adult skills in human capital formation. As will be further detailed in Section 1.5, this demographic approach manifests itself partly in a substantive focus on the importance of human capital in demographic processes, but mainly in applying and transferring demographic methods to the field of education.

1.4. Research Objectives and Questions

This dissertation project has three main aims which are closely tied and partly build on each other, as follows: (i) to understand changes in literacy skills over the life course; (ii) to create a composite indicator of skills-adjusted human capital that is comparable across time and space; and (iii) to analyze among- and within-country differences in skills-adjusted human capital, focusing particularly on population heterogeneity.

In the absence of longitudinal data on adult literacy skills, it is crucial to understand how skills evolve over the life course and whether there are common patterns for different countries and points in times (i). This information is relevant in itself but can also be used as the time component of the development of a global indicator on skills-adjusted human capital (ii)—both for reconstructing skills into the past or potentially projecting them into the future. Finally, the development of a novel indicator to measure human capital can only be a means to an end. It is the conclusions and implications drawn from its analyses that matter (iii). Improving our measures of human capital, as attempted in this dissertation, is only an important first step to help societies to better monitor progress and advance policies that improve people's skills and ultimately empower people around the world to improve their lives.

Based on the research problem and aims outlined above, the following research questions and sub-questions are addressed within this dissertation project:

RQ 1: How do adult skills change over the life course and over time, both from a cohort and a period perspective?

- How does this differ among countries, genders, and different educational attainment groups?

RQ 2: How can we comprehensively measure the human capital of the working-age population over time and among countries, considering both educational attainment and actual skills?

- What additional findings can be drawn from analyzing this new measure?

RQ 3: What are the differences in skills-adjusted human capital, both among and within countries?

- Do literacy skills differ substantially among otherwise similar subpopulations and can thus be considered as a relevant source of population heterogeneity?

1.5. Research Approach

To answer these research questions successfully, I based my research on a quantitative approach and conducted it from a demographic perspective, as further detailed in the following.

Demographic approach

As mentioned, this dissertation takes, for the most part, a demographic approach. In contrast with most of the research in this field, which is typically conducted through the lens of the economic production function of education and based on aggregate cross-sectional indicators, my research follows the view that individual education behavior and outcomes, as well as their aggregate dynamics at the population level, can usefully be studied as demographic events and characteristics. Likewise, the level of skills and the changes in them can be seen as important demographic characteristics that contribute to the overall human capital of a population or subgroups of a population—with strong implications for demographic processes and socioeconomic outcomes.

This demographic research approach leads not only to a substantive focus on the role of human capital in demographic processes, most notably through its effect on fertility and mortality outcomes, but also to the application and transfer of demographic methods of analysis to the field of education. Using demographic perspectives and techniques can help gain new insights into socioeconomic, long-term, and spatial dimensions of human capital, and it can also improve our understanding of the role of human capital in progress towards human development.[4]

In contrast to previous demography-based research which studied the demography of educational attainment, my research explicitly considers skills as being an important component of human capital. While the substantive role of skills in demographic processes is covered only superficially in this dissertation project (see Section 2 in Paper 3), the

[4] The connection between education and demography in its various forms has been highlighted and analyzed in a number of publications. Most notably, I refer to the special issue of the Vienna Yearbook of Population Research 2010 (vol. 8) on education and demography (Lutz & Sobotka, 2010), which covers both theoretical thoughts on the complex interrelation between education and demography and a vast variety of empirical studies. Other important contributions on this topic include Lutz and KC (2011), Lutz, Cuaresma, and Sanderson (2008), and Lutz et al. (2019).

demographic approach manifests itself mainly through the use of demographic methods and techniques. In this dissertation, skills are understood as characteristics that vary along age, time, and cohort dimensions, and great importance is attached to demographic consistency (e.g., applying adult skills rather than using the skills of the young cohorts in school to represent the skills of the working-age population). Finally, using a demographic approach also guides the analyses: by explicitly taking into account population heterogeneity, such as age, gender, and educational attainment, I analyze how otherwise similar subpopulations differ in terms of skills.

Quantitative approach

The research design chosen to fulfil the above-mentioned aims and to successfully answer the research questions follows a purely quantitative approach. As collecting international data on tested skills would go beyond the scope of this dissertation project, all analyses and calculations rest on already available data, collected by renowned international organizations such as the OECD, World Bank, and the Wittgenstein Centre for Demography and Global Human Capital.

Different quantitative methods are applied to different parts of the project. To answer RQ1, the empirical analysis rests on a cohort analysis investigating the skills development of different age groups over a period of roughly 20 years and identifying country-specific differences and similarities, as well as the particularities of different subpopulations. The development of the indicator for comprehensively measuring skills-adjusted human capital (RQ2) is based on data harmonization, demographic modeling, and statistical estimation. For the time component of the indicator, research insights obtained from the life course analysis of skills are applied to reconstruct literacy skills along cohort lines. Finally, for RQ3, I combine measures of literacy skills with population distributions by age, sex, and educational attainment to create skills-adjusted education pyramids, capturing population heterogeneity in skills among and within countries. All methods are discussed in detail in each of the individual papers.

Finally, it is important to highlight that the quantitative approach used in this dissertation rests on the implicit assumption that skills can be reliably assessed through tests. This is a strong assumption, challenged by a broad body of literature questioning the premises, constructs, and outcomes of literacy and other skills assessments. To meet these concerns, the following section summarizes the critique, limits, and constraints of large-scale international skills assessments.

Quantifying quality: can we measure skills?

Recent years have seen a continuing trend towards the use of surveys to try to measure the level of skills in a population and thereby produce international comparisons. Yet, the actual value of these assessment regimes has been extensively debated in the social sciences, with an increasing number of studies raising questions about the ambitions, power, and rationality of large-scale surveys, their institutional and technical characteristics, and also whether cross-cultural comparisons are indeed valid (Gomez, 2000; Hamilton et al., 2015b; Hamilton & Barton, 2000; St. Clair, 2012; Sticht, 2001). Here, I will focus particularly on a critique of international literacy assessments, which are the main data source for the research conducted within the framework of this dissertation.

Quantifying literacy skills is not a new phenomenon. The first literacy statistics (e.g., in the form of census data or marriage registers) were already being collected in the 1800s. In the second half of the 20th century, UNESCO was the first organization to systematically collect international literacy data, mainly from self-reported literacy statistics from governments around the world. These statistics, however, were placed solely within the dichotomy of literacy vs. illiteracy. Following a general consensus that this dichotomous paradigm is inadequate and because of rising dissatisfaction with the self-reporting measures, new psychometric programs of literacy assessments were developed in the early 1990s (Hamilton et al., 2015a). As of today, there are three major adult literacy surveys available at the international level: the International Adult Literacy Survey (IALS, conducted between 1994 and 1998), the Adult Literacy and Lifeskills Survey (ALL, conducted between 2003 and 2008), and the Programme for the International Assessment of Adult Competencies (PIAAC, 1st cycle conducted between 2011 and 2017)—all coordinated by the OECD in partnership with national statistical research agencies in Canada and the United States. While these surveys have become more sophisticated over time, they all share an underlying logic and thus many of the same strengths, but also weaknesses, as will now be discussed.

On the most basic level, the surveys were designed to identify and measure adult literacy skills so as to be comparable across countries and to help assess the impact of literacy in societies, thus informing and influencing policy decisions. The instrument used in these surveys largely draws on measurement approaches developed by Kirsch and colleagues in the early 1980s (Kirsch & Guthrie, 1980); its conceptual framework builds on the basic logic that literacy is, at its heart, a process of retrieving information from a text in order to complete a task successfully. In line with this conceptualization, literacy reflects a universal set of cognitive characteristics that can be reliably assessed through tests. Reading and writing, rather than being considered as social activities, are conceptualized as individual matters of mental processing, invariant of cultural differences and the wider context in which the text is used. This narrow literacy construct has come in for strong criticism, particularly from advocates of the so-called New Literacy Studies (Barton, 1994; Barton et al., 2000; Gee, 1990; Street, 1995). These authors' approach, which is rooted in social constructivism, is based on the belief that literacy has meaning only within its particular context of social practice and hence cannot be transferred unproblematically across contexts; from their point of view, any separation of individual performance in literacy from the context or the social relations that constitute it would fundamentally change its meaning. Consequently, this perspective is particularly critical of the validity of cross-cultural comparisons.

Literacy assessment regimes have also been questioned in terms of their ideological agenda. Darville (1999), for example, argues that the assessment framework, test items, and survey reports of international literacy surveys typically support neoliberal competitive agendas; they can be seen as a global response to demands for an internationally comparable measure of human capital that aims to boost global performance competitiveness. Other scholars critically stress the focus on economic aspects in these surveys, for example, how many test items are connected with shopping or being a consumer, with money management or employment, while participants are never asked to respond critically to an argument (St. Clair, 2012). Overall, criticism is commonly directed at the fact that literacy is framed in narrow terms around agendas of economic competitiveness rather than human development or social justice (Barton et al., 2000; Blum et al., 2001; Darville, 1999).

The quantification of literacy skills is often praised for offering clarity and unambiguity for evidence-based literacy policy, with numbers commonly seen as the most objective and scientific form of information (Rose, 1991), but the quantification of skills has also come under strong criticism. In particular, critics argue that the great complexity of education and skills cannot be captured through numbers, that doing so renders skills assessments inherently reductive, and that any quantified results coming out of international assessments cannot capture the “true picture” of the state of literacy (Gorur, 2015). Other lines of criticism stress that numbers are becoming increasingly hegemonic, thus marginalizing other pathways to knowledge check; this ultimately prohibits space for fruitful debates, it is suggested, given that numbers are usually associated with "cold hard facts" and thus difficult to argue against (Barry & Slater, 2005). Moreover, the quantification of literacy is sometimes dismissed as positivist, with numbers being considered not to be objective but rather political (Haraway, 1988).

Finally, literacy assessments are often criticized for taking place in an artificial test situation with questionable real-world validity in the lives of most adults over the age of 25 who are no longer in school (Sticht, 2001). Despite the notable efforts to use as many real-life examples as possible, literacy surveys in many ways resemble ordinary school tests. Consequently, as with any test, test-taking anxiety or the general (in)ability to take tests may heavily impact the performance, especially when conducted under observation by a stranger (St. Clair, 2012). While the exact effect of these test situations is hard to measure, potential biases must be given consideration—particularly, when older age groups are being assessed—that is, people who may not have experienced a test situation for decades.

It is important to take all such criticisms seriously when using and interpreting the results of large-scale literacy assessment surveys. The papers of this dissertation implicitly rest on the claim that it is possible to understand the amount and distribution of human capital within an economy by understanding the levels and patterns of tested literacy skills. I wish, however, to acknowledge right from the outset that I am aware that literacy, as measured in large-scale surveys, is based on a very particular construct, namely the ability to retrieve certain types of information from certain types of texts and diagrams that can be measured in a test situation. It certainly does not represent a complete measure of human capital or literacy abilities, as it excludes some important aspects of an individual's complex multi-layered set of literacy practices, such as critical evaluation of texts, creative writing, or social literacy practices. Nevertheless, I argue that as long as we are aware of these limitations, assessment surveys as used in this dissertation can provide evidence and insights to help inform policy-makers and facilitate evidence-based decisions. It is exactly because numbers are reductive and can hence express a large amount of information that they can be useful in governance.

Finally, I consider such criticisms necessary and useful to further improve literacy survey designs and frameworks. The project of reframing literacy around globalized and standardized assessment regimes is still a work in progress; and, particularly in terms of integrating diverse cultures, contexts, and relational literacy practices, further progress needs to be made on improving the validity of cross-cultural comparisons.

1.6. Thesis Structure

The dissertation is structured into three parts according to the research questions. Each of the three research questions is answered in a separate, self-contained publication that establishes an important aspect of the overall contribution. Relevant related work, data and methods used, as well as limitations and future work are discussed in each paper individually.

In the first paper "Changes in Literacy Skills as Cohorts Age" (2022, published *in Population and Development Review*), I investigate the level, distribution, and life-course development of literacy skills over time and across countries, using data from three international large-scale assessment surveys (IALS, ALL, PIAAC). More specifically, I estimate how adult literacy skills change over the life cycle and over time, both from a cohort and a period perspective, and investigate whether different countries and educational attainment groups experience different patterns.

In the second paper "Skills-adjusted human capital shows rising global gap" (2021, published in *Proceedings of the National Academy of Sciences of the United States of America*)[5], we present a new comprehensive measure for human capital, the Skills in Literacy Adjusted Mean Years of Schooling (SLAMYS).

The third paper, entitled "Inequality in Quality: Population Heterogeneity in Literacy Skills Around the World" (2022, submitted to *Population Research and Policy Review*), focuses

[5] This paper is co-authored with Wolfgang Lutz, Caner Özdemir, Dilek Yildiz, Raquel Guimaraes, and Anne Goujon.

on population heterogeneity with regard to skills-adjusted human capital. While a summary measure (as presented in paper 2) is certainly a useful way of capturing the entire human capital of a population at one point in time in one single number, there is much to be gained from breaking down this highly aggregate measure based on different observable characteristics of the population. By combining the level of skills with the population size by age, sex, and educational attainment, I am able to study inequality in skills within a population and uncover inter-cohort changes.

Finally, all findings, as well as the overall contribution of my research to the academic debate, are highlighted in the Conclusion.

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2. Thesis Publications

2.1. Changes in Literacy Skills as Cohorts Age

The first publication was published on January 18, 2022 as

Reiter, C. (2022). Changes in Literacy Skills as Cohorts Age. *Population and Development Review*. https://doi.org/10.1111/padr.12457

Abstract: As our societies transform into knowledge societies, skills are playing an ever-increasing role in life. Despite recent efforts to consistently measure adult skills across countries, a challenge remains to understand how skills evolve over time and what the main drivers behind these changes are. By applying demographic methods to estimate the development of skills over the life course, this paper presents the reconstruction of empirical adult literacy test results along cohort lines by age, sex, and educational attainment for 44 countries for the period 1970–2015. Results suggest significant heterogeneity in the pattern of changes in literacy skills with age, reflecting the differential exposure to cognitive stimulation over the life course and suggesting that the development of skills in a country is also the consequence of a changing composition of its population. Gender, however, was found to have hardly any effect on how literacy skills evolve between the ages of 15 and 65. On the aggregate level, findings reveal considerable differences between countries—regarding both the level of skills and their development over time. Overall, it was found that massive educational expansions happening globally in the recent past only partly resulted in a corresponding rise in skills.

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Changes in Literacy Skills as Cohorts Age

Claudia Reiter

As our societies transform into knowledge societies, skills are playing an ever-increasing role in life. Despite recent efforts to consistently measure adult skills across countries, a challenge remains to understand how skills evolve over time and what the main drivers behind these changes are. By applying demographic methods to estimate the development of skills over the life course, this paper presents the reconstruction of empirical adult literacy test results along cohort lines by age, sex, and educational attainment for 44 countries for the period 1970–2015. Results suggest significant heterogeneity in the pattern of changes in literacy skills with age, reflecting the differential exposure to cognitive stimulation over the life course and suggesting that the development of skills in a country is also the consequence of a changing composition of its population. Gender, however, was found to have hardly any effect on how literacy skills evolve between the ages of 15 and 65. On the aggregate level, findings reveal considerable differences between countries—regarding both the level of skills and their development over time. Overall, it was found that massive educational expansions happening globally in the recent past only partly resulted in a corresponding rise in skills.

Introduction

Over the last decades, policymakers have been focusing primarily on universalizing access to education. With the average educational attainment increasing for younger cohorts around the globe, however, attention is now shifting toward how successfully people can acquire skills during and beyond school, and why populations in some countries are learning more than others. As an example, while Goal 2 of the Millennium Development Goals (MDGs) in 2000 proposed to "achieve universal primary education," Goal 4 of the successional 2015 Sustainable Development Goals (SDGs) aimed to "ensure inclusive and equitable quality education and promote lifelong

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learning opportunities for all." In addition, economists, demographers, and sociologists have recognized not only the intrinsic value of skills, but also provided evidence of their social and economic benefits (Becker 1994; Crespo Cuaresma, Lutz, and Sanderson 2014; Gupta 1990; Lutz 2013; Mincer 1974; Muttarak and Lutz 2014; Schultz 1961).

This new policy focus also calls for monitoring the level of skills in a population. Qualitative measures of human capital, that is, measures of skills, began evolving in the 1960s, when the International Association for the Evaluation of Educational Achievement (IEA) pioneered development of international student assessments. Consistent data for comparing the educational achievement of different school systems over time, however, have only been available since the late 1990s and early 2000s, when surveys such as "Trends in Mathematics and Science Study" (TIMSS), "Progress in International Reading Literacy Study" (PIRLS) (both coordinated by IEA), or the "Programme for International Student Assessment" (PISA, coordinated by the Organisation for Economic Co-operation and Development [OECD]) started to collect data on a regular basis for a large number of countries around the globe. These tests, however, focus exclusively on the school-age population, which proves problematic for various reasons when aiming to measure the skills of a population. First, school tests naturally exclude large parts of the population—not only those who already finished school, but also those who never attended school in the first place or did not continue education until the age of 15, when international assessments usually take place—thus potentially resulting in some kind of selection bias. Second, school assessments do not provide information about changes in skills over the life course (or beyond the age when formal education is usually attained). Therefore, using student assessments, it is not possible to account for increases of skills over the life course (e.g., lifelong learning), or for potential depreciation of skills with age. Finally, the prevalence of skills in an adult population at a given time reflects a rather complex interplay of several factors, in particular age and cohort effects. Therefore, when school participation rates or the length of schooling change over time—as recently happened in virtually all countries—there is a little value from using test scores of 15-year-olds currently in school to make inferences about the cognitive skills of today's working-age population.

Only recently there have also been initiatives to test the skills of adults on an international level. The Educational Testing Service (ETS; in partnership with a number of agencies and international organizations including the OECD) collected large-scale data on adult skills that are comparable between countries via the "International Adult Literacy Survey" (IALS) between 1994 and 1998 and the "International Adult Literacy and Life Skills Survey" (ALL) between 2003 and 2008 for a limited number of countries. In addition, between 2011 and 2017, the OECD implemented the "Programme for the International Assessment of Adult Competencies" (PIAAC), where skills of numeracy, literacy, and problem-solving in technology-rich environments of adults aged between 16 and 65 were tested in a total of 37 countries—at present, the most important international large-scale assessment of adult skills. For developing countries, the World Bank has developed a similar test, named the "Skills Toward Employment and Productivity Survey" (STEP) that includes a literacy test link with items that are linked to the literacy scale used in PIAAC.

Despite these recent efforts to consistently measure adult skills, a major challenge remains to track changes in skills over time. To better understand skills-related effects on economic growth, sustainable development, or demographic changes, we not only need to understand how skills differ between populations, but also how skills have evolved over time within the same population and what the main drivers are behind these changes. At present, however, there are not enough longitudinal data available to understand the complex interplay of age, cohort, and period effects—all potentially impacting skills development over the life course. This is the gap this research intends to fill. By applying demographic methods to estimate the changes in literacy skills as cohorts age, I reconstruct adult literacy test results for 44 countries back to 1970.

In this paper, I exclusively focus on literacy skills—mostly because of the availability of high-quality cross-country data (which is larger for literacy than for any other skill domain), but also because they play a central role in human well-being. Without adequate literacy skills, individuals cannot meaningfully participate in society and engage in political discourse (Barrett and Riddell 2019). Moreover, studies have shown that literacy skills also have a strong impact on economic well-being: those with greater literacy enjoy better employment opportunities and receive higher earnings (Green and Riddell 2013; Hanushek et al. 2015). Finally, literacy skills have been shown to be closely correlated with other skill domains (see Figure A1 in the Appendix in the Supporting Information), thus also providing a good proxy for the overall skill level in the population.

It is important to mention that, by using large-scale adult literacy skills assessment data, this paper rests on the implicit assumption that literacy ability reflects a universal set of cognitive characteristics that can be reliably assessed through paper and pencil tests. This is a strong assumption and although it is not the topic of this paper, it is worth referring to the broad body of literature questioning the premises, constructs, and outcomes of literacy and other skills assessments (see, e.g., Hamilton and Barton 2000; Sticht 2001; or St. Clair 2012 for a summary of the arguments). Here, I only want to acknowledge that literacy as measured in large-scale surveys is a particular construct, namely, the ability to retrieve certain types of information from certain types of texts and diagrams, that can be measured in a test situation. It certainly does not represent a complete measure of human capital or literacy abilities as it excludes some important parts that make up an individual's complex multilayered set of literacy practices, such as critical evaluation of texts, creative writing, or social literacy practices. Nevertheless, I argue that as long as we are aware of these limitations, assessment surveys as used in this paper can be a high-quality source of data for researchers, educators, and policymakers, revealing detailed information on measurable skills and competencies of adults around the world.

The remainder of this paper is structured as follows. In "Effects on skills over the life course" section, a short literature review is provided on skill gain and skill loss over the life span, as well as the main factors impacting these changes. "Data sources" section presents the data sources used in this paper, followed by "Methodology" section explaining in detail the methodology. After presenting the results in "Results and discussion" section, I conclude and discuss potential limitations in "Conclusion" section.

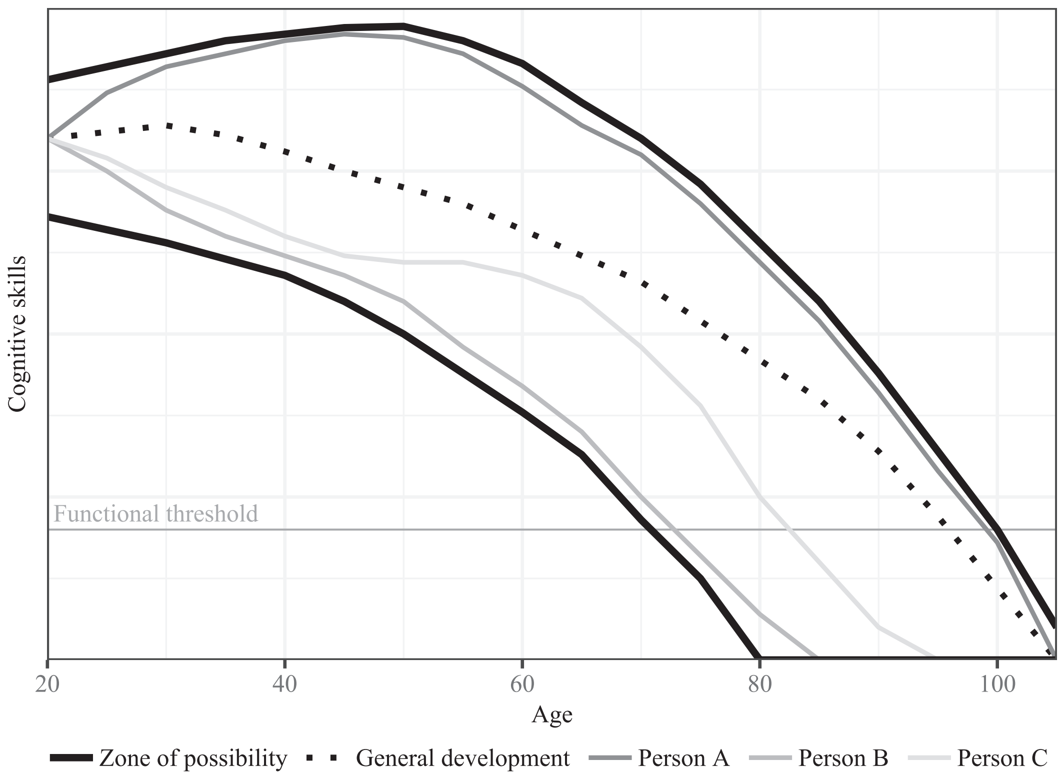
Effects on skills over the life course

Three main effects that impact the changes of skills over the life course, that is, age, cohort, and period effects, have been identified in the literature. In the following, each of these effects and their impact on skill gain and skill loss over the life span will be discussed in a little more detail.

"Age effects," that is, the mere impacts of growing older, have been identified as key drivers of skills change over the life course. Several studies have found a tendency for cognitive skills to rise in the early years and then eventually decline as adults age (Hertzog et al. 2008; Desjardins and Warnke 2012; Skirbekk, Loichinger, and Weber 2012; Green and Riddell 2013; Barrett and Riddell 2016; Paccagnella 2016a). However, aging and skills do not have a straightforward relationship, with many individual, contextual, and social factors influencing its development. Nevertheless, there are attempts in the literature to define a "normal age effect" related to skill development. Hertzog et al. (2008), for example, suggest that skill decline for an individual under "typical" circumstances can begin as early as age 20 and continue into old age, accelerating particularly after the age of 50. However, especially for young adults, individual trajectories may vary considerably, depending on biological, behavioral, environmental, and social influences. Figure 1 depicts a zone of possible cognitive development across adult life, which is delineated by optimal and suboptimal boundaries. This zone of possibility suggests that growing old eventually constrains cognitive functioning, but not all individuals need to follow the general trend. Depending on a variety of factors, including education or practice factors (e.g., practices at work that require cognitive application), individuals' trajectories may vary within this zone, as exemplified by the very different trajectories for persons A, B, and C.

Similarly, Desjardins and Warnke (2012) highlight that until about the age of 18–20, cognitive skills of all kinds are expected to increase, but

FIGURE 1 Zone of possible cognitive development across adult life



SOURCE: Adapted from Desjardins and Warnke (2012).

thereafter, development patterns are expected to diverge. For some people and types of skills, this would mean a decline already in early adulthood, while others may experience a continuous rise of skills, followed by stagnation, and eventually a decline. Factors found to influence skill gain and skill loss over the life span and over time include education and training, behavioral and practice factors, as well as social factors. An extensive literature overview of the evidence on the factors causing skill gain and skill loss can be found in Desjardins and Warnke (2012).

In addition to pure age effects, "cohort effects" may also influence the development of skills over time (Flisi et al. 2019). Cohorts, as interpreted in this context, can be defined as a group of individuals who are characterized by some shared temporal experience or common life experience, such as year of birth, or year of exposure to a phenomenon (Desjardins and Warnke 2012). Given the specific age–period combination, cohort effects are always generation-specific. An important example of a cohort effect on skills is the nature and quality of schooling: a change to compulsory schooling laws, for instance, affects only a particular age cohort, while those who are older than a certain age cutoff are not impacted by the structural change. Similarly, the quality of education may not be constant across all age cohorts, but rather might have steadily improved or declined over time.

Finally, "period effects" can also play an important role, when assessing skills over time (Desjardins and Warnke 2012). Similar to cohort effects they are related to a specific event or phenomenon, however, with one distinctive feature: period effects impact everyone at the time of assessment, regardless of age or generation. Examples for such occasion-specific influences include economic conditions or the occurrence of a war or famine at the time of the study. Assessing the skills of the same population at a later time may thus lead to a very different performance. In practice, however, it is not always easy to identify the underlying reasons for observed changes, that is, whether a skill loss is a result of the contextual conditions between the measurement points, or the result of skill decline because of aging. The scarcity of data further hampers the undertaking of country-specific, age–period–cohort analyses on a global scale. Surveys measuring adult skills have traditionally been cross-sectional, hence only reflecting combinations of age, cohort, and period effects. Only recently, internationally comparable large-scale assessments of the same population at different points of time became available, allowing for a separation of these effects and a better understanding of skill development across generations.

The following sections will present these data sources and explain in more detail the methodology used to disentangle the above-mentioned effects.

Data sources

As mentioned in the introduction, large-scale, international adult literacy skills assessments have only recently emerged. Following the pioneering work of national adult literacy assessments undertaken in the United States and Canada in the early 1990s, the "IALS," developed by Statistics Canada and ETS in collaboration with participating national governments, was the first survey of this kind with 22 countries participating between 1994 and 1998. As a successor to IALS and with the goal of measuring a broader range of adult skills than had previously been covered in IALS, the "ALL" was administered in 11 countries between 2003 and 2008. Finally, the OECD's "PIAAC" was designed to assess the current state of the skills of individuals and nations in the new information age. It builds upon earlier conceptions of literacy from IALS and ALL to facilitate an appropriate assessment of the broad range of literacy skills required for the twenty-first century.

Given the lack of panel data on adult skills, particularly on an international level, all three above-mentioned surveys are used in this paper in order to track changes in skills over time. Due to the continuity in survey methodology and the usage of trend items that were asked in all three surveys, it is possible to analyze trends over time in countries that participated in at least two of these surveys. In addition, and to increase coverage among developing countries for the base-year estimates, I rely on the "STEP" data, a survey coordinated by the World Bank, which is also designed to allow for linkages with the PIAAC survey. In the following, all data sources are explained in greater detail.

Programme for the International Assessment of Adult Competencies, Adult Literacy and Life Skills Survey, and International Adult Literacy Survey

PIAAC provides the main data source for this research. It is a program of assessment and analysis of adult skills coordinated by the OECD. The major survey conducted as part of PIAAC is the Survey of Adult Skills, which assesses proficiency of adults (aged 16–65) in three information-processing skills considered essential for successful participation in the information-rich economies and societies of the twenty-first century: literacy, numeracy, and problem-solving in technology-rich environments.

PIAAC aims to assess how well people are able to access, understand, analyze, and use text-based information as well as representations of various types (e.g., pictures, graphic representations, mathematical notations, etc.). In addition, all competencies measured in PIAAC aim to fulfil the following requirements:

- They should be preconditions for successful integration into and participation in the labor market, in education and training, as well as in social and civic life.
- They should be relevant to all adults, regardless of cultural or socioeconomic background.
- They need to be highly transferable, that is, relevant to multiple social fields and work situations.
- They should be "learnable" and, therefore, subject to the influence of policymakers (OECD 2016a).

The PIAAC survey design is based on a latent regression item response model, with proficiency scores scaled between 0 and 500. To increase the accuracy of the cognitive measurement, PIAAC uses plausible values (PVs), which are multiple imputations, drawn from *a posteriori* distribution. This is done by combining the Item Response Theory (IRT) scaling of the cognitive items with a latent regression model using information from the background questionnaire in a population model. For each survey participant, a set of 10 PVs for all proficiency domains was estimated to replicate a probable score distribution that summarizes how well each respondent answered a small subset of the assessment items, and how well other respondents from a similar background performed on the rest of the assessment item pool. Further details on the statistical test design of PIAAC can be found in the "Technical Report of the Survey of Adult Skills" (OECD 2016b). In addition to the module on the direct assessment of skills, PIAAC also includes a detailed background questionnaire that collects information about demographic and socioeconomic characteristics, use of skills in daily life, and characteristics of working life.

In total, 37 countries have participated in PIAAC so far. The first round of the survey collected data from around 166,000 adults aged 16–65 in 24 countries or regions in 2011 and 2012. In 2014, the second round of the survey was conducted, with data collection in nine additional countries. Finally, in 2017–2018, five new countries participated in the survey and the United States conducted the survey for the second time. In each participating country, a nationally representative sample of around 5,000 respondents were selected. The survey's plan is to repeat the survey every 10 years, with preparations for the second wave of data collection currently in process.

PIAAC builds on knowledge and experiences gained from previous international adult assessments: the IALS and the ALL. Both data sources are also used within this paper, which allows me to analyze literacy outcomes at different points of time. IALS was conducted between 1994 and 1998 as the first-ever, large-scale, international comparative assessment designed to identify adult literacy skills in 22 countries and regions. A few years later, ALL measured the literacy and numeracy skills of a nationally representative sample of 16- to 65-year olds in 11 participating countries/territories. Table 1 provides an overview of which PIAAC countries have also participated in IALS and/or ALL.

Literacy definitions in OECD adult skills surveys. As mentioned in the introduction, analyses throughout this paper focus exclusively on literacy skills, as these are tested in all of the three previously described surveys as well as in the World Bank's STEP Skills Measurement Program (see "Programme for the International Assessment of Adult Competencies, Adult Literacy and Life Skills Survey, and International Adult Literacy Survey" section). Literacy skills are considered a core requirement for developing higher order skills as well as for positive economic and social outcomes. As shown by previous studies, literacy is also closely linked to positive outcomes at work, to social participation, and to lifelong learning (OECD 2013). The following section describes how literacy is defined and conceptualized in each of the three surveys.

PIAAC literacy definition. In PIAAC, literacy is defined as the "ability to understand, evaluate, use and engage with written texts to participate in society, achieve one's goals, and develop one's knowledge and potential" (OECD 2013, 4). The literacy assessment in PIAAC encompasses a wide range of skills, such as vocabulary, language proficiency, and comprehension, combined with the ability to apply these in circumstances that arise in everyday life. To get a better understanding of how literacy is conceptualized

TABLE 1 PIAAC countries that have also participated in IALS and/or ALL by year and assessment

	IALS			ALL		PIAAC		
Country	1994	1996	1998	2003	2006–2007	2011–2012	2014	2017
Australia		√			√	√		
Belgium		√				√		
Canada	√			√		√		
Chile			√				√	
Czech Republic			√			√		
Denmark			√			√		
Finland			√			√		
Germany	√					√		
Hungary			√					√
Ireland	√					√		
Italy			√	√		√		
The Netherlands	√				√	√		
New Zealand		√					√	
Norway				√		√		
Poland	√					√		
Slovenia			√				√	
Sweden	√					√		
UK		√				√		
USA	√			√		√		

SOURCE: Author's elaboration.

in PIAAC, two examples of literacy items are referred to in the Appendix in the Supporting Information.

The PIAAC literacy assessment is further complemented by a test of "reading components" skills to provide more detailed information about adults with poor literacy skills. It focuses on the basic set of decoding skills that enable individuals to extract meaning from written texts: knowledge of vocabulary, ability to process meaning at the level of the sentence, and fluency in reading passages of text (OECD 2016a). As "reading components" is a new domain, not available in IALS and ALL, results are not included in the analyses of this paper.

IALS literacy definition. Quite similar to PIAAC, the 1994 IALS definition of literacy refers to "the ability to understand and employ printed information in daily activities, at home, at work and in the community, to achieve one's goals and to develop one's knowledge and potential" (OECD 2000, x). IALS measured three domains of literacy: (1) prose literacy, defined as the knowledge and skills needed to understand and use information from texts including editorials, news stories, poems, and fiction; (2) document literacy, defined as the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables, and graphics; and (3) quantitative literacy, defined as the knowledge and skills required to apply arithmetic operations to numbers embedded in printed materials (National Center for Education Statistics 2018). For reasons of comparability, only results from (1) prose literacy and (2) document literacy were used in this paper.

ALL literacy definition. Finally, literacy in ALL was defined as "using printed and written information to function in society, to achieve one's goals, and to develop one's knowledge and potential," drawing attention to the fact that literacy is not seen "as a set of isolated skills associated with reading and writing, but more importantly as the application of those skills for specific purposes in specific contexts." Rather, it is meant to "capture the full scope of situations in which literacy plays a role in the lives of adults, from private to public, from school to work, to lifelong learning and active citizenship" (Murray, Clermont, and Binkley 2005, 95). As in IALS, literacy skills in ALL were again assessed separately for prose and document literacy. Examples of literacy items included in both IALS and ALL are referred to in the Appendix in the Supporting Information.

Although these definitions are quite similar, direct comparability of the constructs measured and the content of the instruments used to assess literacy skills is crucial when using data from different surveys to analyze skills over time; hence, all issues related to comparability between IALS, ALL, and PIAAC will be discussed in the next section.

Comparability between IALS, ALL, and PIAAC. As shown by the definitions above, there is, by design, considerable overlap between the definition of literacy skills in IALS, ALL, and PIAAC: the conceptualization of the cognitive processes used in gaining meaning from text, the definition of the contexts in which reading takes place, and the factors affecting the difficulty of test items are similar among all three surveys. Furthermore, PIAAC is linked to IALS and ALL through a number of common test items: 29 of the 52 literacy items included in the computer-based version of the literacy assessment were linking items (i.e., they had been used in the assessment of literacy in IALS and/or ALL); in the paper-based versions, 18 of the 24 items administered were linking items. Despite these similarities, however, PIAAC conceived literacy more broadly than IALS and ALL, encompassing the domains of prose and document literacy, which were assessed separately in IALS and ALL. To overcome these differences, results for prose and document literacy from IALS and ALL have been combined and re-estimated by Statistics Canada to make them comparable to PIAAC (Paccagnella 2016b). Within my analyses, I am therefore exclusively using these rescaled data.

Another major difference between PIAAC and IALS and ALL is related to the mode of delivery: whereas PIAAC was designed as a computer-based assessment (with a pencil-and-paper option for respondents without sufficient computer skills), both IALS and ALL were exclusively pencil- and paper-based surveys. This difference in the delivery mode could potentially affect the comparability of results. However, results of a field test, where a proportion of respondents were randomly assigned to either the computer-based or paper-based version of the assessment, identified no significant mode effects, suggesting that the mode of delivery does not affect comparability of results (OECD 2019).

Finally, the extent to which comparisons can be made between the surveys depends not only on the psychometric assessments, but also on the definitions of relevant subpopulations (e.g., educational attainment) that are derived from the background questions. To ensure consistency, derived trend variables were created in order to facilitate comparisons between assessments. These trend variables were used in my analyses for defining any subpopulations (Paccagnella 2016b).

In summary, PIAAC literacy results can be directly compared to literacy results from the previous OECD, IALS, and ALL surveys, as confirmed by the following statement in the OECD Reader's Companion that accompanies the report "Skills Matter: Additional Results from the Survey of Adult Skills": "[…] [T]he Survey of Adult Skills was designed to be linked psychometrically with IALS and ALL in the domain of literacy […]. Analysis of data from the field trial and from the main data collection confirmed that results from IALS, ALL, and the Survey of Adult Skills could be placed on the same scale in literacy [...]."(OECD 2019, 81). Nevertheless, caution is always advised when using nonpanel data to estimate trends over time.

Skills toward Employment and Productivity Survey

The "STEP" was developed by the World Bank in order to better understand the interplay between skills, on the one hand, and employability and productivity, on the other hand. The STEP program developed survey instruments tailored to collect data on skills in low- and middle-income country contexts. Three broad types of skills are measured within STEP: cognitive skills, defined as the "ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought" (as derived from Neisser et al. 1996, 77); socioeconomic skills (such as social, emotional, personality, behavioral, and attitudinal skills); and job-relevant skills (task-related skills, e.g., computer use). Data were collected between 2012 and 2017 in Albania, Armenia, Azerbaijan, Bolivia, Bosnia and Herzegovina, Colombia, Georgia, Ghana, Kenya, Kosovo, Lao PDR, Macedonia, Serbia, Sri Lanka, Ukraine, Vietnam, and the Yunnan Province in China. Each sample consisted of around 3,000 individuals and was representative of the urban adult population between the ages of 16 and 65 (World Bank 2014).

The measurement of cognitive skills, which is used in this paper, includes a direct assessment of reading literacy designed to identify respondents' levels of competence at accessing, identifying, integrating, interpreting, and evaluating information. A primary goal for the design of the STEP literacy assessment was to be able to link it to the PIAAC Survey of Adult Skills. Therefore, the STEP literacy test is capitalized on the same item pool as PIAAC, allowing for results to be reported on a common scale with common descriptions for interpreting the proficiency levels of the scale. This makes the two assessments directly comparable to each other. As in PIAAC, the STEP design is based on matrix sampling, where each respondent is administered a subset of items from a larger pool, resulting in different groups of respondents answering different sets of items. By using IRT, the distribution of the performance in a population or subpopulation can be described through estimating the relationships between proficiency and background variables, while at the same time reducing the response burden for each individual (Educational Testing Services 2014).

The STEP literacy assessment was administered in a total of 12 countries. However, only eight of them, namely, Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam, have implemented the full cognitive assessment including both the paper-based literacy assessment as in PIAAC and a short reading test. The remaining countries conducted only the core reading test, consisting of eight short items which thus were not relatable to PIAAC literacy scores. For this reason, only data from the above-mentioned eight countries are included in the analyses used throughout this paper. Given that items selected for these countries are derived from the literacy framework of PIAAC, PIAAC sample items referred to in the Appendix in the Supporting Information also apply to the STEP literacy assessment.

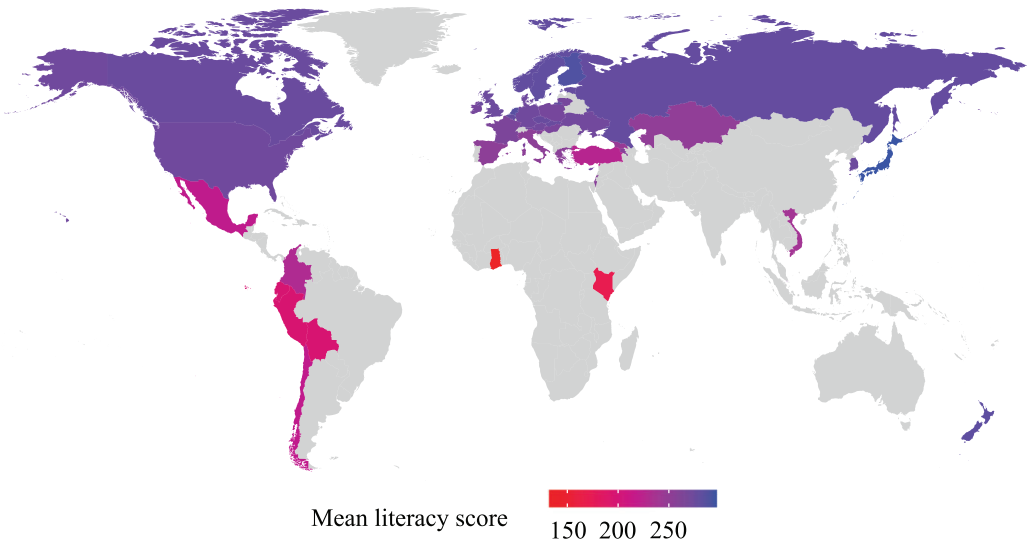
As mentioned previously, the target population in the STEP Skills Measurement Program is limited to urban adults. Therefore, STEP results for the eight countries included in the analysis were further adjusted to be representative for the entire country. Urban–rural corrections in literacy skills were derived from the Demographic and Health Survey (DHS),[1] with the ratio between DHS literacy results of the total population and those of the urban population serving as the correction factor. For three countries (Bolivia, Ghana, and Kenya), country-specific DHS information was used; for five countries (Armenia, Colombia, Georgia, Ukraine, and Vietnam), where no tested literacy data from DHS are available, corrections are based on regional averages.[2]

It is important to mention that although STEP and PIAAC use similar psychometric methods to estimate the literacy proficiency of participating adults (i.e., a common scale on which literacy proficiency is evaluated), there are still considerable differences, giving reason to treat any direct comparisons of results with caution. First and as already mentioned, the target population in STEP is limited to adults living in urban areas, while PIAAC is representative of all adults living in a country. Furthermore, this requires additional adjustments to the STEP data, making STEP results automatically more error-prone. Second, STEP uses—similar to IALS and ALL—only paper-based instruments, while the PIAAC assessment was designed to be primarily administered on a computer. However, and as mentioned in "Comparability between IALS, ALL, and PIAAC" section, differences in the delivery mode were shown to not significantly affect the comparability of results. Finally—and arguably most importantly—differences in the underlying distribution of proficiency of the population may impact the comparability, particularly when a large proportion of the population performs at the very bottom of the proficiency distribution—as is the case in some of the STEP countries. This will be discussed in more detail in the following section.

Both STEP and PIAAC survey designs are based on a latent regression item response model, built on the assumption that the "true" and unobservable proficiency of respondents lies in a unidimensional continuum and can be estimated on the basis of observed proxies such as the answers to a test. These answers are most informative when the test contains items with a difficulty level appropriate to the respondents. Consequently, an assessment might not perform equally well across heterogeneous populations with different levels of proficiency. Moreover, in both PIAAC and STEP, the assessment begins with a short module including eight easy items (the "core assessment") with the aim of identifying respondents with low proficiency who would have little chance of successfully completing most items included in the assessment. To pass the core and move on to the full assessment, respondents must give a correct answer to at least three items in STEP and four items in PIAAC.[3] The share of adults failing the core is generally higher in lower income countries—which are overrepresented in STEP. A larger share of populations failing the core is, however, also associated with a larger share of people whose literacy proficiency estimates rely on little information about their actual performance, and much more on their background characteristics and the design of the underlying statistical model—ultimately resulting in a larger amount of error (Keslair and Paccagnella 2020).

Having said that, and being aware of the limitations of the STEP survey and their impact on comparability with the results of the OECD adult skills surveys, I still decided to include STEP data as base-year data for the reconstruction of the eight low- and middle-income countries that have implemented the full STEP literacy assessment.[4] On the one hand, this is to increase geographic coverage and extend my analyses (and conclusions drawn from them) to a wider spectrum of countries—not just looking at rich OECD countries. On the other hand, previous studies have shown that the basic patterns observed in the analysis of multiple rounds of PIAAC data are confirmed in STEP (Keslair and Paccagnella 2020),

FIGURE 2 Mean PIAAC/STEP literacy score by country



SOURCE: Author's elaboration based on PIAAC and STEP data.

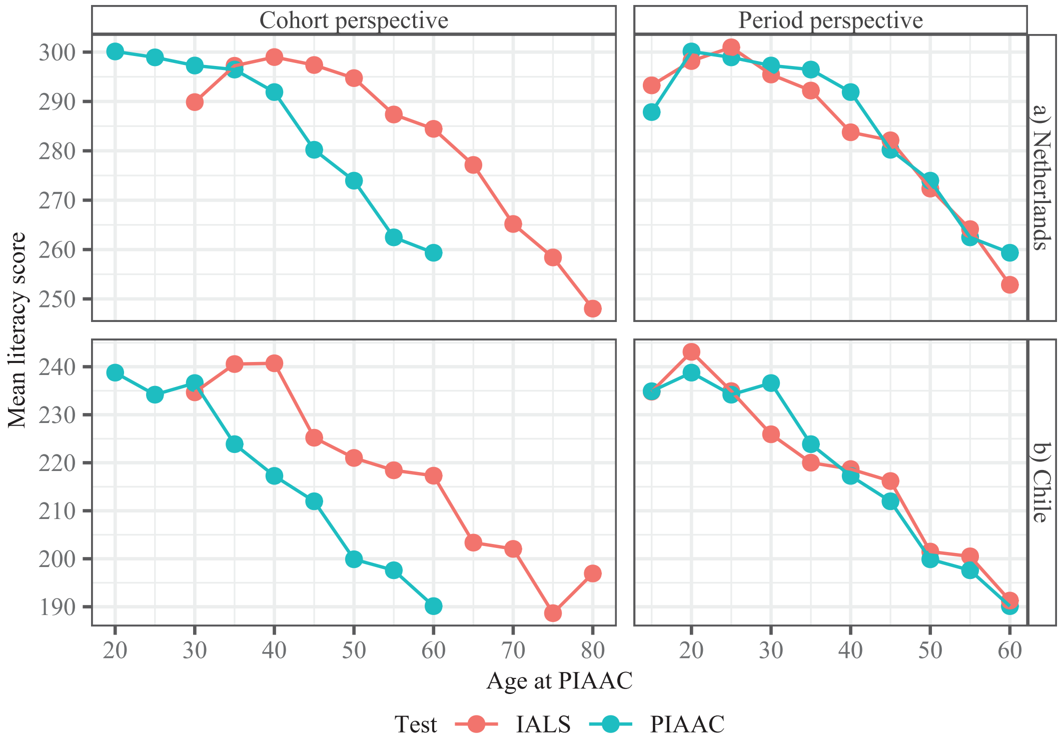
suggesting that—given the matched psychometric methods—results are still largely comparable. Nevertheless, it is important to be transparent about all the data issues involved so that readers can interpret the results with adequate caution.

To provide an overview about data availability and mean performance on literacy, Figure 2 shows the mean literacy score by country for the population aged 15–65 for the 44 countries[5] that participated in PIAAC or STEP. As depicted on the map, there is a considerable North–South divide, suggesting that the average level of skills is much lower in the Global South than in the Global North. Ghana, Kenya, and Peru are bringing up the rear, with scores considerably less than 200. On the other hand, Japan, Finland, and the Netherlands are leading the ranking, performing significantly better than the OECD average.

Methodology

For the reconstruction of adult literacy test results, the first step involves the identification of the extent of changes in skills with age and over time. For this purpose, data from three international, large-scale assessments were used: (1) the 1994–1998 IALS, (2) the 2003–2008 ALL, and (3) the 1st cycle PIAAC (2011–2017). This is possible because trend items from IALS and ALL were included in PIAAC, allowing data from previous surveys to be linked to trend data from participating countries in PIAAC. As highlighted in Table 1, countries for which tested adult literacy data are available for at least two points in time include Belgium, Canada, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, the Netherlands, New Zealand,

FIGURE 3 Changes in literacy skills over time from a cohort and period perspective, the Netherlands and Chile



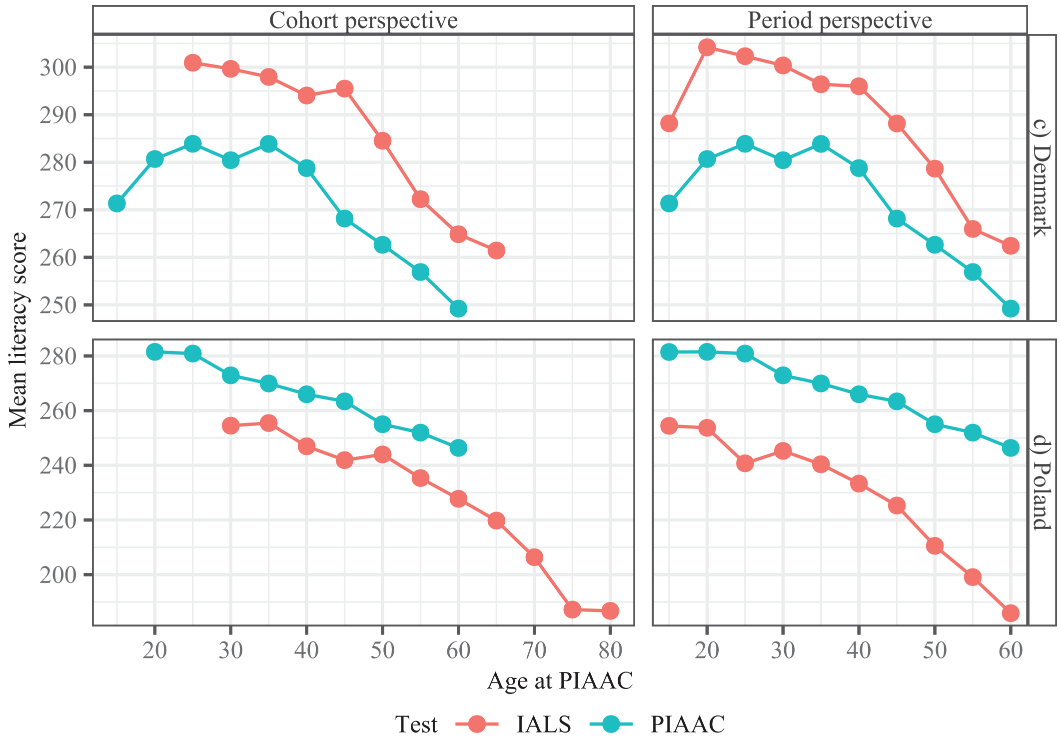
SOURCE: Author's elaboration based on IALS and PIAAC data.

Norway, Poland, Slovenia, Sweden, Switzerland, the United Kingdom, and the United States.

The empirical analyses are based on a pooled dataset from IALS, ALL, and PIAAC, from which I built cohorts[6] to investigate the skill development of different age groups over a period of roughly 20 years. Ideally and when available, I used single-year age groups, which were then aggregated to five-year age groups, depending on the year the surveys took place and the time lag between different surveys in each country. For example, in the United States surveys took place in 1996 (IALS), 2007 (ALL), and 2014 (PIAAC); hence, my analysis follows a cohort, which was, for example, 25–29 years old in IALS, 36–40 years old in ALL, and 43–47 years old in PIAAC. In this way, I was able to conduct country-specific cohort analyses for 17 countries[7] (see Figure A2 in the Appendix in the Supporting Information).

In line with literature findings, the empirical cohort analysis results indeed suggest that deterioration in the level of skills is happening because of age effects, with the beginning and extent of the decrease strongly depending on educational attainment. Figure 3 exemplifies this, showing two countries: the Netherlands and Chile. On the left panel, cohorts are represented vertically, that is, the x-axis represents the age at PIAAC, while participants in IALS are accordingly younger (e.g., x = 40 represents an age

FIGURE 4 Changes in literacy skills over time from a cohort and period perspective, Denmark and Poland

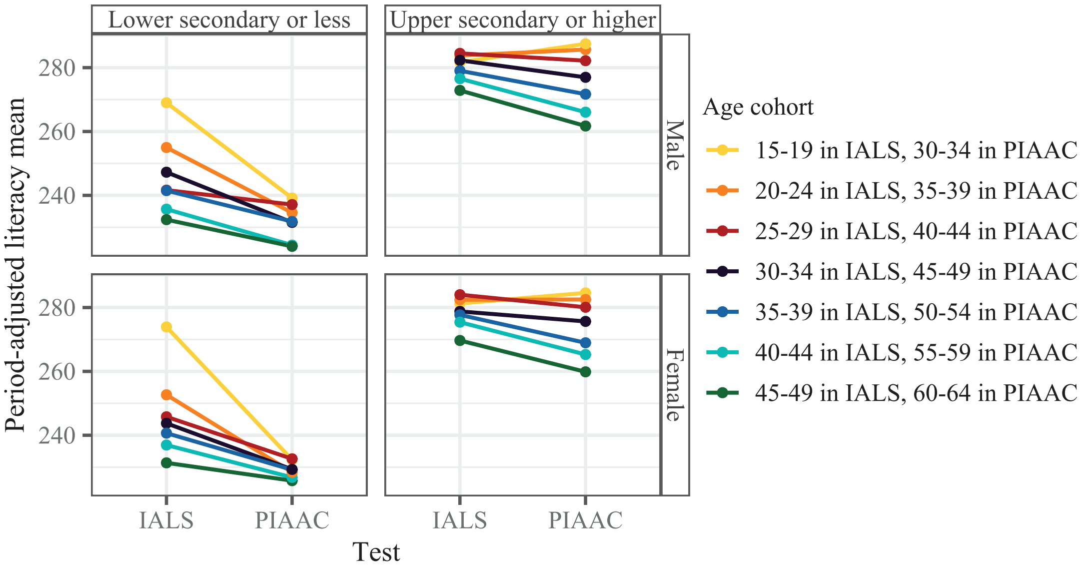


SOURCE: Author's elaboration based on IALS and PIAAC data.

cohort that was aged 23–27 years old in IALS 1994 and 40–44 years old in PIAAC 2011). On the right panel, test results are depicted from a period perspective, with the x-axis representing the age at the time of the test. In both countries, when looking from a cohort perspective, literacy skills declined considerably after age 20 for all but the youngest age groups, with stronger skill deterioration among older adults. In the Netherlands, where educational attainment is high, skills are still increasing until the age of about 35; in Chile, where educational attainment is lower, a minor skill gain is only observable until the age of 30. From a period perspective, however, mean literacy scores by age group are roughly identical between the two surveys, suggesting that no significant period effect occurred.

These results, however, were not found to be consistent among all countries. Figure 4 shows the changes in skills over time for two additional countries: Denmark and Poland, with Denmark experiencing significant skill loss, and Poland experiencing considerable skill gain between 1998 and 2011. In both countries, this development holds among all age groups, both from a cohort perspective and from a period perspective, suggesting that these countries were faced with period effects that had an impact on their overall level of skills.

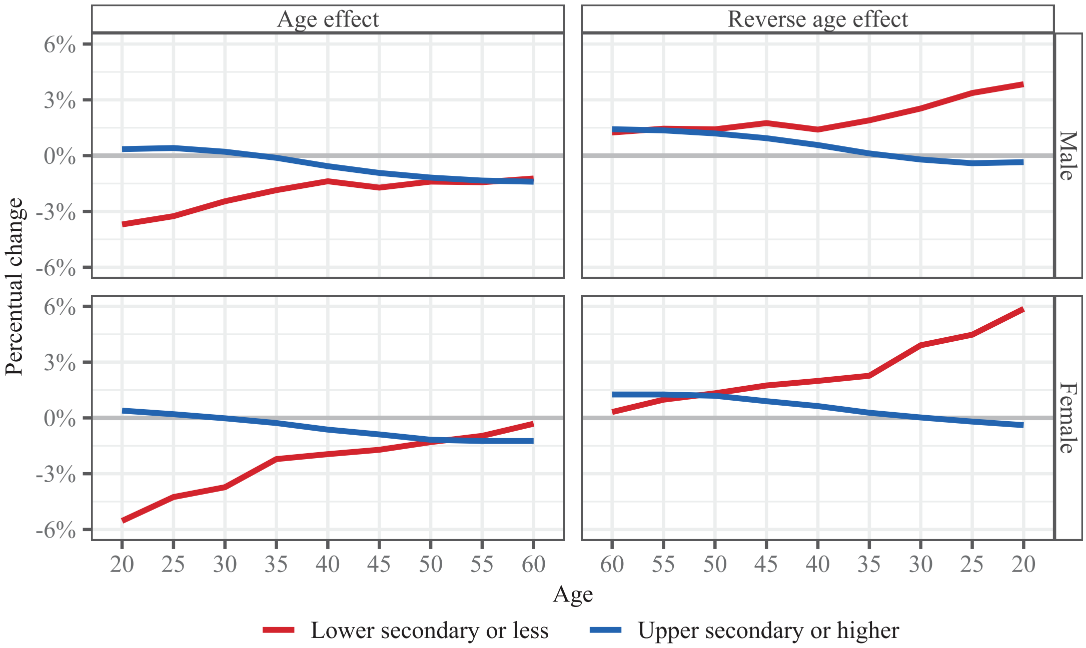
FIGURE 5 Estimated standard age effect, cohort perspective, IALS 1994–98 and PIAAC 2011–2017



SOURCE: Author's elaboration based on IALS and PIAAC data.

These findings give us important insights on cohort effects and shifts in the level of skills between generations for a specific time and country. At the same time, they prove that cohort effects can reveal very different trends for relatively similar countries (see Figure 4). Given the fact that, at present, there are not enough data available to expand these analyses to a global scale and for a longer period, additional assumptions for the reconstruction of adult literacy test results were made. First, a standard skill-age decay pattern was estimated by pooling all countries that participated in both IALS and PIAAC.[8,9] Since both IALS and PIAAC were conducted in different years for different countries, I applied the average duration of 15 years between the two tests to build age cohorts. Next, I adjusted for the mean score difference between IALS and PIAAC for each age group, respectively (as depicted in the period perspective of Figures 3 and 4). In this way, I was able to separate the pure age effect—which is assumed to be more stable across countries and time—from the more context-sensitive cohort and period effects. These calculations were done for two broad education categories ("lower secondary or less" and "upper secondary or higher"), and for women and men separately, to account for potential differences in skill loss/gain due to attainment of formal education as well as potential gender differences. Figure 5 depicts the resulting standard age effect for different age cohorts that were used to reconstruct literacy test results until 1970. Sensitivity analyses of conducting the same kind of analysis separately for different countries confirmed that the age effect tends to be largely constant across different populations (see Figure A3 in the Appendix in the Supporting Information).

FIGURE 6 Estimated percentage change in literacy skills due to age effect (reverse direction used for reconstruction)

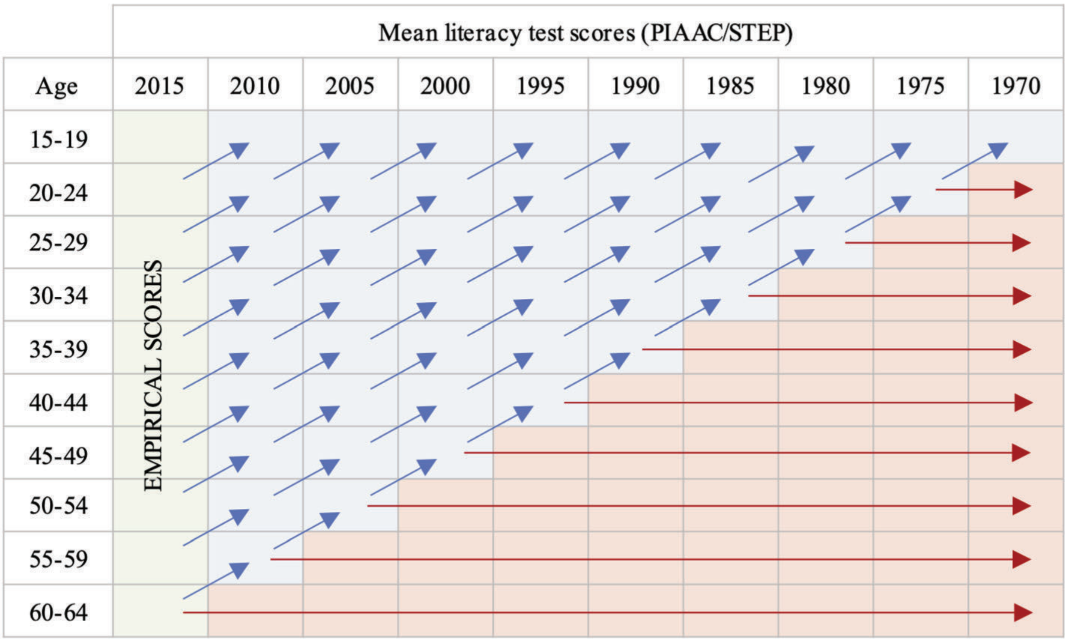


SOURCE: Author's elaboration.

As shown in Figure 5, the pattern implies that the skill loss due to age effects significantly differs for different age cohorts and by educational attainment. Those with lower education tend to lose the highest share of their skills rather soon after leaving school. This can be explained by the fact that less educated people frequently enter jobs in which they need fewer of the cognitive skills that are tested and thus do not practice some of those skills they learned in school.[10] In addition to that, parts of the PIAAC 30- to 34-year-old cohort (15- to 19-year olds in IALS) may have still been in education at time of IALS, thus potentially moving to the higher education group when participating in PIAAC. On the contrary, higher educated people are still able to moderately gain skills up to the age of 35. After that, skills remain largely constant until the age of approximately 45 when cognitive skills eventually start decreasing.

With regard to gender differences, variations are less observable. A closer look reveals, however, that the skills decline for lower educated women up to the age of 35 is a little bit steeper than for their male counterparts; similarly, the skill gain for higher educated women is slightly flatter compared to men. This may be explained by the fact that women are more likely to stay at home when they enter parenthood, thus facing lower cognitive demands than young fathers who tend to be continuously active on the labor market. For older age groups, gender differences in the development of skills due to age effects can hardly be identified.

FIGURE 7 Schematic depiction of demographic reconstruction of PIAAC/STEP literacy skills



SOURCE: Author's elaboration.

Based on these period-adjusted trends of cohorts over time, I further derived an age-, sex-, and education-specific skill growth function over the life course (presented in Figure 6), depicting the percentage change in literacy skills as cohorts age. This function is assumed to be constant for all countries and over time.

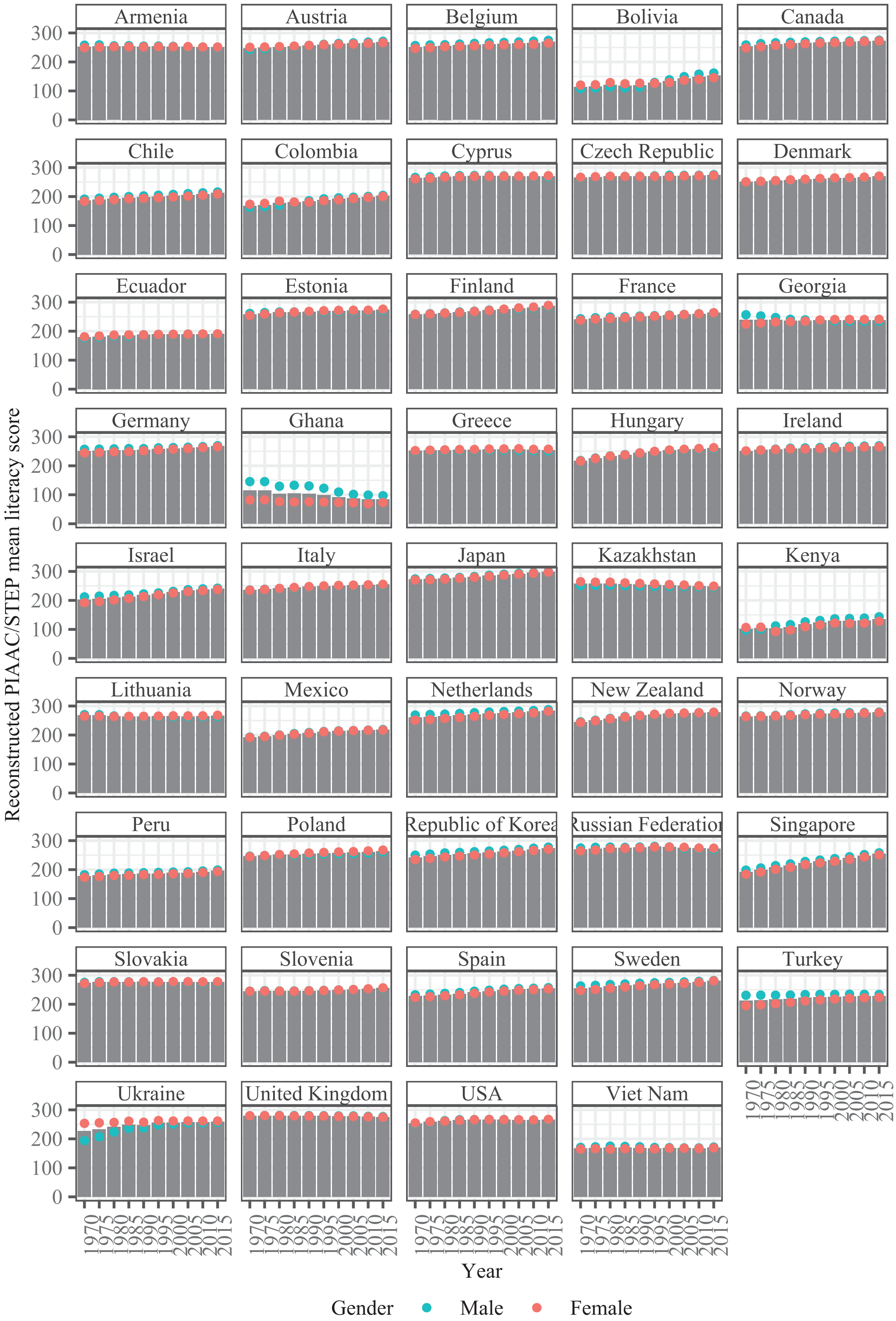
This estimated percentage change in skills is essential for the reconstruction of literacy test scores along cohort lines. The starting point for the reconstruction is provided by the empirical mean literacy scores of 2015 (coming from PIAAC and STEP results available for 44 countries), disaggregated by age, sex, and four educational-attainment categories: primary or less, lower secondary, upper secondary, and post-secondary education.[11] The reader should note, however, that empirical literacy scores serving as base-year data originate from any round of data collection in PIAAC cycle 1 (2011–2017) or STEP data collection between 2012 and 2016. As the interpolation of skills data in single-year intervals to obtain 2015 values is not possible because of the nonavailability of more than one data point over time for most countries, PIAAC and STEP literacy test results provide the unmodified basis for the 2015 base-year scores—despite small variations in time. Starting from these base-year data, for each age group literacy scores are reconstructed in five-year time steps by applying the percentage change in skills due to the reverse age effect (as depicted in Figure 6). Figure 7 shows a schematic depiction of how this reconstruction works. As an example, take the mean score of 60- to 64-year olds tested in 2015 (green area in Figure 7) that provides the basis for the estimated mean score of 55- to 59-year olds in 2010 (blue area in Figure 7), adjusted by the sex- and education-specific percentage change. For age groups for which I was not able to build cohorts for the whole or parts of the reconstruction period (e.g., 60- to 64-year olds in 2010 were too old to be tested in 2015, depicted as the red area in Figure 7), I assumed the age-, sex-, and education-specific scores to be constant over time. In this way and based on empirical literacy scores from PIAAC and STEP, I was able to obtain estimated mean scores by five-year age groups, sex, and four educational attainment categories[12] from 1970 to 2015 for 44 countries.[13]

Results and discussion

Based on the methodology described in "Methodology" section, literacy test scores by age, sex, and educational attainment were reconstructed for 44 countries back to 1970—in five-year steps and for the age groups 15–19 to 60–64. Figure 8 highlights the results by depicting the mean literacy scores by country and year for the working-age population aged 20–64, with the dots representing the gender-specific mean literacy scores.[14]

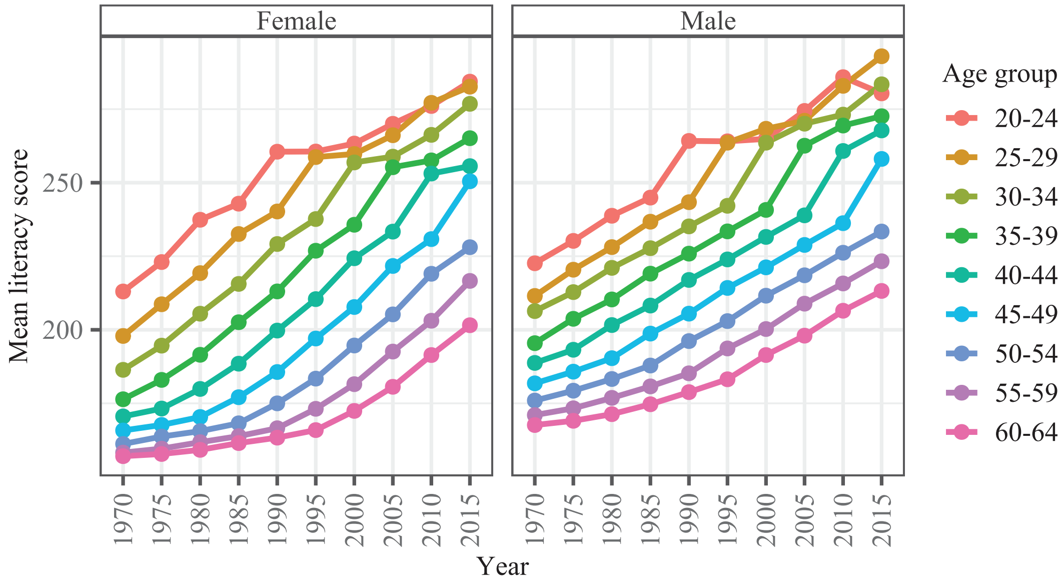
As can be seen on the figure, not only does the level of literacy skills vary greatly for different countries, the development over time shows different trends for different populations. Although in most countries, skills have remained roughly constant or even increased slightly over the last 45 years, there are a few exceptions where skill loss of the working-age population can be observed. In Ghana, for example, skills started declining in the early 1990s—despite significant educational expansion in recent years. This is consistent with previous findings of the existence of a quantity–quality trade-off, in which the quality of the education system is expected to decline when the education system expands, at least in the initial stage (Mare 1979, 1981; Raftery and Hout 1993; Shavit and Blossfeld 1993). This phenomenon partly results from a reduction in selection effects, that is, in more restricted education systems (before educational expansion happened) only the "strongest" students would have remained in the schooling (Spaull and Taylor 2015). In addition, educational expansion may also result in the potential inability of the education system to cope with the increase in the number of students, as well as insufficiency of school inputs and low government spending—particularly in low-income settings. However, highly developed countries are also not immune to these developments. The United Kingdom, for example, has also experienced a minor decline in literacy skills over the last decades—albeit at a much higher skill level. Overall, when comparing the results with the increase in the average duration of schooling for the same age group and period (Wittgenstein Centre for Demography and Global Human Capital 2018), the development of

FIGURE 8 Reconstructed mean literacy scores of adults aged 20–64 by country and gender, 1970–2015



SOURCE: Author's elaboration.

FIGURE 9 Reconstructed mean literacy scores by five-year age groups and gender, Singapore, 1970–2015



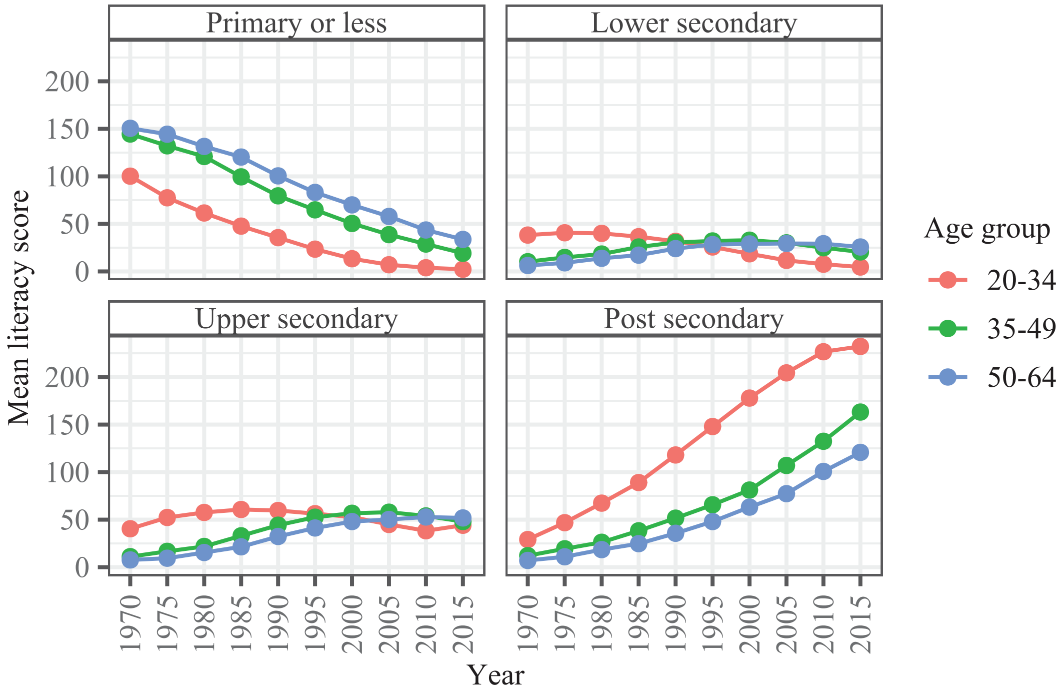
SOURCE: Author's elaboration.

skills can hardly keep up with the steep increase in mean years of schooling in any country.

When looking at gender differences, most countries do not show significant gender gaps in literacy skills among the working-age population. However, there are a few exceptions: in Ghana, Kenya, or Turkey, for example, men are still significantly higher skilled than women—even though the gap slowly decreases over time. This gender disparity is likely to result from girls being denied equal access to education. In other countries, most notably in Ukraine or Kazakhstan, the reconstruction reveals quite the opposite results: while women used to have considerably higher literacy skills than men, there are hardly any gender variations in more recent years. This phenomenon is a result of women in older age groups having performed considerably better than men in recent PIAAC/STEP surveys; given the small sample sizes in some of the country–age–sex–education groups, however, the reconstruction results need to be treated with caution. In addition, it is important to note that although literacy skills are generally strongly correlated with other skill domains, gender was shown to influence different kinds of skills in different directions (OECD 2013, 2016a).

As previously mentioned, the prevalence of adult skills in a population at a given time reflects a complex interplay of age and cohort effects, not discernible when looking only at the aggregated value, as changes in the level of skills in a country may be the consequence of a changing composition of the population (i.e., younger cohorts with a different educational attainment distribution slowly replacing older ones). Therefore, disaggregating skills by age, sex, and educational attainment can further help disentangle the different effects and their impact on a population's level of skills.

FIGURE 10 Reconstructed mean literacy scores by broad age groups and educational attainment, Singapore, 1970–2015

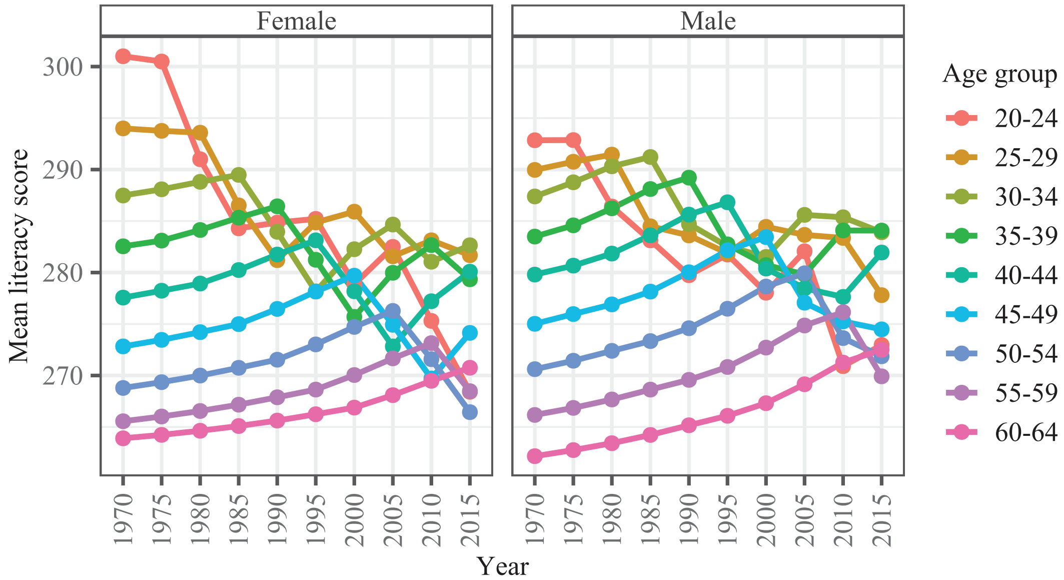


SOURCE: Author's elaboration.

Consider the case of Singapore, a country where the educational attainment distribution differs widely between different age and gender groups: while in 2015 more than 80 percent of the population aged 25–29 in 2015 had some kind of post-secondary education, over one-third of women aged 60–64 in Singapore had only a primary education or never attended any school. This is a result of a cohort effect: the cohort of women aged 60–64 in 2015 were 5–9 years old in 1960—at that time, Singapore did not have universal primary education because it was still a poor developing country. Hence, under conditions of rapidly expanding school systems, skills-averaging over the entire adult population provide a poor measure as they combine the literacy skills of highly educated young cohorts with poorly educated older ones. This is also reflected in Figure 9 that shows Singapore's mean literacy score by age group and sex over time: during the whole period, older people have had consistently lower literacy skills. This results partly from the skill loss that comes with the age effect; on the other hand, this also reflects the continuously lower education of the elderly. Furthermore, while older age groups only recently experienced a skill gain, for younger cohorts, 1970–1990 marked the main period of skill gain—again reflecting the rapid educational expansion that started shortly before.

When further disaggregating the results by educational attainment, however, it becomes clear that skills in Singapore have been increasing only among those with higher education. Figure 10 shows the reconstructed

FIGURE 11 Reconstructed mean literacy scores by five-year age groups and sex, the United Kingdom, 1970–2015



SOURCE: Author's elaboration.

mean literacy score from 1970–2015, disaggregated by four educational attainment categories. While those with post-secondary education experienced rapid skill growth, the opposite holds true for those with only primary or no education: for these people, skills have continuously declined over the last decades, indicating again some kind of quantity–quality tradeoff. These effects seem to be even larger for younger age groups and suggest that the country's rise in skills (as depicted in Figure 8) is first and foremost driven by a growing group of highly educated individuals, rather than by a high-quality-education society at large. Although the number of Singaporeans with little or no education is rapidly decreasing, this of course raises questions about inequality and gives reason to suspect that the gap between high-performing and low-performing individuals will further increase in the future.

Quite contrasting but equally interesting results are presented in Figure 11, depicting—equivalent to Figure 9—the mean literacy score by age group and sex between 1970 and 2015, but this time for the United Kingdom. As can be seen on the graph, while older age groups have continuously experienced a skill increase corresponding to the ongoing educational expansion, younger age groups—despite country-wide lower secondary education—reveal a significant skill decline over the last decades. This is in line with recent international student assessments: PISA results, for example, show for the United Kingdom, relative to other countries, a decline in literacy, math, and science since 2000 (the first round of PISA) (Heath et al. 2013), with only the latest PISA tests again indicating a minor rise in international schooling rankings. However, once again it is important to note that these reconstruction results—in the absence of better data availability—rely solely on a standard education- and gender-specific age effect, which does not account for country-specific circumstances or events, such as education policies or reforms.

The examples of Singapore and the United Kingdom nicely illustrate the importance of disaggregating skills by subpopulations. Especially in societies where inequality is high or cohort effects took place that may have impacted the level of skills, mean values averaged over the whole population can be particularly biased. Results of this research, therefore, include reconstructed literacy scores disaggregated by age, sex, and educational attainment back to 1970 for all 44 countries.

Conclusion

As our societies transform into knowledge societies, sophisticated comprehension and advanced skills of all kinds become essential for successful integration and participation, not only in the labor market, but also in social and civic life. Despite this rising importance, consistent measures of adult skills across countries are still scarce and have evolved only recently. Even less is known about trends and developments of skills over time. The current paper, therefore, aimed to reconstruct literacy test results of the working-age population back to 1970 by applying the demographic method of cohort analysis. Based on empirical PIAAC and STEP results available for the base year, I was able to estimate literacy test scores by age, sex, and educational attainment for 44 countries in five-year steps between 1970 and 2015.

Reconstruction results reveal significant differences between countries for the period 1970–2015—both regarding the level of skills as well as their development over time. Although in most countries, skills have remained roughly constant or even increased slightly over the last 45 years, other populations have experienced minor skill loss. Overall, results suggest that the massive educational expansion that happened globally in the recent past only partly resulted in a similar rise in skills. Moreover, the level of skills vastly differs for different subpopulations, suggesting that the development of skills in a country is also the consequence of a changing composition of its population. While cohort effects, such as the nature and quality of schooling, usually impact the level of skills of the working-age population with a certain time lag, skill changes due to age effects tend to significantly differ with educational attainment and for different age cohorts. Gender, on the other hand, was found to have hardly any effect on how skills change over the life course.

Nevertheless, this study has potential limitations. Because of the limited data availability, assumptions had to be made in order to arrive at the results presented. First of all, the standard age pattern was assumed to be constant among all 44 countries and over time. Given that existing country-specific analyses have proven that cohort effects may reveal very different trends for relatively similar countries, this is indeed a strong assumption. Moreover, this standard age effect is based on a limited number of countries, most of which are high-income OECD countries. However, given the fact that, at present, there are not enough data available to expand these analyses to a global scale and a longer period, and by being transparent about underlying assumptions and shortcomings, I still believe that this work is an important first attempt to consistently reconstruct literacy skills over time. Finally, it is important to recall that this work only covers a very specific type of skills, namely, literacy skills as measured in large-scale assessment surveys. Despite studies having shown that these skills are closely correlated with other type of skills (Reiter et al. 2020), one should be cautious when transferring these results to all kinds of competencies. As more empirical information on tested adult skills become available, I hope to further improve and validate current results in future research.

Data availability statement

Results for all 44 countries, including reconstructed literacy scores disaggregated by age, sex, and educational attainment back to 1970, can be found in the following GitHub repository: https://github.com/clreiter/Adult-literacy-test-results-reconstruction.

Notes

The author wants to thank Anne Goujon, Wolfgang Lutz, Caner Özdemir, and Dilek Yildiz for their valuable inputs and comments.

1 The Demographic and Health Survey (DHS) is an international household survey program that, since 1984, has conducted more than 400 surveys in over 90 developing countries. Since 2000, the standard DHS questionnaire includes a short literacy test, where each respondent with low education is asked to read a sentence on a cue card aloud in their preferred language. Further information about the DHS can be found in Croft et al. (2018) and Rutstein and Rojas (2006).

2 Regions are defined based on the United Nations' geographic regions (United Nations Statistics Division 2021).

3 Reasons for introducing this screening mechanism are mostly practical: not passing the core assessment indicates that the skills of these individuals are so low that undertaking the full assessment would have generated little additional information and would only have been a frustrating and negative experience for the respondent.

4 STEP data were not used, however, to derive the estimated standard age effect as depicted in Figure 7. Therefore, STEP results do not have any impact on reconstruction results of countries participating in the PIAAC survey.

5 Australia was excluded from the analysis as PIAAC microdata are not publicly available for this country.

6 Ideally, I would be able to follow the same individuals over their life course. However, as no true panel data on adult skills exist, I made use of the fact that although we cannot observe the same people at different points in time, we are able to observe representative samples of the population at different points in time.

7 From the 19 countries for which at least two literacy assessments are available, two had to be excluded from the analysis: Australia because microdata are not publicly available for this country; and Canada as age

was only reported in 10-year age groups in the Canadian IALS and ALL microdata. Results of the country-specific cohort analyses for the remaining 17 countries can be found in graphs in the Appendix in the Supporting Information (see Figure A2 in the Appendix in the Supporting Information).

8 As the number of countries participating in ALL is much smaller than for IALS and PIAAC, ALL test results were excluded from the estimation of a standard age effect. To additionally integrate ALL results, either the country coverage would need to be further reduced, or comparisons would be made between noncomparable (i.e., differently composed) populations, both potentially distorting the results.

9 The following 17 countries were merged to develop the standard age effect: Belgium, Chile, Czech Republic, Denmark, Finland, Germany, Hungary, Ireland, Italy, the Netherlands, New Zealand, Norway, Poland, Slovenia, Sweden, the United Kingdom, and the United States.

10 It might be argued that it is not so much the higher use of skills among the better educated that leads to lower skill loss, but rather that those with more education had more and longer practice on standardized testing because of longer time spent in education. While this cannot be proved (all measurements of literacy used in this paper are derived from a standardized test situation), sensitivity analyses included in the Appendix in the Supporting Information (Figure A4 in the Appendix in the Supporting Information) suggest that the more rapid decline in assessment scores among lower educated populations might indeed be caused by a lack of use of cognitive skills. By plotting the self-declared use of reading skills (as included in the PIAAC background questionnaire) against age and education, it becomes clearly visible that use of literacy skills (both at work and at home) is significantly lower for less educated people. In addition, those with only lower secondary education or less tend to reduce their use of reading skills at home most strongly soon after leaving school.

11 To account for the complex sample design of PIAAC and STEP (i.e., replicate weights and plausible achievement values), the R package intsvy, which provides tools and analyses specifically designed to work with international assessment data, was used to calculate means. For further information on the intsvy package, please see https://CRAN.R-project.org/package=intsvy.

12 While the empirical scores of the base year are disaggregated by age, sex, and four levels of educational attainment, the estimated standard skill growth function over the life course is only defined for two education categories and by sex. This cruder disaggregation was found to be most consistent between countries. Given the different scores in the base year, reconstruction results still differ between four education categories.

13 To test the robustness of the reconstruction results, I have added a sensitivity analysis in the Appendix in the Supporting Information where I compared PISA mean reading scores (at age 15) with the (reconstructed) PIAAC mean literacy scores (at age 15–19) for all years and countries available (see Figure A5 in the Appendix in the Supporting Information). The resulting correlation coefficient is $r = 0.62$, which is reasonably high given the well-known differences between the two surveys (different scales, different constructs measured, different target population, etc.). In addition, the level of correlation was not found to systematically decrease if we go further back in time, suggesting that the correlation between the reconstruction results and PISA scores (in the respective year) is similar to the correlation between empirical PIAAC scores and PISA scores.

14 Mean scores by country were aggregated based on the population distribution by age, sex, and education in the respective years, retrieved from the Wittgenstein Centre Human Capital Data Explorer (Wittgenstein Centre for Demography and Global Human Capital 2018).

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Appendix: Supplemental Materials

1. Literacy Sample Items

In order to get a better understanding of how literacy is conceptualized in the assessments used in the analyses, examples of literacy items in English language can be found under the following links:

- PIAAC: https://nces.ed.gov/surveys/piaac/sample_lit.asp
- IALS: https://nces.ed.gov/surveys/ials/items.asp
- ALL: https://nces.ed.gov/surveys/all/items.asp?sub=yes

For Review Only

2. Sensitivity Analyses

The following figures depict results from additional sensitivity analyses, conducted to test the robustness of the assumptions used for the reconstruction as well as of the reconstruction results themselves:

Figure A1. Correlation between PIAAC mean literacy and numeracy scores (left) and PIAAC mean literacy and problem-solving in technology-rich environment scores (right), by age, sex and country, all PIAAC countries 2

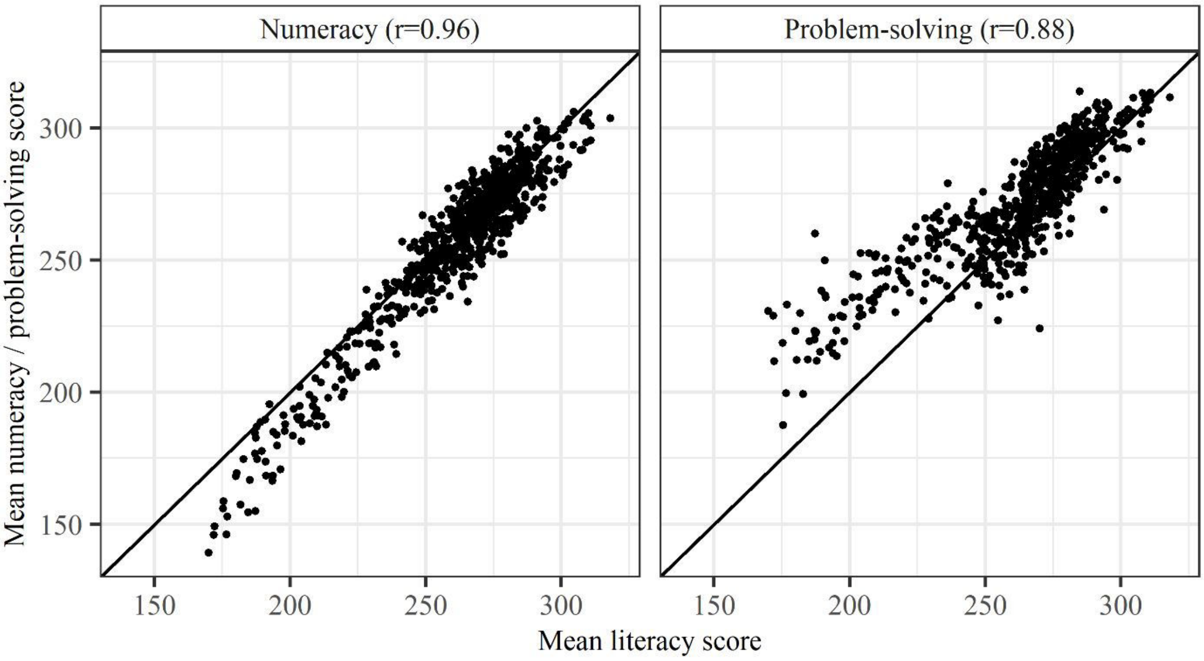
Figure A2. Country-specific cohort analyses, IALS 1994-98, ALL 2004-08, PIAAC 2001-17 3

Figure A3. Country-specific ageing pattern, IALS 1994-98, PIAAC 2001-17. ...8

Figure A4. Self-declared use of reading skills at home (left) and at work (right) by 5-year age group, all PIAAC countries..13

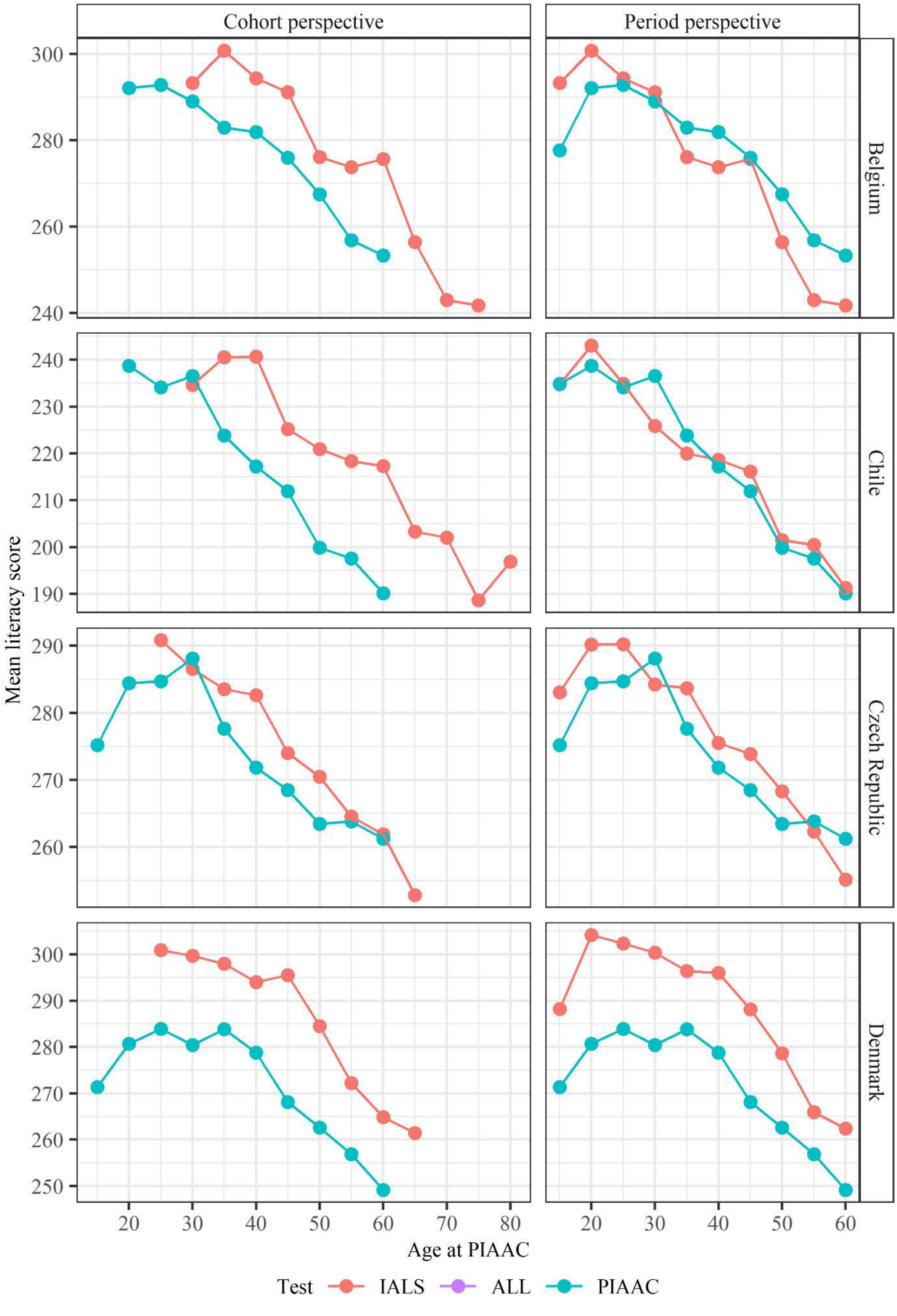
Figure A5. Correlation between PISA mean reading score (age 15) and PIAAC mean literacy score (age 15-19) by country and year 14

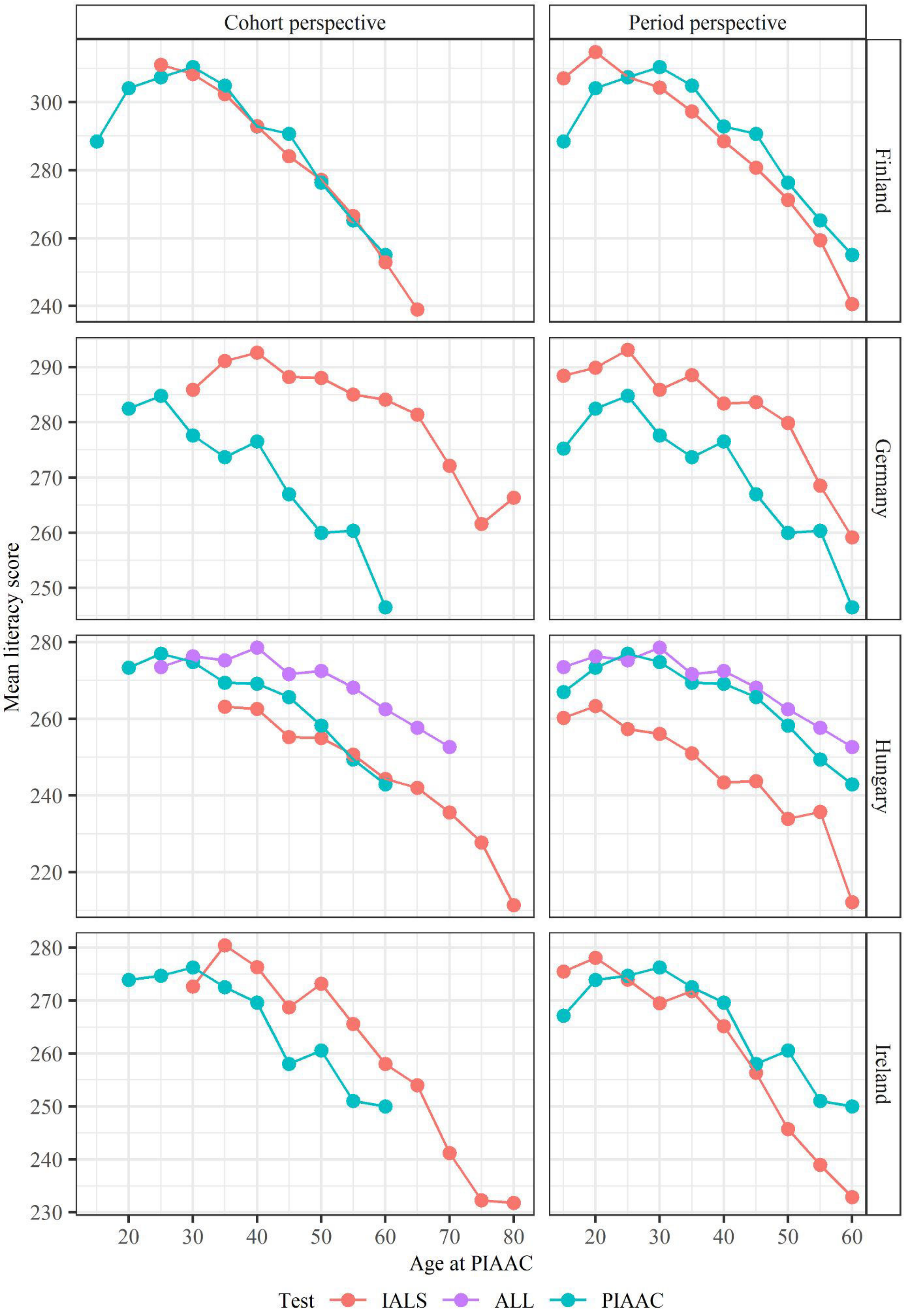
Figure A1. Correlation between PIAAC mean literacy and numeracy scores (left) and PIAAC mean literacy and problem-solving in technology-rich environment scores (right), by age, sex and country, all PIAAC countries



Source: Author's elaboration based on PIAAC data

Figure A2. Country-specific cohort analyses, IALS 1994-98, ALL 2004-08, PIAAC 2001-17




Cohort perspective
Period perspective
Finland
Germany
Hungary
Ireland
Mean literacy score
Age at PIAAC
Test
IALS
ALL
PIAAC
300
280
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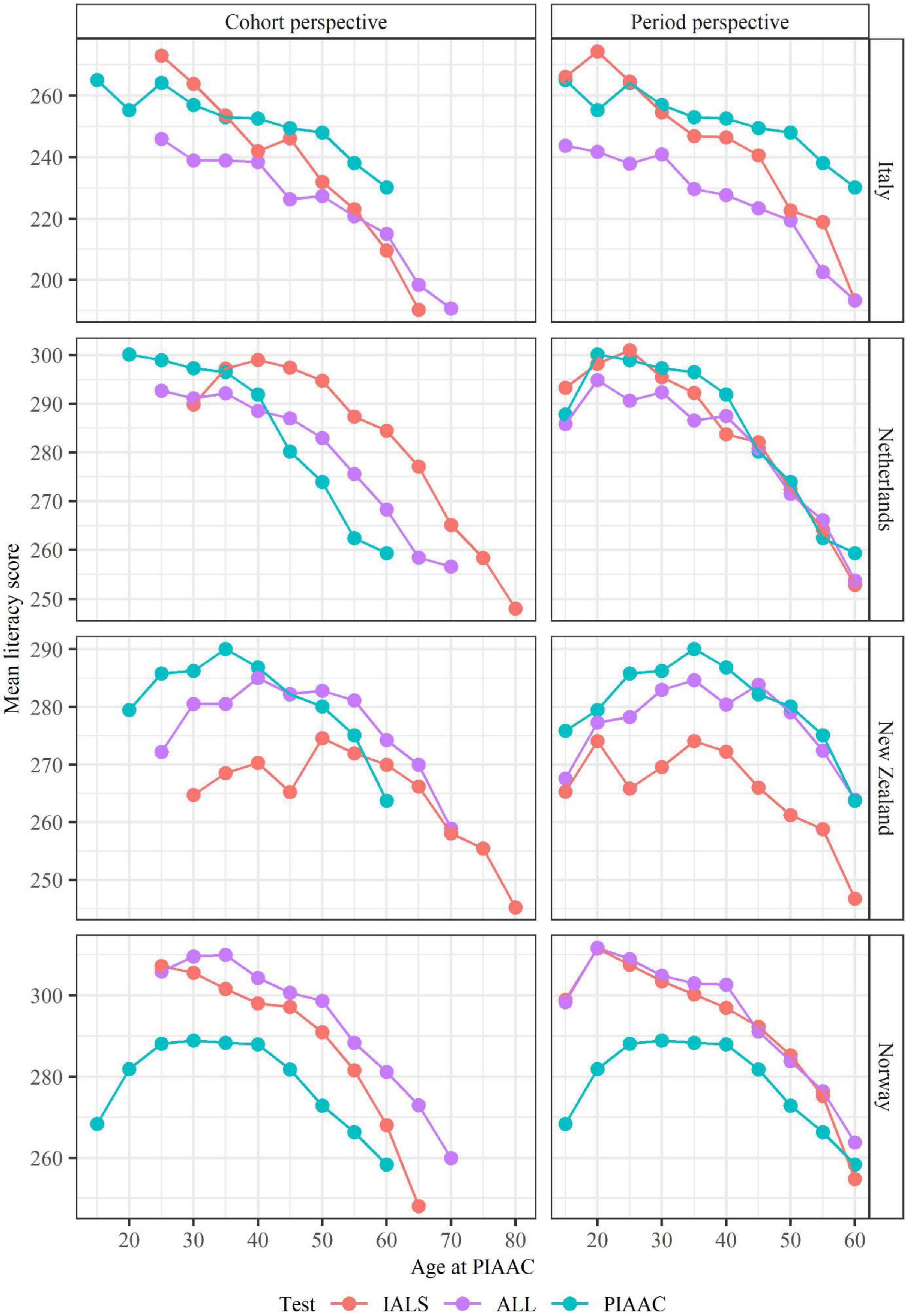
Cohort perspective
Period perspective
Italy
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Norway
Mean literacy score
Age at PIAAC
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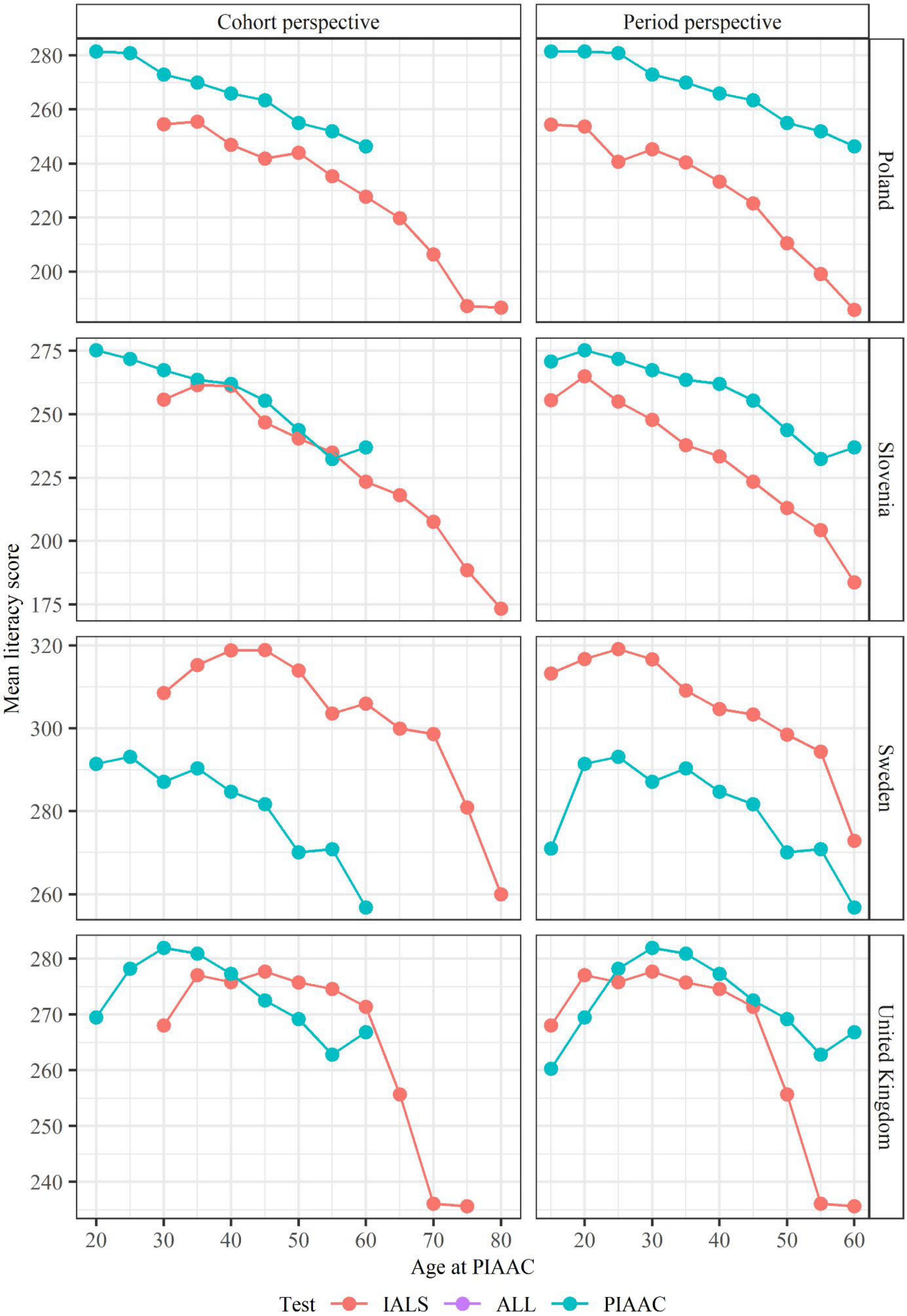

Cohort perspective
Period perspective
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Slovenia
Sweden
United Kingdom
Mean literacy score
Age at PIAAC
Test
IALS
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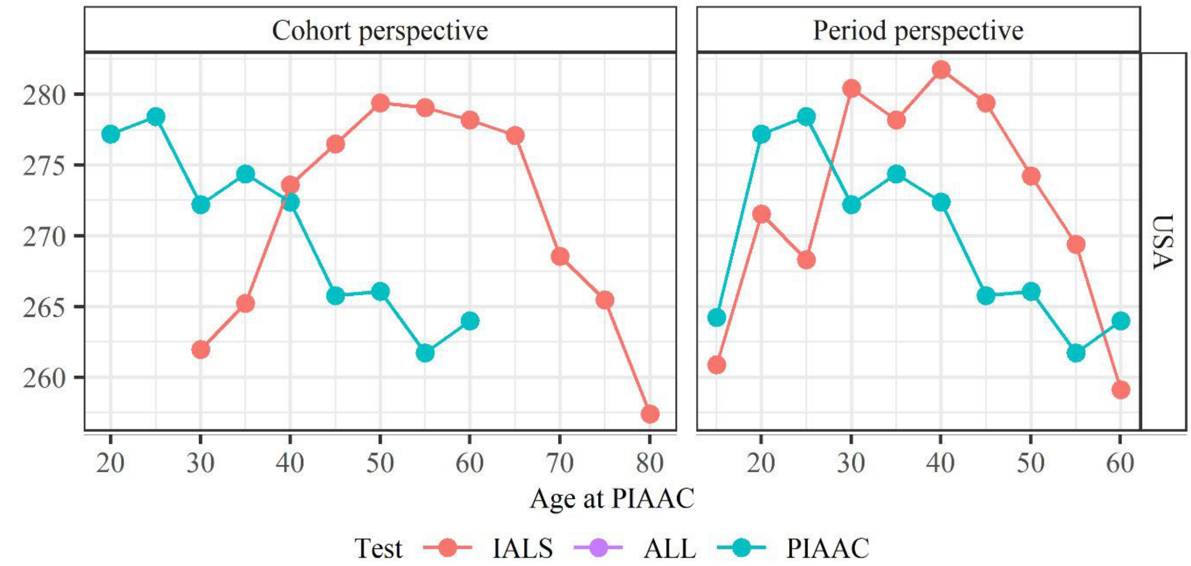
PIAAC

6



Source: Author's elaboration

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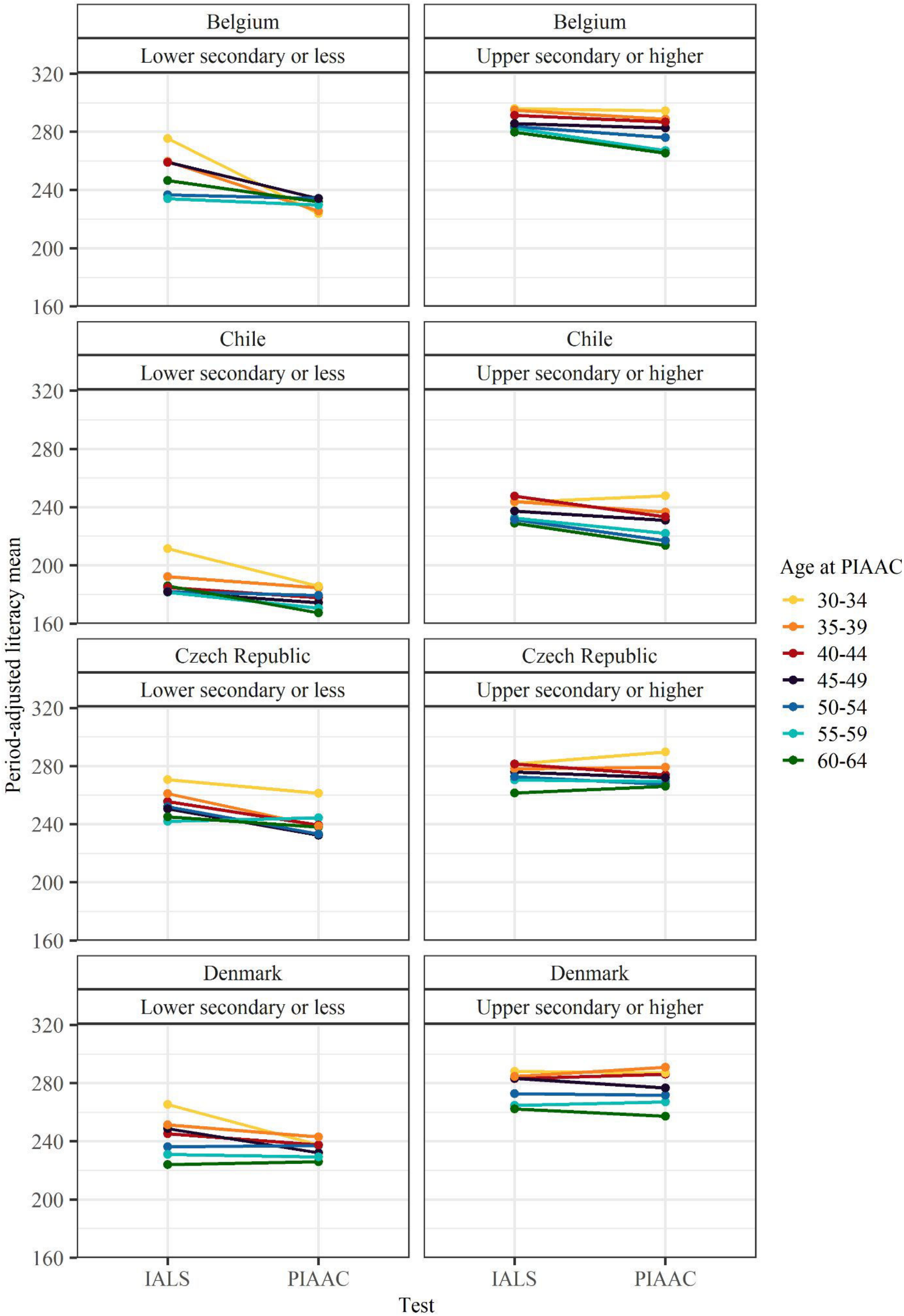
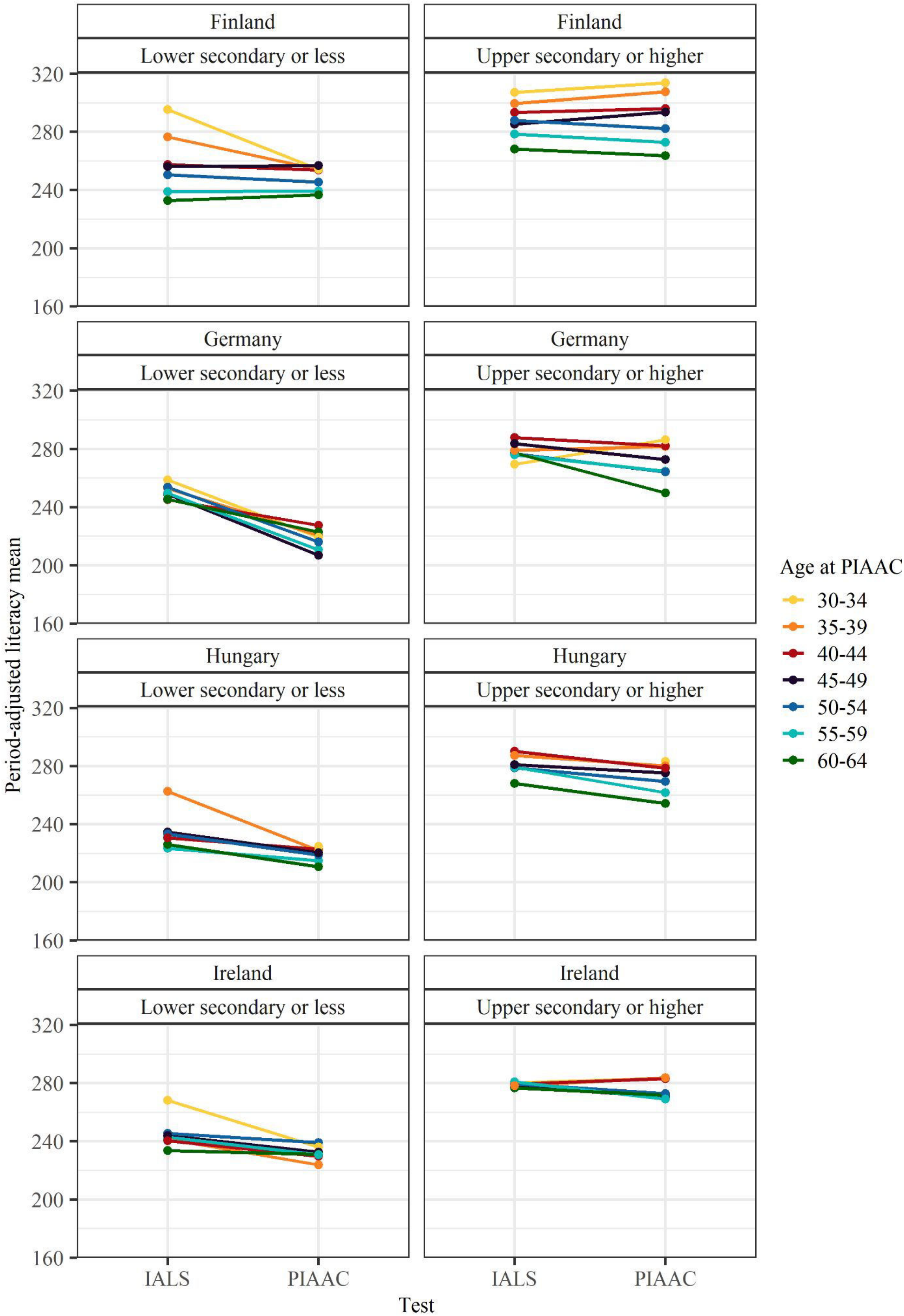
Figure A3. Country-specific ageing pattern, IALS 1994-98, PIAAC 2001-17.

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Period-adjusted literacy mean
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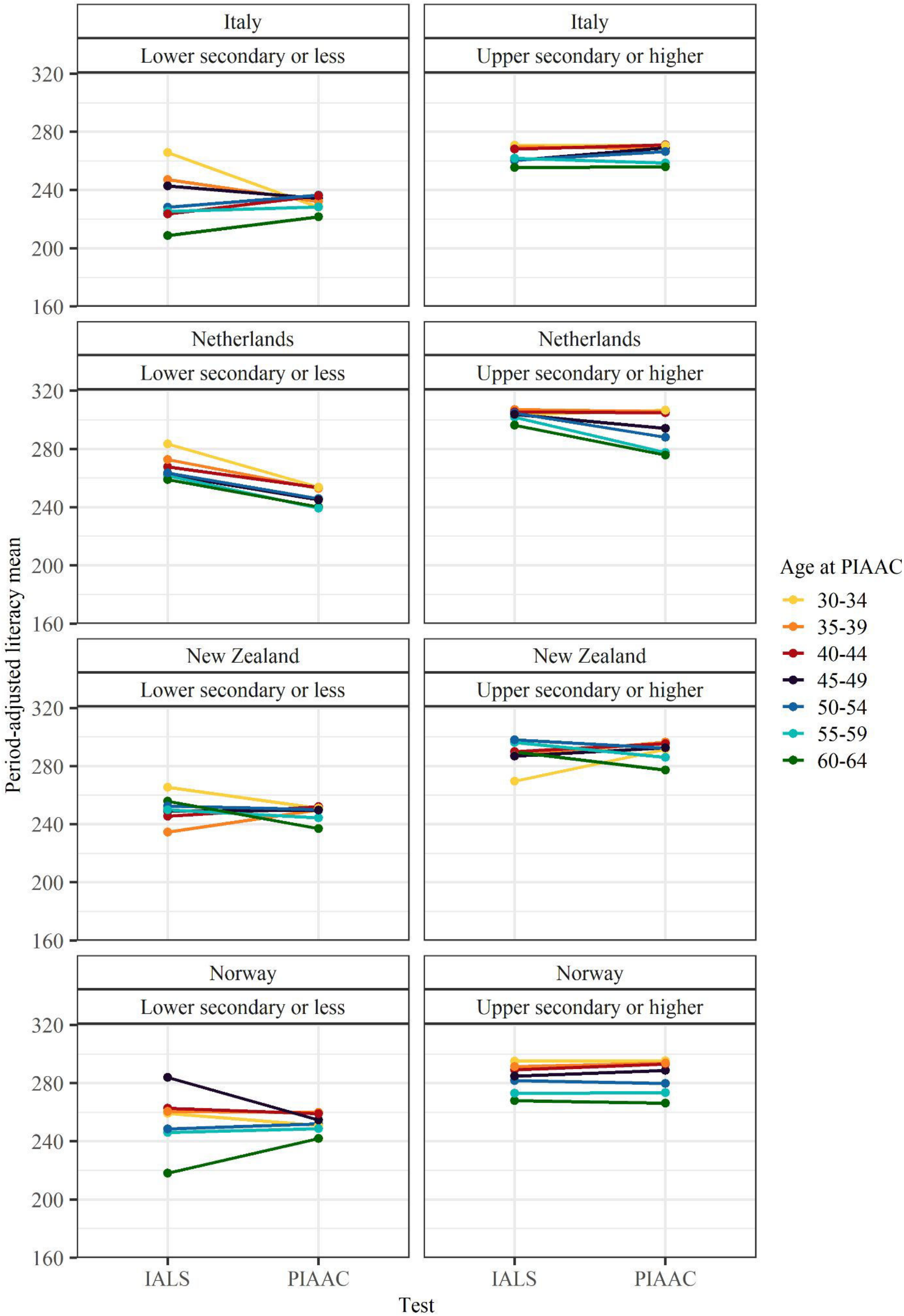
9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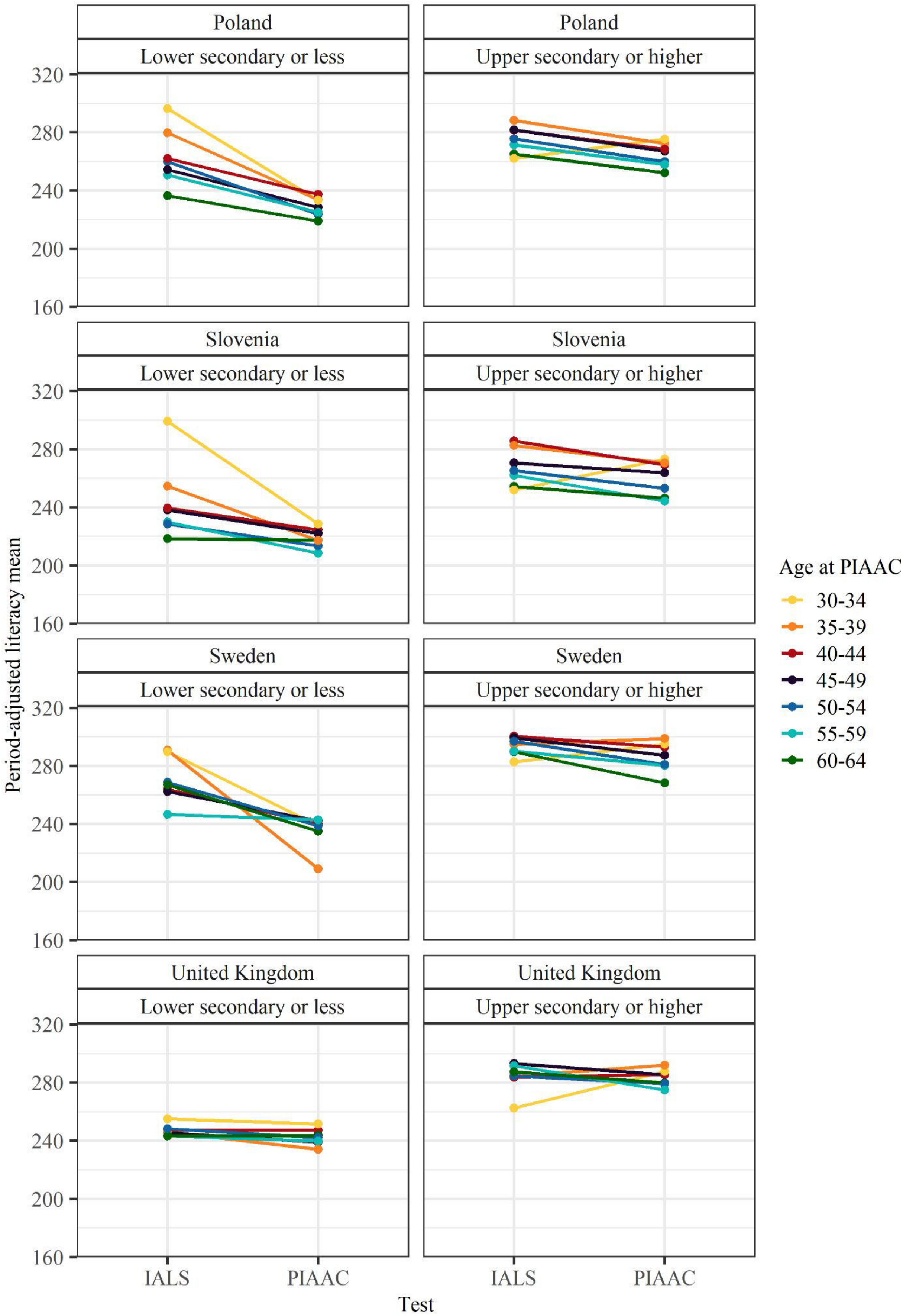
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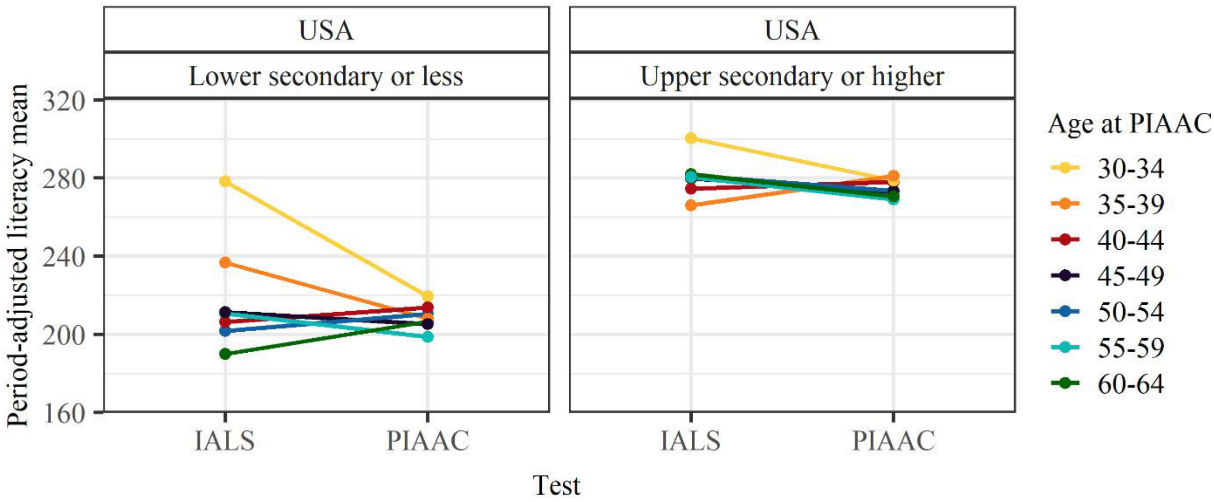

Source: Author's elaboration

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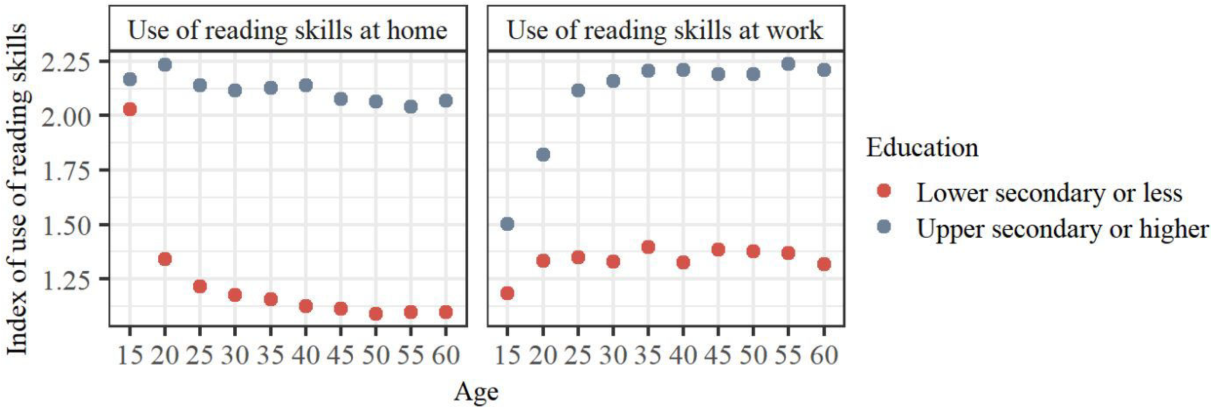
Figure A4. Self-declared use of reading skills at home (left) and at work (right) by 5-year age groups, all PIAAC countries



Source: Author's elaboration based on PIAAC data

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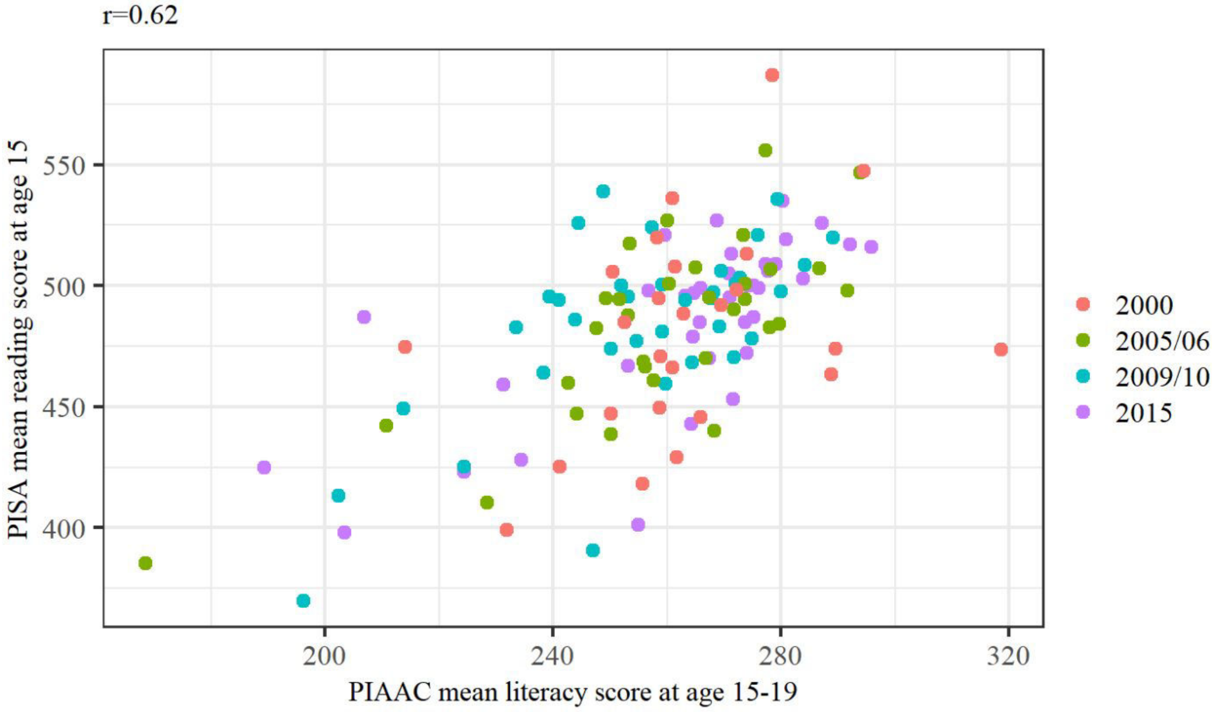
Figure A5. Correlation between PISA mean reading score (age 15) and PIAAC mean literacy score (age 15-19) by country and year



Source: Author's elaboration

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2.2. Skills-adjusted human capital shows rising global gap

The second publication was co-authored with Wolfgang Lutz, Caner Özdemir, Dilek Yildiz, Raquel Guimaraes, and Anne Goujon, and published on February 16, 2021 as

Lutz, W.; Reiter, C.; Özdemir, C.; Yildiz, D.; Guimaraes, R. and Goujon, A. (2021). Skills-adjusted human capital shows rising global gap. *Proceedings of the National Academy of Sciences of the United States of America 118*(7).
https://doi.org/10.1073/pnas.2015826118

Abstract: Human capital, broadly defined as the skills acquired through formal education, is acknowledged as one of the key drivers of economic growth and social development. However, its measurement for the working-age populations, on a global scale and over time, is still unsatisfactory. Most indicators either only consider the quantity dimension of education and disregard the actual skills or are demographically inconsistent by applying the skills of the young cohorts in school to represent the skills of the working-age population at the same time. In the case of rapidly expanding or changing school systems, this assumption is untenable. However, an increasing number of countries have started to assess the literacy skills of their adult populations by age and sex directly. Drawing on this literacy data, and by using demographic backprojection and statistical estimation techniques, we here present a demographically consistent indicator for adult literacy skills, the skills in literacy adjusted mean years of schooling (SLAMYS). The measure is given for the population aged 20 to 64 in 185 countries and for the period 1970 to 2015. Compared to the conventional mean years of schooling (MYS)—which has strongly increased for most countries over the past decades, and in particular among poor countries—the trends in SLAMYS exhibit a widening global skills gap between low- and high-performing countries.

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Skills-adjusted human capital shows rising global gap

Wolfgang Lutz[a,b,c,d,1], **Claudia Reiter**[a,b,d,1], **Caner Özdemir**[c,d,e], **Dilek Yildiz**[b,c,d], **Raquel Guimaraes**[b,d,f], **and Anne Goujon**[b,c,d,g]

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Contributed by Wolfgang Lutz, September 16, 2020 (sent for review July 27, 2020; reviewed by Martin Carnoy, Joel E. Cohen, and Christopher J. Thomas)

Human capital, broadly defined as the skills acquired through formal education, is acknowledged as one of the key drivers of economic growth and social development. However, its measurement for the working-age populations, on a global scale and over time, is still unsatisfactory. Most indicators either only consider the quantity dimension of education and disregard the actual skills or are demographically inconsistent by applying the skills of the young cohorts in school to represent the skills of the working-age population at the same time. In the case of rapidly expanding or changing school systems, this assumption is untenable. However, an increasing number of countries have started to assess the literacy skills of their adult populations by age and sex directly. Drawing on this literacy data, and by using demographic backprojection and statistical estimation techniques, we here present a demographically consistent indicator for adult literacy skills, the skills in literacy adjusted mean years of schooling (SLAMYS). The measure is given for the population aged 20 to 64 in 185 countries and for the period 1970 to 2015. Compared to the conventional mean years of schooling (MYS)—which has strongly increased for most countries over the past decades, and in particular among poor countries—the trends in SLAMYS exhibit a widening global skills gap between low- and high-performing countries.

human capital indicator | literacy skills | education | cross-country analysis | demography

Since antiquity, education has been considered one of the most important investments into young people aside from health. From Confucius and Socrates to modern enlightenment and up to the recent Sustainable Development Goals, the enhancement of the skills of the young generations has been an almost universal aspiration of human civilization. However, access to learning opportunities was limited to small elites, and only from the 19th century onward has it been gradually spreading to all men and subsequently women, first in Northern Europe and over the 20th century in most countries (1).

To describe the relevance of education for the individual life and for national prosperity, researchers have developed the concept of human capital. In a narrow economic sense, the term refers to the level of skills embodied in an individual that could be used to generate earnings in the labor market (2–4). A broader definition includes health and general cognitive empowerment (5, 6), and looks at benefits far beyond monetary returns, ranging from demographic trends (7, 8), to criminality (9), quality of institutions, and social cohesion (10).

To comprehensively assess the multiple benefits of investments in education, large globally comparable sets of data are required (11–13). So far, global indicators of adult human capital estimated at the country level and over time include mean years of schooling (MYS) (14–16) and full educational attainment distributions disaggregated by age and sex (17–21). Attempts to address the quality of education in addition to or instead of the quantity mostly use international school assessment data (22–25). While human capital theory clearly focuses on the benefits of adult skills, so far global harmonized datasets on education quality have focused on the school-age population (26, 27), despite the fact that the skills assessed in schools were found to be a poor measure of the concurrent level of adult skills in a population (28).

To fill this important gap in global human capital data, we present an indicator, the skills in literacy adjusted mean years of schooling (SLAMYS). This indicator improves on currently available human capital indicators in four dimensions: 1) reliance on adult skills surveys; 2) demographic consistency; 3) global availability; and 4) temporal evolution since 1970. By introducing SLAMYS, we not only provide insights in the evolution of inequality in adult skills between countries and over time, but also present researchers with a consistent global dataset for further studies on the relationship between human capital and development outcomes.

Our empirical exercise relies on data harmonization, demographic modeling, and statistical estimation for 185 countries. Empirical adult literacy skills assessment scores came from four different survey types: International Adult Literacy Survey (IALS) (29), Program for the International Assessment of Adult Competencies (PIAAC) (30), Skills toward Employment and Productivity Survey (STEP) (31), and Demographic and Health Survey (DHS) (32). Existing estimates of educational attainment distributions and resulting MYS by age and sex for all countries for 1970 to 2015 were collected from the Wittgenstein Centre (WIC) Human Capital Data Explorer (20). For countries without direct empirical evidence on adult literacy skills, the statistical estimation model included among others, adult literacy, school enrolment rates, educational expenditure, and pupil–teacher

Significance

After a rapid expansion of primary school enrollment rates in many developing countries starting around 2000, progress toward development goals was widely acknowledged. However, the comprehensive focus on tested literacy skills presented in this paper shows that, in many countries, this expansion in quantity came at the expense of quality. Given the overriding importance of skilled human capital in modern knowledge societies, this is a worrisome trend with the possible negative implications of the current COVID-19 crisis on schooling possibly exacerbating the situation.

Author contributions: W.L., C.R., C.Ö., D.Y., R.G., and A.G. conceptualized the study; C.R., C.Ö., and D.Y. performed methods; W.L., C.R., C.Ö., D.Y., R.G., and A.G. wrote the paper; W.L., C.R., C.Ö., D.Y., R.G., and A.G. reviewed the paper; and W.L., C.R., C.Ö., D.Y., R.G., and A.G. edited the paper.

Reviewers: M.C., Stanford University; J.E.C., The Rockefeller University and Columbia University; and C.J.T., Stanford Graduate School of Education.

The authors declare no competing interest.

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ratios from the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute of Statistics (33), and harmonized learning scores from the Global Dataset on Education Quality (34). The specific data and methods applied are described in detail in *SI Appendix*.

The Demography of Educational Attainment and Skill Changes over the Life Course

In nearly all societies, the transmission of skills starts at very young ages and takes different forms through the stages of child development. This child-centered system of education is based on the highest plasticity of brain functioning at young age (35). In modern societies, formal education in schools starts at ages 5 to 7, and typically ends before age 25, with only some postgraduate education thereafter. The highest level of formal educational attainment rarely changes over the life course afterward. On the other hand, when it comes to the stock of skills and knowledge that individuals possess at certain ages, research has shown that it can increase or decline with age (36).

The prevalence of adult skills in a population at a given time therefore reflects a rather complex interplay of several factors, in particular age and cohort effects. When school participation rates and the length of schooling change over time, as they have recently in virtually all countries, the educational attainment distribution by age portrays the history of educational expansion.

Consider the case of Singapore, for which the educational distribution of the population by age and sex in 2015 is displayed in Fig. 1. More than 80% of men and women aged 25 to 29 have some postsecondary or higher education (dark blue area), which is the highest attainment of young cohorts in the world today, rivalled only by South Korea. At the same time, over a third of women aged 60 to 64 in Singapore have only primary education or never attended any schools (dark red area), which is a result of a cohort effect: The cohort of women aged 60 to 64 in 2015 were 5 to 9 y old in 1960 when Singapore did not have universal primary education because it was still a poor developing country. Hence, under conditions of rapidly expanding school systems, the human capital indicators averaging over the entire adult population provide a poor measure by combining education outcomes of highly educated young cohorts with poorly educated older ones. It is also misleading when researchers use the average education of the youngest cohorts as a proxy for the human capital of the entire adult population in the analysis of the economic returns to education (25). The explicit consideration of age-cohort–specific human capital in economic growth regressions helped to resolve past ambiguities (11). In the context of Singapore, its economy displayed the fastest rates of economic growth when the better-educated young cohorts entered the working ages (37).

Here, we present a way to estimate the quality/literacy skills dimension of human capital, while still maintaining the advantages of cohort-specific analysis. For this, we use PIAAC literacy skills data disaggregated by age, sex, and educational attainment categories. Fig. 1 shows the skills-adjusted educational attainment distribution depending on whether the age–sex–education group is above (filled) or below (striped) the Organisation for Economic Co-operation and Development (OECD)-average literacy skill level of that group. While for the youngest cohorts skills of most people are above the OECD average, for age groups above age 30 the filled areas for all education categories cover less than half of the bars, indicating that literacy skills in Singapore for older cohorts are still predominantly below the OECD average. This implies that while the quantity of education increased rapidly the quality of education improved even faster than the OECD average.

To construct our dataset of SLAMYS, it was necessary to also make assumptions concerning the changes of literacy skills with age. Whereas for backward projections of highest educational attainment distributions only assumptions on differential mortality and migration are required, for the equivalent reconstruction of the literacy skills of the population along cohort lines, the situation is more complex because skills can further increase or decline with age. Fig. 2 compares average literacy test scores from the 1994–1998 IALS and 2011–2017 PIAAC surveys, which use comparable tests for the same cohorts, who were of different ages at the time of the surveys. As expected (36, 38), there is heterogeneity in the pattern of changes with age according to education groups, which reflects the different exposure to cognitive stimulation over their life course. As the figure displays, individuals who completed upper secondary or higher education have, on average, considerably higher test scores in both surveys and an age-pattern of skills different from

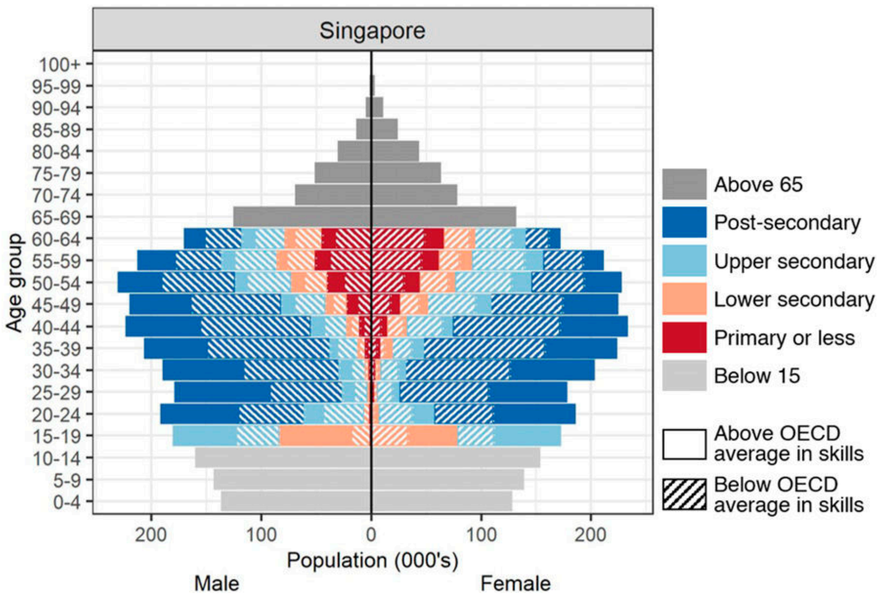

Fig. 1. Age and education pyramid of Singapore 2015 with skills levels at each attainment category being classified as being above (filled) or below (striped) OECD average. Calculations are based on data from the PIAAC Survey of Adult Skills (30) and the WIC Human Capital Data Explorer (20).

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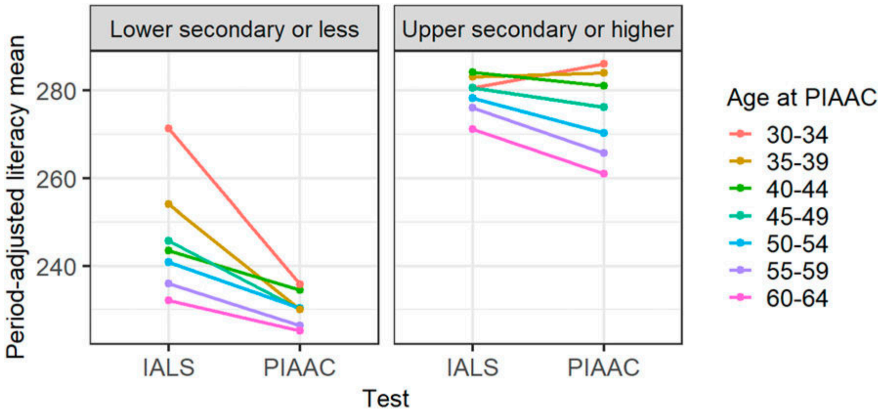

Fig. 2. Changes of skills with age for different age and education groups resulting from a comparison between IALS 1994–1998 (29) and PIAAC 2011–2017 (30) for 16 countries.

other educational categories. Highly educated individuals experience modest gains in literacy skills until the age of 40 when a modest decline starts. In contrast, low-educated individuals face the most dramatic decrease in literacy skills up to age 40, followed by a more moderate decline thereafter. It may be plausible that this pattern is the result of lower skill demand after individuals leave school: While better educated individuals gain some further literacy skills in the work environment, low-educated individuals do not use their formal skills sufficiently, and thus rapidly lose them soon after leaving school. This differential age effect on literacy skills development over the life course is also taken into account when reconstructing the full set of skills-adjusted human capital for men and women along cohort lines from 2015 back to 1970 as described in detail in *SI Appendix*.

Cross-Country and over Time Trends in MYS and SLAMYS

Our method to develop a skills in literacy adjusted human capital indicator, SLAMYS, resulted in a unique dataset of the skills of the working-age population for 185 countries for the period 1970 to 2015. We present here results for selected countries as well as a comparison between trends in SLAMYS and a traditional measure of educational attainment—the MYS, which were drawn from the WIC Human Capital Data Explorer (20). Table 1 presents these indicators for all world regions and selected large countries over 45 y. Data for 185 countries and for quinquennial time intervals are provided in *SI Appendix*.*

At the global level, MYS of the working-age population increased from 4.81 in 1970 to 8.53 in 2015. This is an impressive increase in average educational attainment of the world population, particularly considering that, over the same period, world population also increased from 3.7 to 7.4 billion (39), making school expansion an uphill battle. The respective global improvement in the skills in literacy adjusted human capital, SLAMYS, was from 3.73 y in 1970 to 6.88 y in 2015. Although the absolute difference was smaller for SLAMYS, the relative difference was higher (84 versus 77% increase).

These global average trends hide considerable regional and national differences. In terms of SLAMYS, Eastern Asia displayed the largest increase over time: from 3.16 SLAMYS in 1970 to 8.35 in 2015. On the other hand, sub-Saharan Africa observed an increase from the extremely low level of 0.79 SLAMYS in 1970 to 3.19 in 2015. That means that, currently, sub-Saharan Africa has about the same SLAMYS level as Eastern Asia in 1970. If skills are indeed a key driver of social and economic development, this result implies that sub-Saharan Africa lags almost half a century behind Eastern Asia. For other

Table 1. MYS and SLAMYS of selected regions and countries

	MYS			SLAMYS		
Regions and countries	1970	2015	MYS diff.	1970	2015	SLAMYS diff.
World	4.81	8.53	3.72	3.73	6.88	3.15
Oceania	9.63	13.31	3.68	9.74	14.04	4.30
Northern America	10.68	12.93	2.25	10.32	13.33	3.01
Europe	8.15	12.07	3.92	7.81	12.26	4.45
Eastern Asia	4.53	9.29	4.76	3.16	8.35	5.19
Latin America	4.26	8.71	4.45	2.91	6.84	3.93
MENA	2.69	8.08	5.39	1.65	5.77	4.12
Central and South Asia	2.89	7.32	4.43	1.48	4.92	3.44
Sub-Saharan Africa	1.84	5.91	4.07	0.79	3.19	2.40
Japan	10.68	13.81	3.13	11.09	15.59	4.50
Australia	10.03	13.68	3.65	10.52	14.67	4.15
New Zealand	9.75	13.52	3.77	9.10	14.48	5.38
Finland	8.85	13.03	4.18	8.71	14.27	5.56
Switzerland	10.93	13.40	2.47	11.72	14.14	2.42
Germany	11.94	13.73	1.79	11.41	14.09	2.68
United Kingdom	10.90	13.26	2.36	11.63	13.81	2.18
South Korea	6.02	12.90	6.88	5.57	13.31	7.74
United States	10.69	12.89	2.20	10.34	13.27	2.93
Singapore	4.90	12.64	7.74	3.58	12.28	8.70
Malaysia	3.80	11.61	7.81	2.17	10.12	7.95
Zimbabwe	4.14	10.96	6.82	2.23	8.36	6.13
Saudi Arabia	2.27	10.20	7.93	0.96	8.26	7.30
China	3.61	8.64	5.03	1.98	7.35	5.37
Indonesia	3.63	9.06	5.43	1.99	7.03	5.04
Algeria	1.86	9.70	7.84	0.66	6.48	5.82
Brazil	3.38	7.49	4.11	2.03	5.70	3.67
India	2.43	6.94	4.51	0.95	4.35	3.40
Kenya	2.51	8.28	5.77	0.78	3.61	2.83
Nigeria	1.38	6.75	5.37	0.45	3.28	2.83
Ghana	3.13	7.58	4.45	1.16	2.31	1.15
Burkina Faso	0.26	2.58	2.32	0.07	0.63	0.56
Mali	0.37	2.25	1.88	0.10	0.57	0.47
Niger	0.14	1.95	1.81	0.04	0.56	0.52

MYS, mean years of schooling; SLAMYS, skills in literacy adjusted mean years of schooling.

*Countries were selected based on availability of educational attainment data drawn from the WIC Human Capital Data Explorer. The 185 countries in our sample represent 99.2% of the world's population in 2015.

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major world regions, Latin America in 1970 was only somewhat behind Eastern Asia, but over time has fallen further back. The same is true for Central and South Asia, which displayed an even slower progress than that observed for Latin America, and today has the second lowest SLAMYS after sub-Saharan Africa. Among the industrialized countries, Europe (East and West together) has been catching up with North America, which had a clear advantage in 1970. Recently, Oceania surpassed North America.

A closer look at country-specific trends reveals interesting and unique pathways. Some countries with high levels of SLAMYS in 1970 displayed a remarkable increase over time, even more than the observed rate for the conventional MYS. Japan in 1970 in terms of SLAMYS was fifth after Switzerland, Latvia, United Kingdom, and Germany, and made it to the top of the list with 15.59 SLAMYS in 2015, a performance considerably better than the United States, with 13.27 SLAMYS in 2015. Finland also showed a formidable increase from being only 17th in Europe in 1970 to the highest level of SLAMYS in Europe in 2015. Outside of Europe, South Korea had a very impressive rate of increase in SLAMYS, starting from only 5.57 in 1970 and having surpassed the United States with 13.31 in 2015.

On the other end of the spectrum, many countries in Africa and South Asia were making rather good progress in terms of the conventional MYS, but much less so when considering SLAMYS. For Ghana, for instance, MYS more than doubled from 3.13 to 7.58 between 1970 and 2015, but SLAMYS increased only marginally from 1.16 to 2.31. Africa's most populous country, Nigeria, showed a similar pattern: MYS increased very impressively by a factor of almost five from 1.38 to 6.75 (more than South Korea in 1970); however, SLAMYS for Nigeria only increased from a very low 0.45 in 1970 to 3.28, which equals roughly the current African-continent average. Kenya shows a similar pattern: Formal schooling rates expanded very rapidly over the past decades, but the measured skills could not keep pace with this expansion. Nevertheless, there is also significant heterogeneity across Africa. Niger stays with little improvement at the bottom level, with 1.95 MYS and a mere 0.56 SLAMYS in 2015. On the other hand, Zimbabwe has shown significative gains in SLAMYS, which increased by almost a factor of four (from 2.23 in 1970 to 8.36 in 2015), reaching the same level of skills as the average of Eastern Asia today. The evidence for Zimbabwe again illustrates the momentum of increases in human capital of the working-age population, as the country still benefits from its previously excellent school system, which prevailed before the conflicts and related challenges (40).

This study challenges the view that the partly impressive recent gains in the expansion of schooling in many developing countries lead to a corresponding increase in human capital. When considering the estimated skills of the working-age population rather than school enrolment rates, the picture looks less impressive. Fig. 3 depicts the differences between quartiles of the distribution of MYS and SLAMYS for all countries ranked by their average level over 1970 to 2015 and grouped into quartiles accordingly. The picture shows the change over time in the difference between the mean of the countries above the highest quartile and the mean of the countries below the lowest quartile. For MYS, this difference peaked around 1990 to 1995 and has since declined because some of the countries with very low education levels have made progress in terms of expanding formal education. However, the trend over time in SLAMYS shows no such reversal. The gap between highly skilled and low skilled populations is widening and has increased to the equivalent of over 10 y of schooling.

This widening global gap in the literacy skills of the working-age population will have significant implications for disparities among countries in their economic development, health, and well-being, particularly in the current transition to knowledge societies and the digital revolution. Given the great relevance of our findings for policymakers at all levels, we want to conclude by accentuating the need for internationally comparable widespread testing of adult skills beyond literacy, which would enable us to further extend our analyses to additional skill domains.

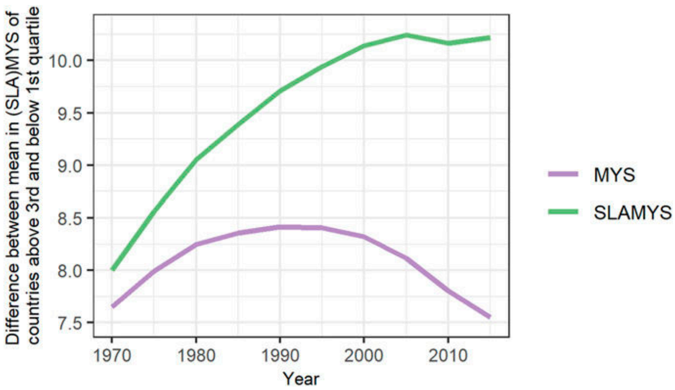

Fig. 3. Difference between the mean of countries above the third quartile and the mean of countries below the first quartile in mean years of schooling (MYS) and skills in literacy adjusted mean years of schooling (SLAMYS), 1970–2015. Calculations are based on data from the PIAAC Survey of Adult Skills (30), the World Bank's STEP Skills Measurement Program (31), the Demographic and Health Survey (32), the WIC Human Capital Data Explorer (20), the International Adult Literacy Survey (29), UIS statistics (33), and the global dataset on education quality (34). Countries are ranked based on their average SLAMYS between 1970 and 2015.

Materials and Methods

Our analyses throughout this paper exclusively focus on literacy skills, as literacy assessments are available for the largest number of countries. Sensitivity analyses revealed, however, that literacy skills are highly correlated with other skills domains, thus also providing a good proxy for the overall skill level in the population—particularly when considering them at the aggregate level. More details on the correlations between literacy skills and other types of skills can be found in *SI Appendix*.

Our empirical exercise relies on data harmonization, demographic modeling, and statistical estimation for 185 countries. More specifically, the SLAMYS dataset was developed in three steps: First, for 44 countries SLAMYS were computed using comprehensive adult literacy skills data from three different survey types: IALS (29), PIAAC (30), and STEP (31). Second, to increase coverage among developing countries, we used DHS tested literacy data (32) to provide skills adjustments for 59 additional countries. Finally, to expand the dataset to a global scale, we used a prediction regression model for countries where no empirical adult skills data are available. This statistical estimation model included, among others, adult literacy, school enrollment rates, educational expenditure, and pupil–teacher ratios from the UNESCO Institute of Statistics (33), and harmonized learning scores from the Global Dataset on Education Quality (34). Data for MYS by country, age, and sex were retrieved from the WIC Human Capital Data Explorer (20).

As our estimates are based on the average performance of populations, our standard of comparison for the literacy skills adjustment equals the 2015 population-weighted OECD mean PIAAC literacy test score, calculated separately for males, females, 5-y age groups, and four educational attainment categories. The skills adjustment was designed in such a way that, for the standard of comparison, the MYS is set to be equal to the SLAMYS for OECD. As a consequence, if a country's age–sex–education subpopulation group performs worse than the population-weighted OECD mean, its SLAMYS will be lower than its MYS; accordingly, for any country-specific age–sex–education subpopulation group, which scores better than the OECD mean, the opposite holds. Demographic modeling techniques were applied to consider the temporal evolution of SLAMYS since 1970: Time-series estimates rest on the reconstruction of mean literacy test results along cohort lines, based on observed age effects from countries where adult literacy skills data exist for more than one point in time. A more detailed description of data sources used and methods applied can be found in *SI Appendix*.

Data Availability. All study data are included in the article and/or supporting information.

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Supplementary Information for

Skills-adjusted human capital shows rising global gap

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Supplementary Information Text

DATA AND METHODS

The SLAMYS dataset was developed in three steps: first, for 44 countries SLAMYS were computed using comprehensive adult literacy skills data (PIAAC (1) and STEP (2)). Second, to increase coverage among developing countries, we used DHS (3) tested literacy data to provide skills adjustments for 59 additional countries. Finally, to expand the dataset to a global scale, we used a prediction regression model for countries where no empirical adult skills data are available. A detailed description of all data sources used can be found elsewhere (4).

Literacy skills represent only one domain of a variety of skills considered essential for the formation of human capital. However, the limited availability of assessment data of other skill domains (e.g. numeracy, problem-solving skills, etc.) for many countries and over time constrains us in using a more comprehensive definition of skills for the estimation of skills-adjusted human capital. Thus, analyses throughout this paper exclusively focus on literacy skills. Despite this limitation, sensitivity analyses revealed that literacy is highly correlated with other type of skills. Figure S1 displays the correlation between mean literacy scores and mean numeracy scores (left-hand plot) and between mean literacy scores and mean scores in problem-solving in technology-rich environments (right-hand plot) by age, sex, and country for all countries participating in PIAAC. The high Pearson correlation coefficients, particularly for numeracy (0.96) but also for problem-solving (0.87), and the high statistical significance (p-value < 0.001 in both correlation tests) point out that the level of literacy skills is a good proxy for the overall skill level in the population - particularly when considering them at the aggregate level.

In addition, it is important to note that even for countries with comprehensive adult literacy skills data available, issues of measurement errors cannot be completely ruled out. Despite advanced and complex survey designs which specifically aim at reducing potential sources of error and maximizing the quality of the data produced, tests as in PIAAC or STEP may still suffer from a variety of problems. Amongst others, these may include the sampling of knowledge in the particular domain, the reliability of question, or the impact of test taking conditions on scores (5). A discussion on potential measurement errors resulting from the prediction regression model and from measuring the quantitative dimension, i.e. Mean Years of Schooling, can be found at the end of the SI.

Calculation of SLAMYS based on empirical PIAAC and STEP data

Computations for the base year (2015)

When adding a skills dimension to educational attainment, a standard of comparison needs to be established, whether it is a perfect (unattainable) score (e.g. 500 in PIAAC; 1,000 in PISA, etc.), a benchmark result of the top-performer, or the performance of any group of individuals. Since our estimates are based on the average performance of populations, we decided to use the mean proficiency of the OECD population, disaggregated by age-sex-education groups, as a standard of comparison. Specifically, our standard equals the 2015 population-weighted[*] OECD[†] mean PIAAC literacy test score, calculated separately for males, females, 5-year age groups (between 15-19 and 60-64), and four educational attainment categories (primary or less, lower secondary, upper secondary, and post-secondary education).

The skills adjustment was designed in such a way that, for our standard of comparison, the Mean Years of Schooling (MYS) is set to be equal to the Skills in Literacy Adjusted Mean Years of

[*] Population estimates by age, sex, and educational attainment come from the Wittgenstein Centre Data Explorer.

[†] Since PIAAC literacy test results are freely available for only 30 of the 36 OECD countries, six OECD countries had to be excluded in the calculation of the benchmark: Australia, Iceland, Latvia, Luxembourg, Portugal, and Switzerland.

Schooling (SLAMYS) for OECD. As a consequence, if a country's age-sex-education sub-population group performs worse than the population-weighted OECD mean, its SLAMYS will be lower than its MYS; accordingly, for any country-specific age-sex-education sub-population group which scores better than the OECD mean, the opposite holds.

Formally, consider $SLAMYS_{c,a,s,e}$ as the skills-adjusted mean years of schooling for country c, age group a, sex s, and education level e in the base year 2015. Also, let $MYS_{c,a,s,e}$ represent the respective mean years of schooling, and $MP_{c,a,s,e}$ the mean literacy score in PIAAC/STEP. Finally, consider $MP^{*}_{a,s,e}$ the mean performance of the benchmark (population-weighted OECD PIAAC mean literacy score) age-sex-education group. The skills-adjusted measure is defined by

$$SLAMYS_{c,a,s,e} = MYS_{c,a,s,e} \text{ x } (MP_{c,a,s,e} / MP^{*}_{a,s,e}) \quad \text{(Eq. 1)}$$

In this way, we estimated SLAMYS for 44 countries for the base year 2015[‡], disaggregated by 5-year age groups, sex, and four levels of educational attainment[§]. SLAMYS for 36 countries are based on PIAAC data; for 8 countries on STEP literacy test results[**]. Data for MYS by country, age, and sex were retrieved from the Wittgenstein Centre (WIC) Human Capital Data Explorer (6).

Reconstruction of SLAMYS along cohort lines (1970-2015)

The estimation of SLAMYS for quinquennial years between 1970 and 2015 is based on the same rationale as provided by Eq. 1, but now including the time dimension t. The 2015 population-weighted OECD mean proficiency is held constant over time as the standard of comparison.

$$SLAMYS_{c,a,s,e,t} = MYS_{c,a,s,e,t} \text{ x } (MP_{c,a,s,e,t} / MP^{*}_{a,s,e,2015}) \quad \text{(Eq. 2)}$$

Since large-scale assessment tests of adult literacy were only introduced in the 1990s for a handful of countries, we had to follow a different approach to estimate SLAMYS for several decades. Therefore, time-series estimates for SLAMYS rest on the reconstruction of $MP_{c,a,s,e,t}$ along cohort lines, based on observed age effects from countries where $MP_{c,a,s,e,t}$ exists for more than one point in time.

Our cohort analyses are based on a pooled dataset of IALS (1994-1998) (7) and PIAAC (2011-2017) (1) from which we built age cohorts[††] to investigate the skill development of different age groups over a period of roughly 20 years. Ideally and when available, we used single age, which were then aggregated to 5-year age groups, depending on the year the surveys took place and the time lag between different surveys in each country. For example, in the United States surveys took place in 1996 (IALS) and 2014 (PIAAC); hence, our analysis follows a cohort, which was e.g.

[‡] Base year estimates within this paper refer to the year 2015. However, skills adjustments originate from any round of data collection of PIAAC cycle 1 (2011-2017) or STEP data collection between 2012 and 2016. As interpolation of skills data in single-year intervals to obtain 2015 values is not possible due to the non-availability of more than one data points over time for most countries, PIAAC and STEP literacy test results provide the unmodified basis for 2015 SLAMYS despite small variations in time.

[§] We refrained from a more detailed disaggregation of education categories as test sample sizes would otherwise become too small.

[**] As the target population of the STEP Skills Measurement Program is limited to urban adults, STEP results were adjusted to represent the entire country. Urban-rural corrections in literacy skills were derived from DHS, with the ratio between DHS literacy results of the total population and DHS literacy results of the urban population serving as the correction factor. For three countries (Bolivia, Ghana, and Kenya) country-specific DHS information was used; for five countries where no tested literacy data from DHS are available (Armenia, Colombia, Georgia, Ukraine, and Vietnam) corrections are based on regional averages.

[††] Ideally, we would be able to follow the same individuals over their life course. However, as no true panel data are available, we take advantage of the fact that although we cannot observe the same people at different points in time, we are able to observe representative samples of the population at different points in time.

25-29 years old in IALS and 43-47 years old in PIAAC. A direct comparison between the two surveys is possible as they are based on the same scoring scale range and trend items from IALS were included in PIAAC, allowing literacy data to be linked for countries participating in both surveys.

At present, not enough data are available to expand these empirical cohort analyses to a global scale and a longer period. Therefore, we assumed a standard skill-age decay pattern by pooling all countries that participated in both IALS and PIAAC. Next, we adjusted for the mean score difference observable for the same age group in different years to separate the pure age effect – which is assumed to be more stable across countries and time – from the more context-sensitive cohort effect. These calculations were done for two broad education categories ('lower secondary or less' and 'upper secondary or higher') separately to account for potential differences in skill loss/gain due to attainment of formal education. Results imply that the skill loss due to age significantly differs by educational attainment levels and age (see Figure 2 in the Main Manuscript): while those with lower education tend to lose the highest share of their skills rather soon after leaving school, higher-educated people are still able to moderately gain skills up to the age of 35. After that, skills remain largely constant until the age of approximately 45 when cognitive skills eventually start decreasing. Sensitivity analyses of conducting the same kind of analysis for different countries separately confirmed that the patterns tend to be largely constant for different populations.

Based on these period-adjusted trends of cohorts over time, we derived an age- and education-level specific skill growth function over the life course, which is assumed to be constant for all countries and over time. This estimated percentage growth of skills over the life course is essential for the reconstruction of literacy test scores over time along cohort lines. More specifically, we take the scores of 60-64-year-olds tested in 2015 as the basis for the estimated score of 55-59-year-olds in 2010, adjusted by the percentage change due to the assumed reverse age pattern[‡‡]. In this way and based on the country-, age-, sex-, and education-specific literacy scores from PIAAC and STEP, we estimated mean scores by 5-year age groups, sex, and four education categories from 1970-2015 for all 44 countries with empirical data available[§§]. SLAMYS were then calculated based on Equation 2, with the 2015 OECD average used as standard of comparison in all years. To aggregate SLAMYS by country and year, we weighted the scores based on the population size by age, sex, and educational attainment for each country and year, as retrieved from the WIC Data Explorer.

Adjustments for calculating SLAMYS using DHS data

As noted above, comprehensive adult literacy skills assessments are available only for 44 countries – most of them highly developed OECD members, thus unrepresentative of the world population. To include more empirical observations in our dataset, we decided to use tested literacy data from DHS for 63 countries that are more diverse in social and economic development.

As literacy assessments in DHS and PIAAC/STEP differ substantially in complexity and scope of the tests, further models had to be applied. We took advantage of the fact that four countries, i.e. Bolivia, Ghana, Kenya, and Peru, have participated in both PIAAC/STEP and DHS. Based on their concordance between PIAAC/STEP literacy proficiency and DHS literacy, adjustment scores were calculated for each population considering the proportion of the population that have tested

‡‡ For age groups for which we were not able to build cohorts for the whole or part of the reconstruction period (e.g. 60-64-year-olds in 2010 who were too old to be tested in 2015), we assumed age-, sex- and education-specific scores to be constant over time.

§§ While the empirical scores of the base year are disaggregated by age, sex, and four levels of educational attainment, the estimated standard age effect as well as the estimated skill growth function over the life course are only defined for two education categories. This crude disaggregation was found to be most consistent between countries. Given the different scores in the base year, reconstruction results, however, still differ between sexes and are available for four education categories.

literacy in DHS. As a result, PIAAC/STEP literacy proficiencies and consequently SLAMYS could be estimated for 59 additional countries. To validate our results, the ratios between the SLAMYS calculated using PIAAC/STEP results and SLAMYS estimated by DHS tested literacy data were checked for Bolivia, Ghana, Kenya, and Peru, i.e. the countries that have both sources of information. Results showed that due to conducting an easier literacy test DHS-SLAMYS estimates were consistently 25% higher than the estimates calculated by empirical PIAAC/STEP scores. For this reason, we made a further adjustment by multiplying the SLAMYS estimates derived from DHS tested literacy data by a factor of 0.8.

Calculation of SLAMYS based on prediction regression models

As explained above, SLAMYS based on PIAAC/STEP and DHS data were calculated for 103 countries. For the remaining countries SLAMYS were estimated using ordinary least squares regression models. In these models, skills-adjustment factors ($SAF_{c,t}$) are predicted as dependent variables for every country c and time t (5-year intervals between 1970 and 2015). Based on these predictions, SLAMYS were calculated as the product of $SAF_{c,t}$ and $MYS_{c,t}$ (as demonstrated in Eq. 1) [***].

Several educational and demographic variables from various data sources were used as estimators in these models. First, to capture the basic literacy skills in the population, we included adult illiteracy rates ($AIR_{c,t}$) from the UIS dataset (8). Because of almost 100 percent literacy rates in most of the developed countries, this indicator is more useful to distinguish the differences among developing countries. Second, to capture the effect of schooling beyond basic education, the percentage of adult population having at least upper secondary educational attainment ($aboveLS_{c,t}$) from WIC Data Explorer (6) is included in the model. Third, country- and time-specific old-age dependency ratios ($ODR_{c,t}$) (also from WIC Data Explorer) are included as a proxy for the state of the demographic transition in a country.

Additionally, to capture the effect of the level of quality of education, we included a 'Quality of Education Indicator'($QEI_{c,t}$) as an additional independent variable in the model. International data on quality of education are, however, limited and relatively new. Recently, the World Bank introduced a Global Data Set on Education Quality (9) (GDSEQ), covering harmonized data from international student assessments for 163 countries between 1965 and 2015. However, since these tests were only recently extended to more countries, the dataset contains many missing values – especially for earlier time periods. For this reason, we constructed a separate model that predicts QEI by using GDSEQ scores for available countries and time periods as dependent variables[†††].

As QEI represents a measure of skills of young cohorts who are still in school at the time of assessment, its effect on skills of the working-age population can only occur with a certain time delay. Consequently, and to be demographically consistent, QEI is – if possible – considered in the model with a time lag of 25 years. However, since QEI data only go back to 1970, which would enable predictions only from 1995 onwards when using a 25-year time lag, we used QEI estimates for 1970 for the time periods from 1970 to 1995 and QEI estimates with a 25-year lag from 1995 onwards.

Dummy variables for the respective time periods are added as further independent variables. By using a stepwise regression procedure, we attain the final model for predicting $SAF_{c,t}$ in Eq. 3.

$$\log(SAF_{c,t})=\beta_0 + \beta_1 aboveLS_{c,t} + \beta_2 ODR_{c,t} + \beta_3 AIR_{c,t} + \beta_4 QEI_{c,1970/t+25} + \Sigma_{t=1970-1990}\,\delta_t + \varepsilon_{c,t} \qquad \text{(Eq.3)}$$

[***] The main reason to predict SAF instead of SLAMYS is to prevent any multicollinearity issues between MYS and other estimators.

[†††] To predict QEI, dummies for UN detailed geographical regions for every country as well as two other quality of education indicators from UIS dataset (government expenditure on education as a percentage of GDP and pupil-teacher ratio in primary education) are used as predictors in the model. The model summary can be found in Table S1.

Using Equation 3, skills-adjustment factors were predicted for 185 countries (in 5-year time steps between 1970 and 2015). Finally, $SAF_{c,t}$ estimates were multiplied with $MYS_{c,t}$ for the given country and time to calculate SLAMYS. The adjusted R^2 of 83 percent and a correlation coefficient of 0.984 between estimated and empirical SLAMYS point at a good model fit. A detailed regression model summary can be found in Table S2 and regression diagnostics are presented below.

Albeit SLAMYS were predicted for all 185 countries, our global SLAMYS dataset as presented in Table S3 is based on empirically sound data (estimates from PIAAC, STEP and DHS) whenever possible, and uses predicted values only if no empirical data are available. Table S4 provides a quantitative assessment of the data quality by summarizing on the continent level how many of the 1,850 data points (185 countries, 10 points of time) are based on PIAAC & STEP, how many on DHS, and how many are predicted from Eq. 3.

Comparison with student test results

To validate our results, we conducted a correlation analysis between SAF and student test scores. Figure S2 depicts the correlation between our estimated SAF and PISA reading scores (10). Given that our estimates cover the total working-age population, whereas PISA measures the skills of 15-year-olds, we used a time lag of 15 years, i.e. we compare PISA scores from the year 2000 with the 2015 SAF for all countries where both data are available. It is important to mention, however, that our prediction model already includes a Quality of Education Indicator as independent variable. As explained before, this indicator is based on the World Bank's Global Data Set on Education Quality (9), which covers harmonized data from international student assessments including PISA, TIMSS etc. Consequently, our measure indirectly already covers student tests; the high level of correlation (r=0.75) is therefore not surprising.

In addition, we ran age-specific correlation analyses (SAF of 15-19-year-olds vs. PISA scores of 15-year-olds in the closest year) for different years for those countries with empirically derived SLAMYS (see Figure S3). Given that SAF estimates for these countries are based on PIAAC/STEP data, these analyses represent in fact the very noticeable correlation between PISA and PIAAC/STEP scores. Relatively high correlation coefficients between 0.67 and 0.84 – depending on different years and combinations of countries – were found, suggesting that validity and reliability of the test results hold.

Regression diagnostics

There are several assumptions for OLS regression models. One of them is the normality of errors. The two plots at the top of Figure S4 shows the distribution of residuals for the model in Table S1. Residuals seem to be distributed normally.

In OLS regression models, predictors should not be correlated with residual terms. The two graphs at the bottom in Figure S4 are the scatter plots between the continuous numerical predictors in the model and residual terms. There seems to be no relationship between the predictors and residuals.

Furthermore, it is assumed that there is a linear relationship between predictors and the dependent variable in OLS models. The top left plot in Figure S5 does not show any pattern between fitted values and residuals. The horizontal line without a distinct pattern can be said to confirm the linearity assumption.

Another assumption is the constant variance of residuals which is called homoskedasticity. The two graphs on the left-hand side of Figure S5 show that there is not a relationship between fitted values and residuals which is indicating homoskedasticity. Moreover, Breusch-Pagan test for homoskedasticity also produces a p-value of 0.32 which means there is not enough evidence to reject the null hypothesis claiming homoskedasticity.

The Residuals vs Leverage plot positioned in the bottom right in Figure S5 helps to detect outliers in the model. In the plot, there are not any cases of outliers that exceed Cook's distance measure.

Finally, in OLS regressions models, independent variables should not have a high correlation (multicollinearity) among themselves. To check this assumption, Variance Inflation Factor (VIF) scores have been calculated. None of the predictor terms have a VIF score above ten and the mean of the VIF scores is below five which means there is no multicollinearity.

Assumptions for OLS regression are also tested for the model in Equation 3. The top two plots in Figure S6 show the distribution of error terms that indicate a nearly normal distribution confirming the normality assumption. The rest of the plots in Figure S6 are scatter plots between the predictors and residuals. It can be said that there are no correlations between them.

However, the decreasing variance for residuals in some of the plots in Figure S6 indicate that there might be some level of heteroskedasticity. This pattern is also visible in the top left plot in Figure S7. Variance for the top end of the fitted values is smaller. Moreover, studentized Breusch-Pagan test produces a p-value less than 0.05 which shows evidence to reject the constant variance of residuals hypothesis.

The violation of the homoskedasticity assumption may lead to an underestimation of standard errors. Zeileis (11) offers a procedure for a robust estimation of standard errors[‡‡‡]. While the coefficients in Eq. 3 are tested with these new standard errors, the significance of the predictor terms have not changed at a 95% confidence level. Moreover, we are more interested in the estimation of the dependent variable than predicting the effects of specific independent variables. Since heteroskedasticity does not lead to a bias in the coefficient estimates (12), it should not affect our SLAMYS estimates.

The bottom right plot in Figure S7 shows that all observations are within Cook's distance which means there are not any cases of outliers that are highly influential. Lastly, VIF scores for all predictors are less than five which confirms that there is no multicollinearity.

The above tested regression diagnostics deal with the assumptions about the error related to the dependent variable. In OLS regression, it is assumed that independent variables are measured without error. However, in most cases independent variables are measured with some degree of error. Errors in variables (EIV) models offer a solution for the potential cases of measurement errors in independent variables (13). In our case, our numerical predictors may contain a degree of measurement error but it is not possible to know the exact levels. Using eivtools package in R (12) we calculated the adjustment scores with varying amounts of reliability for the numerical predictors in Eq. 3 one by one to get an understanding of the sensitivity of our model to measurement errors. For each variable we run three different models with reliability values 0.95, 0.90 and 0.85. Figure S8 plots the fitted adjustment factors of the main model (y-axis) against the fitted adjustment factors from various errors in variance models (x-axis). The figure shows that the fitted values are robust to decreases in reliability scores.

<u>A note on measurement errors in Mean Years of Schooling</u>

Finally, albeit the focus of this paper is on measuring skills, it is important to not completely neglect the potential of measurement errors in the quantitative dimension of our indicator, i.e. potential measurement errors in MYS. Krueger and Lindhahl (14) thoroughly discussed the problem of estimating the extent of measurement error in cross-country data on average years of schooling, concluding that measures tend to be particularly noisy when based on frequently mismeasured enrollment rates. However, also in more advanced measures of educational attainment, such as the widely used Barro and Lee dataset (15), that draws on survey- and census-based estimates reported by UIS, errors in measurement are inevitable given the doubtful quality of UIS enrolment rates in many countries.

‡‡‡ Robust standard errors were calculated via "sandwich" package in R.

Data on MYS used in this paper are retrieved from the WIC Data Explorer (6) which provides an advance over other existing international measures of educational attainment on several grounds: i) the WIC methodology is based on original data (as opposed to data compiled by other institutions, like UIS or EUROSTAT); ii) all data are thoroughly harmonized using available ISCED mappings in order to achieve better comparability and avoid flaws in the primary data; and iii) estimates rely on assumptions and rules, and the consistency of these over countries is important. The detailed methodology for the WIC global MYS estimates can be found elsewhere (16, 17).

Given the before-mentioned advances, variations in the MYS between WIC and Barro-Lee as well as between WIC and UIS are not surprising and can be traced back to different types of source data, different definitions on the educational categories, flaws in the input data, different procedures employed in estimation of the educational shares, and differences in the estimation of durations of schooling for incomplete levels. Consequently, and given the consistency and comparability across countries, MYS estimates used in this paper are unlikely to distort our SLAMYS results.

DATA AND CODES AVAILABILITY

Data and codes used to generate the results are available in the GitHub repository, https://github.com/clreiter/WIC-Skills-Adjusted-Human-Capital/tree/final-preparation-repository.

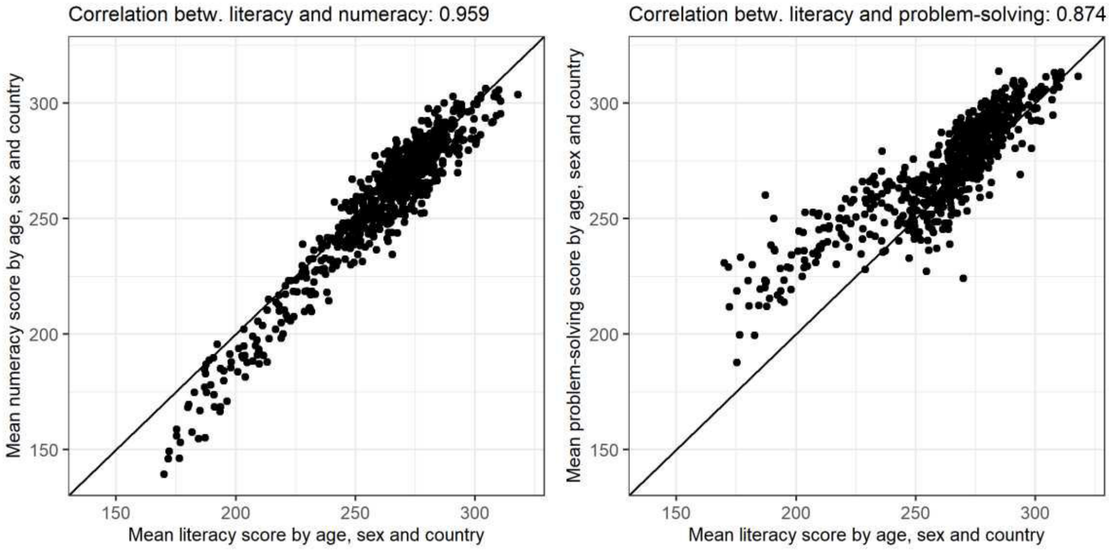

Figure S1. Correlation between PIAAC mean literacy and numeracy scores (left) and PIAAC mean literacy and problem-solving in technology-rich environment scores (right), by age, sex and country, all PIAAC countries.

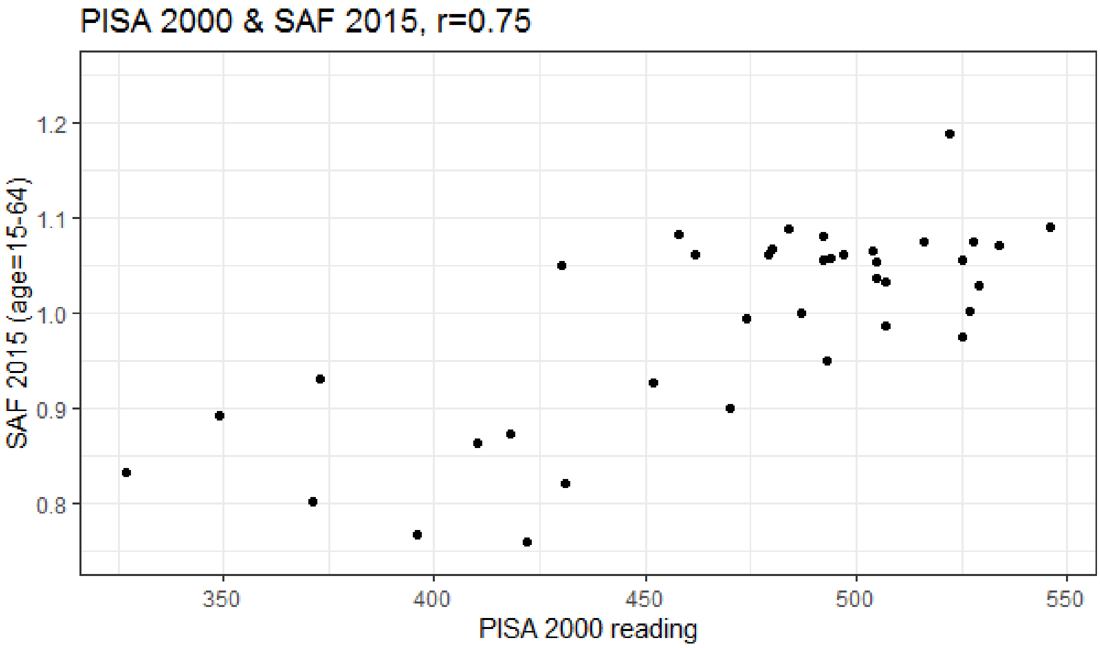

Figure S2. Correlation between estimated SAF 2015 and PISA mean reading score, by country (all countries with available data are considered).

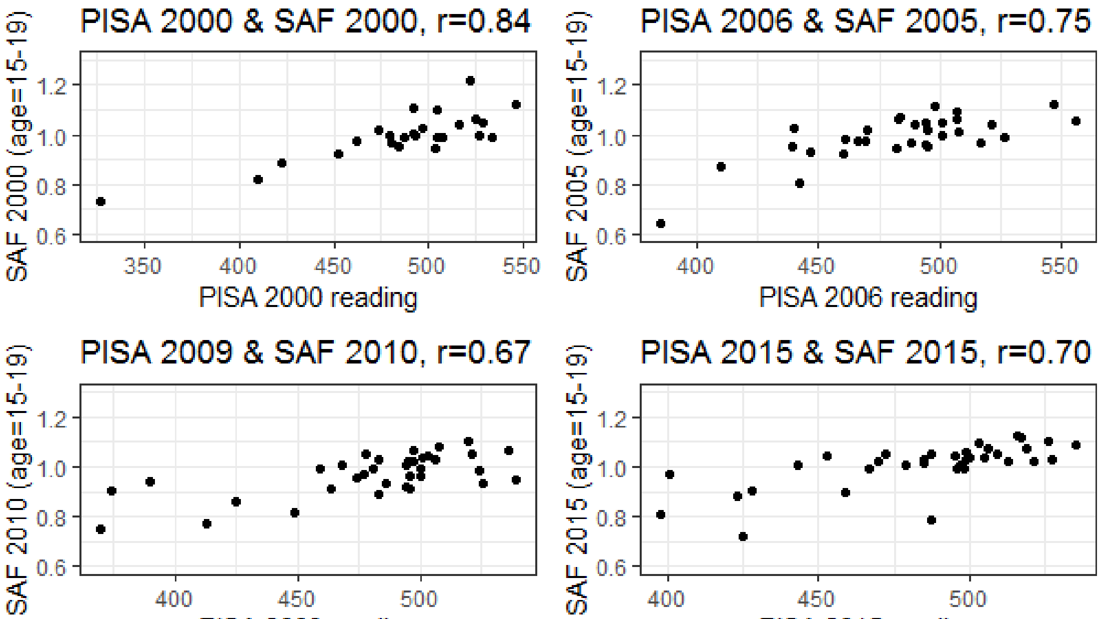

Figure S3. Correlation between SAF for 15-19-year-olds (based on PIAAC/STEP data) and PISA mean reading score, by country (all countries with available data are considered).

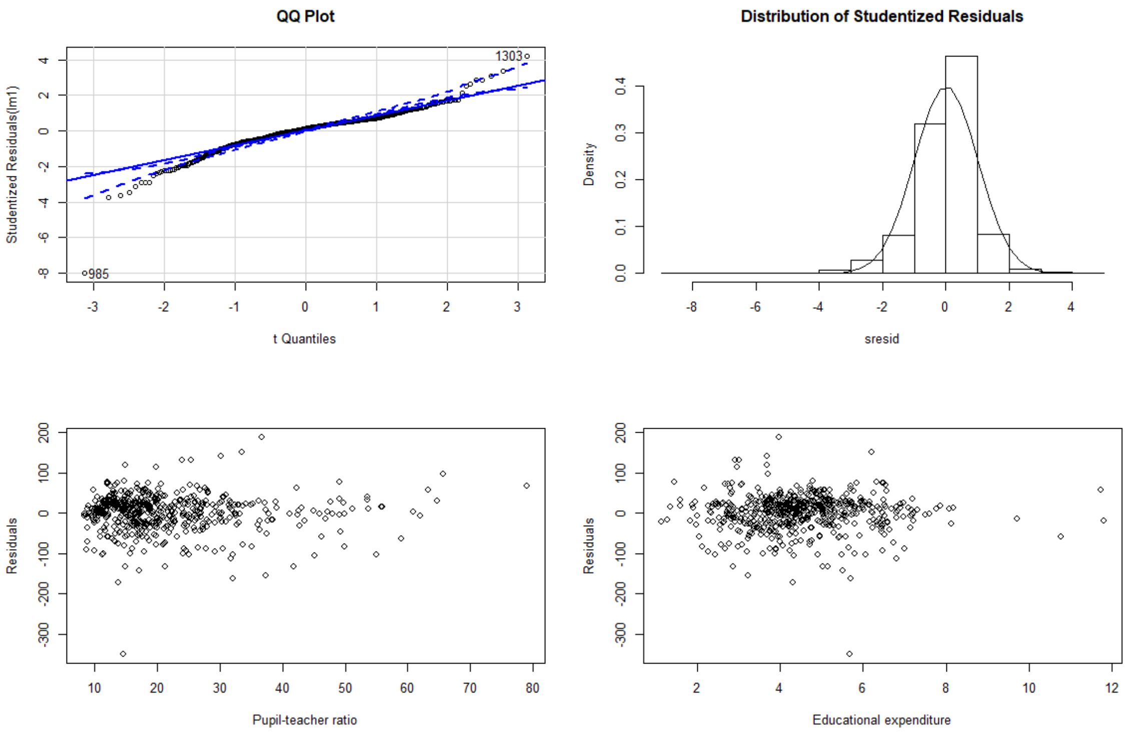

Figure S4. Residual plots for the model estimating QEI scores.

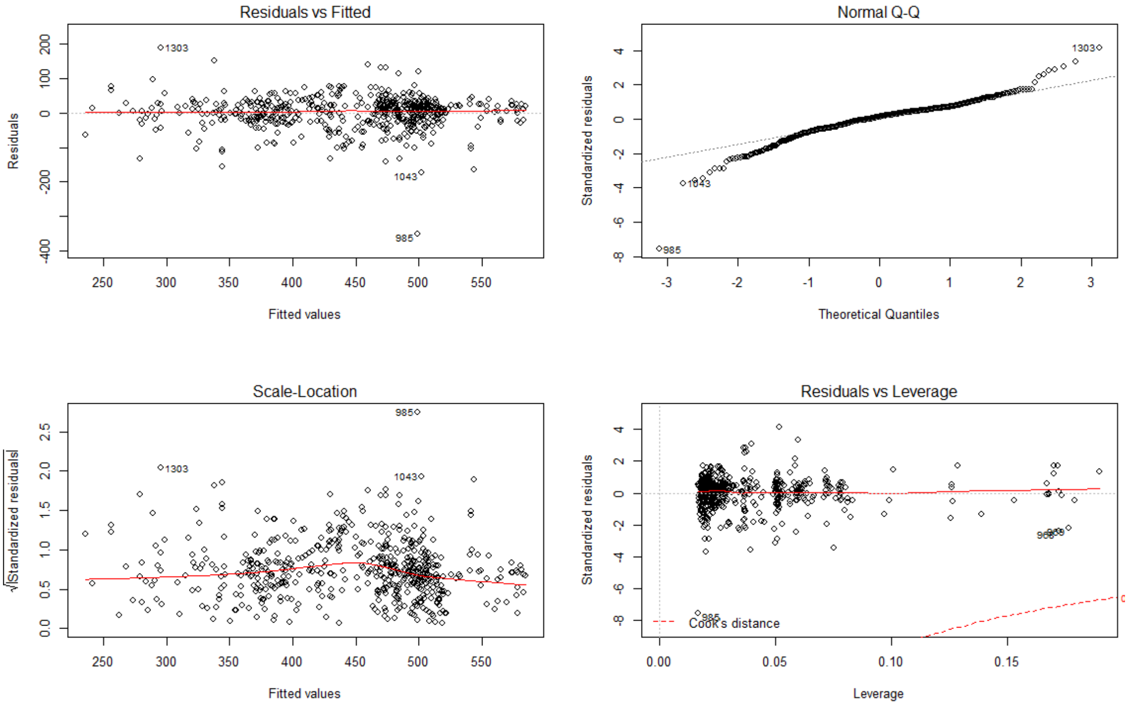

Figure S5. Residual plots for the model estimating QEI scores.

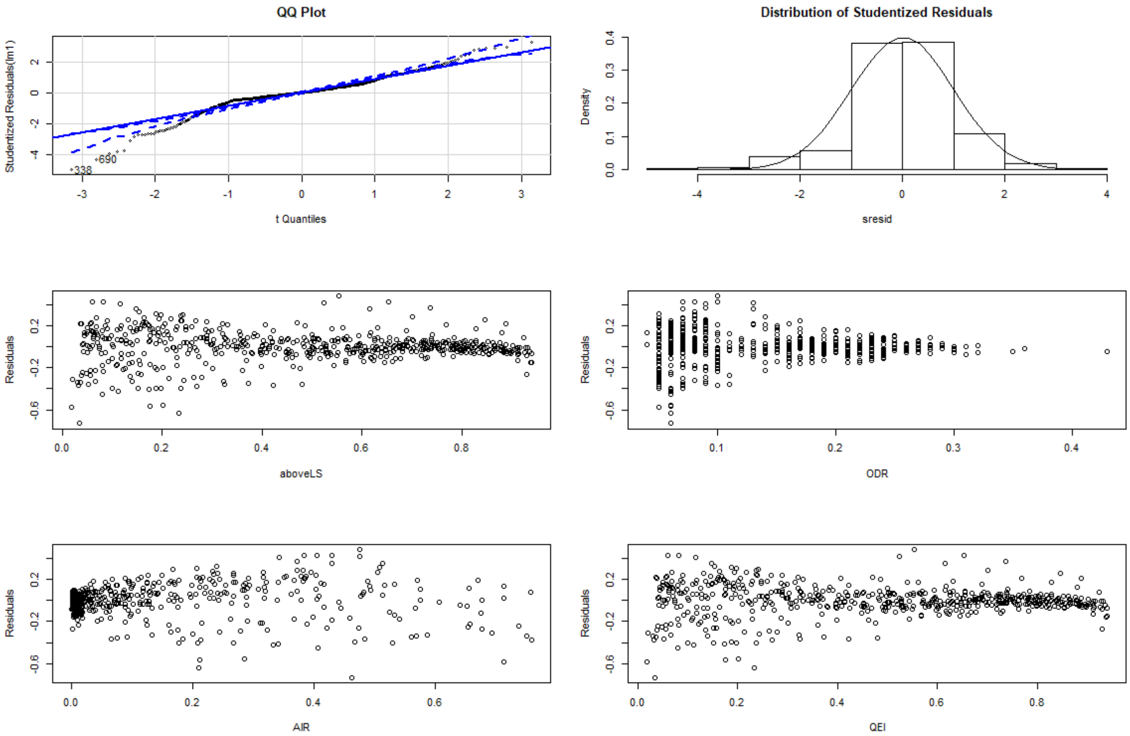

Figure S6. Residual plots for the model estimating SLAMYS (Eq. 3).

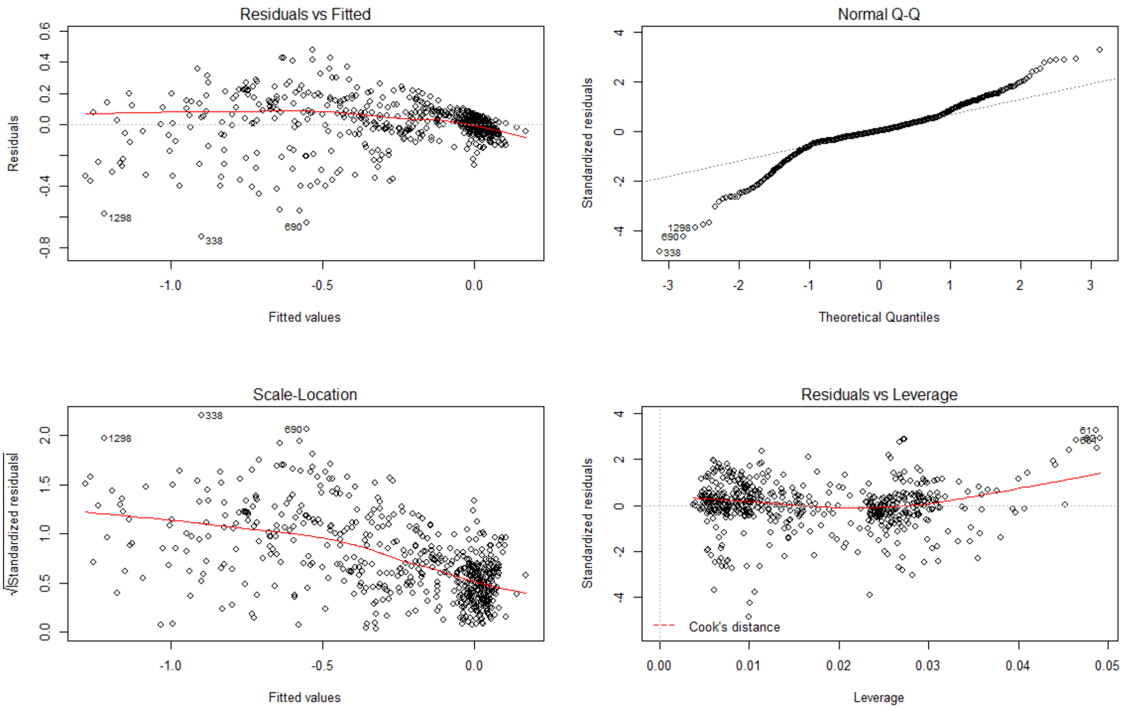

Figure S7. Residual plots for the model estimating SLAMYS (Eq. 3).

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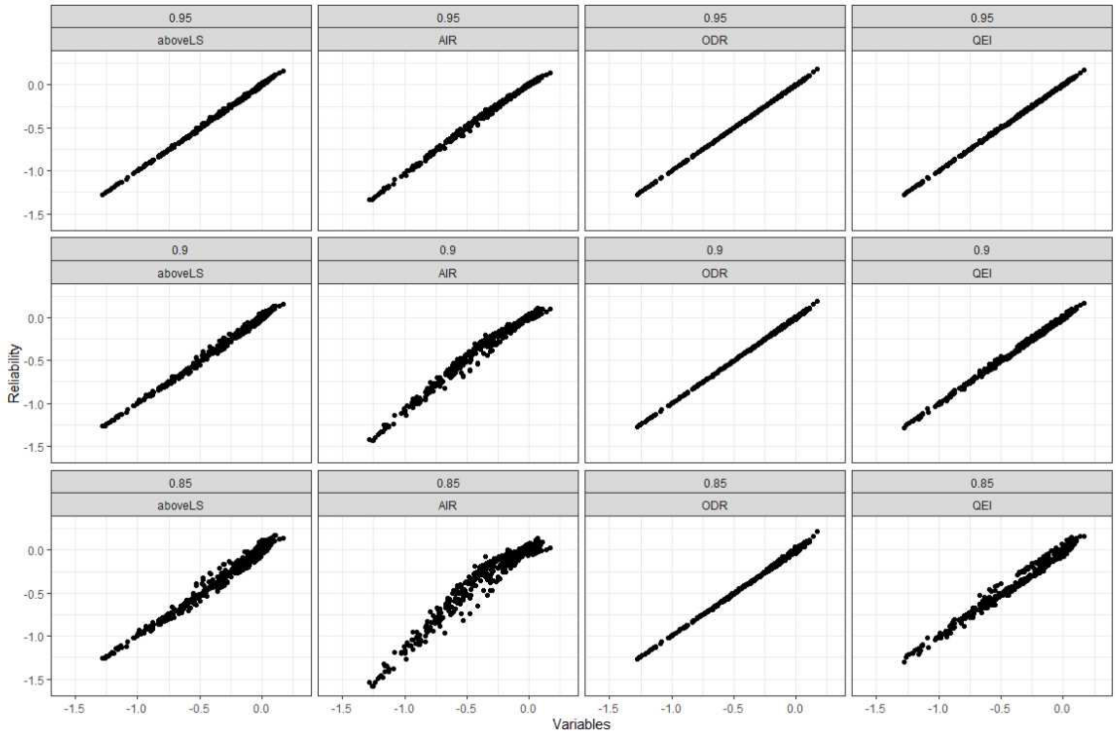

Figure S8. Fitted adjustment factors with different reliability values in Errors in Variance model (x-axis) vs fitted adjustment factors from the main model (Eq. 3) (y-axis).

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Residual std. error	Multiple R^2	Adjusted R^2	F	df	p	n
46.82	0.70	0.69	62.35	20; 525	0.000	546

Coefficients

Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	442.822	20.330	21.782	0.000
Pupil-teacher ratio	-2.608	0.339	-7.697	0.000
Educational expenditure	2.820	1.819	1.550	0.122
Central America	-1.164	19.786	2.334	0.020
Central Asia	59.126	25.334	2.334	0.020
Eastern Africa	7.396	20.696	0.357	0.721
Eastern Asia	168.028	18.538	9.064	0.000
Eastern Europe	88.776	17.962	4.943	0.000
Middle Africa	5.927	27.766	0.213	0.831
Northern Africa	-13.237	21.145	-0.626	0.532
Northern America	85.873	20.114	4.269	0.000
Northern Europe	78.329	17.708	4.423	0.000
Oceania	60.121	19.593	3.069	0.002
South-Eastern Asia	84.936	18.966	4.478	0.000
South America	-12.183	18.157	-0.671	0.503
Southern Africa	-34.752	21.088	-1.648	0.100
Southern Asia	-10.500	21.180	-0.496	0.620
Southern Europe	54.374	17.803	3.054	0.002
Western Africa	-62.567	21.300	-2.937	0.003
Western Asia	11.415	17.823	0.640	0.522
Western Europe	82.966	17.827	4.654	0.000

Table S1. Model summary and estimated coefficients for estimating QEI. Dependent variable is QEI.

Residual std. error	Multiple R^2	Adjusted R^2	F	df	p	n
0.15	0.83	0.83	316.1	9; 566	0.000	576

Coefficients

Variables	Estimate	Std. Error	t-statistic	p-value
Intercept	-0.565	0.069	-8.163	0.000
aboveLS	0.330	0.041	8.103	0.000
ODR	0.328	0.142	2.311	0.021
AIR	-1.151	0.061	-18.994	0.000
QEI	0.001	0.000	2.885	0.004
Year(1970-74)	0.160	0.027	6.025	0.000
Year(1975-79)	0.130	0.026	5.059	0.000
Year(1980-84)	0.097	0.025	3.853	0.000
Year(1985-89)	0.059	0.025	2.388	0.017
Year(1990-94)	0.047	0.025	1.907	0.057

Table S2. Model summary and estimated coefficients for Eq. 3. Dependent variable is log($SAF_{c,t}$). Base period for year dummies is Year(2015-19).

Rank	Country	1970		1975		1980		1985		1990		1995		2000		2005		2010		2015	
		MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS
1	Japan	10.68	11.09	11.06	11.53	11.43	11.99	11.81	12.51	12.23	13.10	12.67	13.77	13.11	14.43	13.51	15.03	13.88	15.61	13.81	15.59
2	Australia	10.03	10.52	10.53	11.08	11.03	11.57	11.47	11.90	11.87	12.43	12.21	12.42	12.59	12.99	12.93	13.53	13.24	14.03	13.68	14.67
3	New Zealand	9.75	9.10	10.41	9.93	11.00	10.76	11.57	11.60	12.05	12.29	12.47	12.90	12.78	13.34	13.05	13.71	13.28	14.02	13.52	14.48
4	Finland	8.85	8.71	9.49	9.41	10.11	10.12	10.67	10.79	11.20	11.46	11.67	12.10	12.01	12.62	12.28	13.02	12.45	13.37	13.03	14.27
5	Switzerland	10.93	11.72	11.18	11.92	11.43	12.07	11.69	12.03	11.96	12.37	12.22	12.24	12.45	12.64	12.67	13.00	12.88	13.46	13.40	14.14
6	Germany	11.94	11.41	12.17	11.68	12.40	11.98	12.60	12.21	12.81	12.49	13.01	12.82	13.15	13.04	13.28	13.25	13.39	13.49	13.73	14.09
7	Norway	10.80	10.89	11.03	11.16	11.29	11.49	11.54	11.82	11.76	12.16	11.95	12.45	12.16	12.72	12.39	13.00	12.67	13.36	13.10	13.95
8	Estonia	9.98	9.80	10.81	10.78	11.38	11.49	11.79	11.96	12.18	12.41	12.46	12.78	12.66	13.05	12.76	13.20	12.71	13.13	13.27	13.93
9	Canada	10.53	10.18	11.11	10.93	11.64	11.62	12.09	12.17	12.49	12.66	12.82	13.09	13.10	13.43	13.33	13.73	13.50	13.99	13.29	13.85
10	Slovakia	10.35	10.80	10.74	11.31	11.07	11.70	11.30	11.93	11.56	12.23	11.76	12.42	11.96	12.65	12.23	12.91	12.43	13.09	13.25	13.83
11	United Kingdom	10.90	11.63	11.12	11.89	11.38	12.17	11.65	12.43	11.93	12.71	12.17	12.95	12.40	13.15	12.63	13.39	12.86	13.56	13.26	13.81
12	Lithuania	8.69	8.87	9.68	9.88	10.56	10.66	11.29	11.36	12.00	12.08	12.62	12.72	13.10	13.22	13.35	13.45	13.36	13.48	13.48	13.67
13	Sweden	9.18	8.95	9.66	9.51	10.16	10.14	10.63	10.73	11.10	11.35	11.49	11.87	11.80	12.26	12.07	12.62	12.34	13.04	12.77	13.62
14	Czech Republic	10.52	10.66	10.84	11.07	11.15	11.47	11.35	11.66	11.57	11.91	11.71	12.08	11.87	12.28	12.12	12.56	12.34	12.82	13.02	13.59
15	Latvia	10.65	11.72	10.96	11.95	11.26	12.09	11.52	12.03	11.78	12.40	12.03	12.39	12.22	12.73	12.30	13.01	12.27	13.07	12.59	13.58
16	Netherlands	9.36	9.29	9.73	9.74	10.11	10.21	10.46	10.67	10.82	11.17	11.13	11.62	11.38	11.98	11.60	12.29	11.82	12.63	12.42	13.42
17	Iceland	10.91	10.91	11.23	11.17	11.51	11.38	11.79	11.47	12.05	11.81	12.27	11.61	12.54	12.00	12.86	12.35	13.04	12.61	13.57	13.37
18	Cyprus	6.55	6.59	7.64	7.75	8.73	8.95	9.64	9.94	10.47	10.82	11.22	11.62	11.85	12.24	12.40	12.79	12.89	13.29	13.01	13.35
19	Republic of Korea	6.02	5.57	7.09	6.66	8.19	7.83	9.18	8.86	10.06	9.82	10.78	10.64	11.40	11.41	11.96	12.12	12.50	12.86	12.90	13.31
20	United States of America	10.69	10.34	11.14	10.99	11.54	11.52	11.87	11.99	12.12	12.30	12.28	12.49	12.38	12.57	12.46	12.61	12.54	12.67	12.89	13.27
21	Luxembourg	9.37	9.44	9.84	9.88	10.31	10.25	10.70	10.41	11.08	10.83	11.43	10.89	11.76	11.37	12.06	11.93	12.34	12.30	13.17	13.23
22	Poland	9.84	9.23	10.26	9.73	10.67	10.23	11.00	10.59	11.30	10.97	11.57	11.31	11.81	11.61	12.03	11.86	12.23	12.16	13.04	13.20
23	Denmark	10.49	10.04	10.77	10.37	11.02	10.71	11.25	11.04	11.47	11.34	11.68	11.63	11.86	11.92	12.03	12.14	12.12	12.32	12.60	13.00
24	Ireland	8.11	7.77	8.53	8.28	9.02	8.84	9.50	9.40	9.92	9.83	10.35	10.32	10.89	10.93	11.62	11.75	12.31	12.49	12.63	12.82
25	Croatia	7.91	7.17	8.59	7.92	9.18	8.54	9.66	8.92	10.16	9.53	10.62	9.90	11.09	10.72	11.46	11.50	11.70	11.94	12.03	12.56
26	Belgium	8.30	7.97	8.73	8.46	9.19	8.97	9.61	9.45	10.08	9.99	10.51	10.49	10.91	10.95	11.23	11.32	11.49	11.66	11.95	12.53
27	Austria	8.63	8.13	9.09	8.64	9.58	9.18	10.02	9.70	10.48	10.27	10.90	10.81	11.20	11.19	11.50	11.56	11.76	11.93	12.16	12.48
28	Hungary	8.15	6.76	8.91	7.68	9.65	8.60	10.11	9.18	10.62	9.89	11.05	10.51	11.41	11.02	11.72	11.44	11.93	11.75	12.41	12.47
29	Belarus	7.62	7.59	8.30	8.34	8.94	9.04	9.37	9.22	9.79	9.94	10.34	10.42	10.83	11.15	11.20	11.76	11.44	12.15	11.56	12.45
30	Taiwan	5.83	4.34	6.84	5.27	7.90	6.29	8.86	7.20	9.68	8.22	10.37	8.86	10.95	9.79	11.50	10.71	11.99	11.65	12.39	12.42
31	Hong Kong	5.15	3.88	6.12	4.75	7.36	5.87	8.36	6.77	9.26	7.77	10.07	8.47	10.73	9.38	11.36	10.36	11.86	11.19	12.54	12.30
32	Singapore	4.90	3.58	6.29	4.77	7.66	6.07	8.78	7.17	9.99	8.49	10.87	9.46	11.58	10.30	12.27	11.23	12.96	12.24	12.64	12.28
33	Bulgaria	8.29	7.76	8.82	8.37	9.31	8.93	9.67	9.19	10.05	9.82	10.34	9.97	10.57	10.35	10.73	10.72	10.91	11.03	11.70	12.24
34	Bahamas	8.50	7.05	9.23	7.77	10.09	8.57	10.90	9.26	11.51	9.96	11.98	10.15	12.35	10.96	12.64	11.43	12.91	11.99	12.94	12.20
35	Serbia	6.90	5.79	7.87	6.85	8.62	7.69	9.23	8.25	9.91	9.10	10.61	9.66	11.16	10.58	11.57	11.23	11.82	11.65	12.06	12.14
36	France	7.97	7.31	8.50	7.92	9.03	8.49	9.48	8.98	10.01	9.57	10.49	10.10	10.92	10.62	11.30	11.10	11.62	11.51	12.14	12.09
37	Montenegro	7.48	6.33	8.45	7.44	9.23	8.02	9.86	9.01	10.35	9.27	10.79	9.95	11.14	10.54	11.44	11.17	11.64	11.49	11.97	12.06
38	Slovenia	10.30	9.62	10.48	9.83	10.63	9.95	10.79	10.10	10.96	10.30	11.13	10.51	11.32	10.75	11.54	11.03	11.85	11.42	12.20	11.87
39	DPR of Korea	7.33	5.95	8.09	6.90	8.95	8.09	9.55	8.70	10.10	9.51	10.45	9.85	10.71	10.68	10.90	11.77	10.99	11.65	11.01	11.82

Rank	Country	1970		1975		1980		1985		1990		1995		2000		2005		2010		2015	
		MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS
40	Romania	7.27	6.57	7.98	7.25	8.68	7.95	9.18	8.32	9.74	8.95	10.28	9.40	10.69	9.93	11.03	10.64	11.24	10.99	11.65	11.67
41	Israel	7.08	5.46	7.74	6.07	8.38	6.69	8.92	7.23	9.67	8.04	10.36	8.80	11.01	9.58	11.61	10.35	11.85	10.69	11.86	11.48
42	Russian Federation	6.43	6.61	7.28	7.55	8.11	8.51	8.72	9.15	9.27	9.77	9.83	10.46	10.16	10.77	10.43	10.94	10.69	11.13	10.87	11.40
43	Greece	6.42	6.17	7.08	6.84	7.78	7.55	8.45	8.21	9.11	8.87	9.84	9.61	10.48	10.23	10.99	10.73	11.38	11.04	11.78	11.37
44	Italy	6.34	5.70	6.99	6.35	7.70	7.08	8.35	7.77	9.01	8.50	9.61	9.15	10.14	9.71	10.65	10.25	11.07	10.69	11.94	11.34
45	Georgia	8.39	7.48	9.28	8.23	10.07	8.86	10.67	9.38	11.20	9.84	11.64	10.24	11.91	10.49	12.09	10.66	12.21	10.78	12.65	11.26
46	Puerto Rico	7.69	6.22	8.53	7.00	9.11	7.35	9.73	8.12	10.30	8.58	10.78	9.10	11.22	9.82	11.64	10.44	11.98	10.58	12.44	11.22
47	Spain	5.58	4.86	6.24	5.49	6.91	6.16	7.57	6.83	8.27	7.61	8.98	8.40	9.66	9.16	10.20	9.77	10.65	10.26	11.47	10.98
48	Bosnia and Herzegovina	4.65	3.59	5.67	4.49	6.58	5.23	7.41	5.96	8.14	6.46	8.82	7.26	9.51	8.40	10.16	9.24	10.65	10.00	11.24	10.95
49	Ukraine	6.66	5.29	7.66	6.40	8.56	7.52	9.16	8.38	9.73	9.00	10.19	9.79	10.40	10.13	10.62	10.44	10.86	10.67	10.98	10.84
50	Turkmenistan	7.99	6.16	8.95	7.34	9.76	8.34	10.33	9.29	10.74	9.70	11.02	10.53	11.21	10.92	10.97	10.58	10.74	10.72	10.73	10.80
51	Kazakhstan	7.62	7.51	8.23	8.09	8.83	8.68	9.32	9.09	9.71	9.41	10.10	9.73	10.45	10.03	10.91	10.42	11.19	10.61	11.31	10.74
52	Moldova	4.43	3.75	5.79	5.01	7.08	6.24	8.10	7.15	9.05	8.26	9.85	8.89	10.40	9.33	10.69	8.62	10.94	10.46	11.06	10.73
53	Azerbaijan	6.95	3.96	7.81	4.68	8.58	5.46	9.14	6.25	9.60	6.78	9.99	9.21	10.37	8.38	10.70	10.30	10.87	10.48	11.00	10.68
54	Kyrgyzstan	6.56	5.07	7.51	6.11	8.38	7.07	9.02	7.99	9.51	8.44	9.93	9.35	10.19	9.75	10.49	10.08	10.63	10.39	10.86	10.63
55	Macao	4.00	2.79	5.14	3.73	6.15	5.05	7.23	5.53	8.07	6.36	8.77	6.91	9.37	7.56	10.10	8.48	10.75	9.48	11.34	10.41
56	Armenia	7.70	7.33	8.68	8.29	9.47	9.02	9.97	9.50	10.37	9.85	10.69	10.16	10.85	10.29	10.95	10.37	11.00	10.37	11.03	10.39
57	Martinique	6.50	5.07	7.04	5.54	7.81	6.19	8.48	6.80	9.11	7.45	9.59	7.82	10.07	8.43	10.38	9.04	10.73	9.48	10.97	10.28
58	Mongolia	5.80	4.33	6.72	5.29	7.55	6.26	8.35	6.97	8.92	7.69	9.36	8.04	9.63	9.02	9.88	9.04	10.18	9.77	10.48	10.17
59	Cuba	6.99	5.53	7.86	6.29	8.69	7.40	9.43	7.57	9.87	8.07	10.27	8.24	10.55	8.98	10.86	9.29	11.08	9.92	11.25	10.16
60	Malaysia	3.80	2.17	4.83	2.94	5.87	3.58	6.96	4.62	7.91	5.59	8.76	6.23	9.59	7.20	10.37	8.25	11.07	9.30	11.61	10.12
61	Trinidad and Tobago	6.78	5.36	7.49	5.94	8.22	6.51	8.94	7.06	9.55	7.65	10.09	7.94	10.55	8.46	11.02	9.14	11.40	9.68	11.63	10.04
62	Fiji	6.04	4.04	6.73	4.65	7.46	5.25	8.19	5.85	8.77	6.43	9.34	6.88	9.92	7.49	10.45	8.19	11.08	9.03	11.52	9.96
63	North Macedonia	3.88	2.93	5.00	3.88	6.03	4.73	6.85	5.43	7.65	6.36	8.42	6.81	9.10	7.74	9.71	8.49	10.17	9.21	10.64	9.88
64	Malta	6.85	4.95	7.38	5.41	7.96	5.88	8.46	6.25	8.89	6.76	9.32	6.76	9.75	7.60	10.17	8.11	10.67	8.83	11.17	9.65
65	French Polynesia	5.67	4.16	6.58	4.93	7.47	5.67	8.19	6.33	8.86	7.09	9.40	7.42	9.86	7.74	10.29	8.78	10.68	9.22	10.91	9.64
66	Chile	7.12	5.09	7.76	5.64	8.38	6.18	8.96	6.70	9.49	7.17	9.97	7.62	10.39	8.04	10.79	8.47	11.08	8.82	11.32	9.43
67	New Caledonia	5.65	3.24	6.32	5.23	6.99	4.15	7.74	6.31	8.52	5.50	9.35	7.76	10.02	6.78	10.65	7.70	11.12	10.14	11.50	9.39
68	Tonga	7.66	4.58	8.00	6.90	8.39	5.92	8.92	5.49	9.53	7.73	9.92	7.88	10.25	6.67	10.47	8.57	10.78	8.93	11.03	9.22
69	Tajikistan	6.67	5.90	7.96	7.24	9.12	8.51	10.04	9.45	10.72	10.30	11.23	10.60	11.49	11.12	11.68	11.41	11.80	11.71	11.79	9.01
70	Argentina	6.75	5.57	7.16	5.86	7.59	6.10	8.02	6.42	8.46	6.87	8.90	7.05	9.31	7.53	9.68	8.08	9.98	8.48	10.31	8.90
71	Samoa	7.39	4.41	7.84	4.72	8.40	5.09	8.95	5.48	9.40	7.55	9.71	6.02	9.96	6.38	10.38	6.95	10.58	8.65	10.74	8.85
72	Palestine	3.90	1.95	4.85	2.52	5.84	3.18	6.84	3.98	7.71	4.62	8.43	5.65	9.09	6.66	9.70	7.32	10.31	8.11	10.74	8.69
73	Guadeloupe	5.01	3.52	5.59	3.75	6.41	4.84	7.18	4.94	7.94	6.26	8.49	5.98	9.03	7.30	9.45	7.34	9.83	8.40	10.14	8.65
74	Curaçao	7.29	5.23	7.79	5.30	8.20	6.22	8.58	5.86	8.90	6.93	9.17	6.30	9.42	7.42	9.73	7.29	10.09	8.25	10.55	8.60
75	Philippines	5.88	4.60	6.43	5.12	6.94	5.18	7.40	5.97	7.80	6.49	8.13	6.60	8.42	6.51	8.79	7.40	9.13	7.16	9.42	8.47
76	Albania	5.52	3.02	6.63	3.89	7.67	4.78	8.52	5.55	9.15	6.32	9.53	6.68	9.92	8.49	10.19	8.58	10.37	8.25	10.57	8.44
77	Guyana	7.02	5.60	7.59	6.10	8.10	6.50	8.51	6.80	8.86	7.14	9.14	7.19	9.37	7.49	9.63	6.63	9.86	7.41	10.06	8.43
78	Saint Lucia	5.30	3.70	6.10	4.02	6.90	5.07	7.63	5.08	8.21	6.28	8.77	5.93	9.31	7.19	9.82	7.20	10.12	8.15	10.58	8.42

Rank	Country	1970		1975		1980		1985		1990		1995		2000		2005		2010		2015	
		MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS
79	Thailand	6.15	4.41	6.82	4.99	7.44	5.47	7.99	5.95	8.45	6.45	8.83	6.68	9.22	6.96	9.59	7.57	9.91	8.14	10.22	8.42
80	Sri Lanka	5.08	3.57	5.71	4.06	6.32	4.55	6.93	4.94	7.66	5.58	8.48	6.07	9.19	6.67	9.86	7.21	10.36	7.76	10.77	8.39
81	Portugal	2.84	1.92	3.39	2.37	4.03	2.76	4.74	3.41	5.48	4.07	6.34	4.74	7.19	5.69	8.01	6.63	8.67	7.37	9.35	8.38
82	Zimbabwe	4.14	2.23	4.98	2.81	5.88	3.70	6.95	4.29	7.96	5.31	8.84	5.95	9.56	6.83	10.06	7.59	10.29	7.89	10.96	8.36
83	Lebanon	3.84	2.24	4.78	2.87	5.63	3.47	6.37	4.00	7.10	4.67	7.96	5.24	8.68	6.02	9.25	6.83	9.87	7.46	10.39	8.33
84	Panama	5.45	3.81	6.09	4.33	6.77	5.02	7.43	5.40	8.00	5.89	8.49	6.21	8.91	6.67	9.30	7.19	9.64	7.66	10.20	8.32
85	Venezuela	5.37	3.60	6.08	4.19	6.80	4.78	7.50	5.33	8.10	5.92	8.62	6.24	9.07	6.78	9.50	7.44	9.88	7.80	10.11	8.32
86	Saudi Arabia	2.27	0.96	2.90	1.31	3.78	1.85	4.85	2.54	6.02	3.47	6.86	3.99	7.87	5.13	8.78	5.93	9.53	7.54	10.20	8.26
87	St Vincent & the Grenadines	6.73	5.59	7.55	5.08	8.31	5.95	8.91	6.00	9.44	6.82	9.89	6.65	10.22	7.51	10.51	7.55	10.67	8.06	10.82	8.23
88	Micronesia	3.98	3.47	4.92	4.25	6.34	5.41	7.38	6.42	8.13	7.10	8.59	7.19	8.99	7.51	9.22	7.81	9.37	7.96	9.72	8.10
89	United Arab Emirates	5.19	2.77	6.73	3.54	8.08	4.89	8.62	5.38	9.02	5.60	9.36	5.72	9.50	6.03	9.61	7.10	9.94	6.66	10.24	7.99
90	Reunion	3.59	2.09	4.49	2.74	5.39	3.48	6.31	4.07	7.16	4.84	7.87	5.33	8.52	6.05	9.06	6.77	9.52	7.50	9.91	7.94
91	Turkey	3.52	2.87	4.17	3.42	4.89	4.04	5.59	4.67	6.30	5.34	6.96	5.95	7.55	6.50	8.08	7.00	8.64	7.51	9.21	7.91
92	Uruguay	6.02	4.91	6.46	5.21	6.96	5.62	7.44	5.87	7.91	6.35	8.35	6.47	8.71	6.92	8.99	7.24	9.19	7.47	9.55	7.88
93	Mexico	3.73	2.74	4.38	3.26	5.09	3.88	5.83	4.53	6.59	5.21	7.29	5.88	7.83	6.38	8.30	6.81	8.75	7.22	9.32	7.82
94	Jordan	4.56	2.43	5.60	3.31	6.52	4.00	7.53	4.90	8.32	5.82	8.96	6.35	9.28	6.81	9.51	7.22	9.67	7.73	9.97	7.82
95	South Africa	5.24	3.18	5.76	3.54	6.32	3.87	6.90	4.28	7.52	4.78	8.13	5.02	8.70	5.78	9.22	6.50	9.56	7.04	10.07	7.79
96	Aruba	4.97	3.45	5.66	3.74	6.28	4.43	6.94	4.63	7.45	5.33	8.01	5.32	8.47	6.53	8.86	6.37	9.17	7.26	9.46	7.77
97	Kiribati	3.94	3.34	4.56	3.78	5.20	4.18	5.97	4.83	6.63	5.35	7.18	5.55	7.75	6.06	8.34	6.70	8.88	7.31	9.43	7.67
98	Jamaica	5.57	3.33	6.19	3.81	7.07	4.47	7.98	5.09	8.63	5.64	9.18	5.56	9.51	6.35	9.85	6.79	10.18	7.06	10.39	7.63
99	Bahrain	2.58	1.33	3.43	1.96	4.37	2.54	5.00	3.16	5.92	3.97	6.78	4.53	7.56	5.16	8.29	6.04	8.90	6.59	9.39	7.53
100	Peru	5.24	3.56	5.90	4.07	6.56	4.59	7.21	5.07	7.84	5.56	8.43	6.01	8.96	6.44	9.40	6.79	9.91	7.28	10.22	7.52
101	Suriname	6.79	4.57	7.18	4.87	7.65	5.16	8.14	5.55	8.59	5.97	8.97	6.09	9.28	6.23	9.54	6.90	9.89	7.17	10.19	7.48
102	China	3.61	1.98	4.31	2.50	4.97	2.96	5.70	3.64	6.36	4.23	6.89	4.65	7.32	5.53	7.74	5.74	8.21	6.72	8.64	7.35
103	Costa Rica	5.36	4.08	5.98	4.58	6.61	5.07	7.14	5.38	7.54	5.74	7.87	5.82	8.20	6.11	8.54	6.57	8.88	6.99	9.14	7.31
104	Mauritius	3.92	2.30	4.62	2.77	5.42	3.32	6.18	3.82	6.86	4.34	7.41	4.72	7.89	5.21	8.35	5.80	8.84	6.54	9.34	7.14
105	Qatar	4.88	2.75	5.83	3.42	6.76	4.17	7.70	4.88	8.16	5.29	8.67	5.75	8.94	6.37	9.16	6.98	9.06	6.64	9.32	7.09
106	Oman	1.10	0.38	1.68	0.63	2.50	1.00	3.32	1.45	4.24	2.05	5.38	2.79	6.37	3.99	7.31	4.96	8.49	6.07	9.21	7.05
107	Indonesia	3.63	1.99	4.23	2.45	4.85	2.79	5.48	3.42	6.16	4.06	6.85	4.58	7.49	5.45	8.05	5.87	8.54	6.46	9.06	7.03
108	Ecuador	4.20	2.87	4.79	3.32	5.48	3.87	6.22	4.40	6.94	4.97	7.58	5.46	8.12	5.85	8.59	6.22	9.04	6.55	9.40	6.98
109	Botswana	2.44	1.11	3.06	1.44	3.77	1.84	4.58	2.32	5.50	2.90	6.44	3.52	7.43	4.50	8.36	5.26	9.08	6.11	9.74	6.79
110	Belize	4.98	3.25	5.42	3.64	5.84	3.98	6.30	4.32	6.72	3.78	7.10	4.98	7.54	5.41	7.95	5.87	8.29	6.29	8.73	6.72
111	French Guiana	5.49	3.91	5.95	4.29	6.54	4.60	7.02	5.11	7.40	5.50	7.70	5.61	7.93	5.85	8.11	6.09	8.26	6.27	8.54	6.69
112	Paraguay	4.58	3.11	5.04	3.47	5.52	3.46	6.01	4.14	6.49	4.51	6.95	4.79	7.38	5.23	7.87	5.68	8.36	6.18	8.79	6.58
113	Swaziland	2.77	1.28	3.52	1.67	4.34	2.18	5.14	2.66	5.99	3.31	6.76	3.80	7.43	4.46	7.87	5.76	8.75	5.53	9.50	6.54
114	Dominican Republic	3.31	1.88	3.82	2.21	4.47	2.57	5.20	3.08	5.91	3.62	6.55	3.98	7.14	5.11	7.72	5.67	8.29	5.87	8.79	6.52
115	Algeria	1.86	0.66	2.73	1.03	3.70	1.49	4.79	2.06	5.87	2.75	6.89	3.39	7.65	4.13	8.44	4.91	9.13	5.81	9.70	6.48
116	Iran	2.14	0.88	2.92	1.15	3.80	1.78	4.59	2.08	5.44	2.89	6.28	3.53	7.15	4.29	7.98	5.25	8.62	5.85	9.19	6.38
117	Namibia	3.01	1.53	3.39	1.77	3.86	2.07	4.48	2.44	5.27	2.98	6.08	3.48	6.83	4.74	7.45	5.41	7.99	5.23	8.43	6.27

Rank	Country	1970		1975		1980		1985		1990		1995		2000		2005		2010		2015	
		MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS
118	Colombia	3.79	2.38	4.32	2.73	4.91	3.15	5.50	3.65	6.04	4.20	6.53	4.66	7.03	5.08	7.52	5.48	7.96	5.76	8.51	6.26
119	Kuwait	3.90	2.18	4.31	2.33	5.07	2.94	5.71	3.47	6.15	3.89	6.74	4.10	7.13	4.62	7.46	5.43	7.77	5.80	8.05	6.20
120	Tunisia	1.38	0.51	2.15	0.85	3.03	1.29	3.82	1.72	4.62	2.21	5.44	2.70	6.34	3.50	7.30	4.25	8.27	5.08	8.99	6.00
121	Maldives	2.09	1.47	2.27	1.47	2.51	1.75	2.84	1.92	3.32	2.33	3.97	2.68	4.79	3.27	5.76	4.02	6.68	4.73	7.40	5.83
122	Brazil	3.38	2.03	3.88	2.38	4.44	2.71	5.00	3.14	5.49	3.56	5.96	3.83	6.44	4.38	6.95	4.95	7.41	5.46	7.49	5.70
123	El Salvador	2.88	1.51	3.35	1.80	3.87	2.12	4.51	2.49	5.11	2.94	5.70	3.27	6.28	3.77	6.80	4.33	7.43	4.96	8.04	5.60
124	Lesotho	3.34	1.82	3.68	2.04	4.07	2.27	4.50	2.52	5.01	2.89	5.55	3.17	6.05	3.63	6.55	4.56	7.10	5.10	7.61	5.59
125	Gabon	2.10	0.76	2.95	1.11	3.88	1.61	4.83	2.03	5.73	3.16	6.54	2.94	7.25	3.56	7.82	3.99	8.10	5.90	8.76	5.47
126	Egypt	2.49	0.97	2.97	1.21	3.46	1.42	4.04	1.69	4.70	2.09	5.37	2.52	6.14	2.49	6.97	3.25	7.76	4.06	8.64	5.12
127	Bolivia	4.33	2.02	4.87	2.26	5.42	2.63	5.94	2.67	6.47	3.00	7.03	3.36	7.64	3.72	8.25	4.21	8.84	4.65	9.53	5.11
128	Viet Nam	3.65	2.02	4.42	2.52	5.18	3.02	5.87	3.49	6.40	3.86	6.78	4.10	7.09	4.35	7.39	4.56	7.73	4.80	8.08	5.11
129	Iraq	2.18	0.82	3.02	1.17	3.92	1.57	4.83	2.00	5.73	2.52	6.42	2.88	6.84	3.90	7.11	3.56	7.32	4.36	7.82	5.09
130	Equatorial Guinea	2.18	0.98	2.53	1.21	3.24	1.63	4.41	2.29	4.96	2.74	5.39	3.00	5.68	3.51	6.31	3.84	6.91	4.64	7.44	4.98
131	Vanuatu	2.77	1.51	3.26	1.62	3.81	1.96	4.33	2.71	4.84	2.71	5.34	3.04	5.82	3.50	6.26	3.87	6.65	4.36	7.20	4.86
132	Congo	2.49	0.92	3.37	1.27	4.35	1.89	5.34	2.38	6.19	3.12	6.85	2.99	7.35	3.68	7.69	5.23	7.91	5.58	8.43	4.83
133	Syria	2.53	1.11	3.07	1.41	3.65	1.75	4.28	2.14	4.89	2.58	5.45	2.93	5.89	3.60	6.24	3.76	6.83	4.32	7.29	4.81
134	Zambia	3.59	1.69	4.30	2.11	4.97	2.52	5.55	2.87	6.05	3.10	6.47	3.28	6.85	3.92	7.17	4.21	7.49	4.55	7.94	4.76
135	Tanzania	2.27	0.92	2.83	1.20	3.45	1.53	4.09	1.88	4.72	2.33	5.30	2.68	5.81	2.84	6.28	3.74	6.69	4.17	7.22	4.54
136	Solomon Islands	2.51	1.36	3.01	1.76	3.57	1.94	4.10	2.54	4.56	2.61	5.06	2.93	5.50	3.21	5.89	3.49	6.25	4.13	6.69	4.54
137	Myanmar	2.62	1.62	3.07	1.91	3.54	2.26	3.99	2.48	4.43	2.81	4.85	3.03	5.24	3.50	5.61	3.63	5.98	3.95	6.36	4.52
138	Guatemala	2.50	1.13	2.81	1.29	3.14	1.47	3.50	1.66	3.90	1.95	4.32	2.14	4.70	2.40	5.23	2.85	5.73	3.38	6.20	4.42
139	Laos	2.17	1.33	2.65	1.67	3.17	2.01	3.83	2.49	4.35	2.93	4.73	2.31	5.02	2.75	5.35	3.07	5.95	2.94	6.48	4.36
140	India	2.43	0.95	2.84	1.14	3.27	1.31	3.71	1.55	4.16	1.77	4.64	2.05	5.15	2.46	5.73	3.11	6.36	3.48	6.94	4.35
141	Nicaragua	2.52	1.28	2.96	1.50	3.49	1.77	4.06	2.05	4.60	2.37	5.06	2.57	5.47	3.75	5.89	3.45	6.37	3.57	6.78	4.27
142	Timor-Leste	0.52	0.32	0.70	0.44	1.05	0.66	1.54	0.98	2.21	1.46	3.05	1.94	3.57	1.35	4.67	2.09	5.62	3.34	6.72	4.25
143	Cameroon	2.28	0.87	2.84	1.14	3.45	1.49	3.99	1.83	4.54	2.25	5.08	2.62	5.60	2.78	6.15	3.63	6.85	4.20	7.49	4.21
144	DR of the Congo	2.40	0.86	2.80	1.03	3.29	1.34	3.82	1.58	4.40	2.01	4.99	2.22	5.53	2.73	5.97	3.49	6.35	3.53	6.74	4.14
145	Cape Verde	1.77	0.71	2.25	0.94	2.62	1.15	3.25	1.50	3.67	1.73	4.19	2.09	4.74	2.50	5.57	3.10	6.15	3.68	6.61	4.01
146	Honduras	1.98	0.98	2.35	1.18	2.78	1.42	3.24	1.67	3.72	1.98	4.18	2.21	4.62	2.66	5.07	3.67	5.49	4.07	5.91	3.81
147	Uganda	2.64	1.07	3.04	1.26	3.43	1.46	3.82	1.67	4.21	1.89	4.61	2.17	4.96	2.78	5.57	3.13	6.15	3.52	6.68	3.77
148	Haiti	1.25	0.43	1.42	0.50	1.63	0.60	1.92	0.70	2.27	0.86	2.77	1.07	3.41	1.82	4.18	2.40	4.99	3.07	5.71	3.72
149	Malawi	2.19	0.89	2.50	1.02	2.85	1.18	3.24	1.33	3.65	1.57	4.04	1.89	4.50	2.47	5.05	2.90	5.61	3.23	6.16	3.64
150	Kenya	2.51	0.78	3.23	1.04	4.02	1.26	4.89	1.68	5.76	2.18	6.59	2.58	7.08	2.91	7.47	3.07	7.67	3.15	8.28	3.61
151	Nepal	0.79	0.25	1.06	0.35	1.37	0.44	1.71	0.58	2.06	0.73	2.62	0.95	3.20	1.38	3.92	2.13	4.75	2.93	5.62	3.57
152	Cambodia	2.26	1.12	2.60	1.30	2.85	1.43	3.07	1.55	3.26	1.69	3.48	1.81	3.75	2.03	4.15	2.33	4.50	2.85	5.28	3.42
153	Comoros	0.65	0.28	1.06	0.45	1.65	0.70	2.35	1.02	3.07	1.37	3.77	1.67	4.54	2.27	5.40	2.58	6.20	3.53	7.18	3.38
154	Nigeria	1.38	0.45	1.68	0.58	2.08	0.75	2.61	1.00	3.27	1.43	4.02	1.78	4.78	2.04	5.50	2.75	6.17	2.88	6.75	3.28
155	Morocco	0.60	0.20	0.99	0.34	1.46	0.51	1.95	0.70	2.49	0.95	3.04	1.18	3.55	1.49	4.00	1.64	4.85	2.54	5.66	3.20
156	Sao Tome and Principe	0.69	0.25	1.01	0.38	1.39	0.67	1.94	0.81	2.50	1.38	2.98	1.32	3.39	2.06	3.73	1.91	4.02	2.91	4.68	3.08

Rank	Country	1970		1975		1980		1985		1990		1995		2000		2005		2010		2015	
		MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS	MYS	SLAMYS
157	Bangladesh	2.06	0.71	2.25	0.78	2.50	0.85	2.84	0.98	3.16	1.11	3.54	1.25	4.01	1.56	4.57	2.06	5.10	2.59	5.66	3.04
158	Rwanda	1.18	0.42	1.41	0.54	1.65	0.64	1.95	0.79	2.32	1.03	2.74	1.23	3.10	1.79	3.57	2.14	4.10	2.63	4.56	3.02
159	Sudan	0.71	0.25	0.95	0.34	1.27	0.47	1.70	0.66	2.25	0.92	2.81	1.19	3.34	1.54	3.80	1.88	4.25	2.24	4.98	2.79
160	Bhutan	0.41	0.17	0.61	0.25	0.85	0.36	1.11	0.47	1.48	0.66	1.94	0.87	2.52	1.20	3.41	1.42	4.31	1.90	5.12	2.56
161	Madagascar	2.02	0.81	2.44	1.01	2.85	1.21	3.28	1.42	3.73	1.69	4.01	1.83	4.10	2.04	4.12	2.43	4.14	2.44	4.48	2.56
162	Togo	0.99	0.33	1.29	0.45	1.72	0.61	2.25	0.82	2.77	1.07	3.20	1.26	3.63	1.43	4.09	1.70	4.64	2.02	5.25	2.51
163	Pakistan	1.38	0.46	1.59	0.54	1.88	0.62	2.23	0.79	2.57	0.95	2.92	1.09	3.35	1.35	3.91	1.14	4.50	2.01	5.08	2.48
164	Burundi	0.81	0.28	1.04	0.34	1.26	0.44	1.43	0.51	1.59	0.57	1.87	0.70	2.38	1.05	2.82	1.08	3.23	1.76	3.95	2.34
165	Ghana	3.13	1.16	3.87	1.49	4.55	1.65	5.13	1.90	5.59	2.12	5.98	2.20	6.38	2.16	6.78	2.17	7.10	2.14	7.58	2.31
166	Liberia	1.04	0.33	1.38	0.45	1.81	0.63	2.29	0.80	2.79	1.05	3.25	1.28	3.64	1.56	3.99	1.79	4.29	1.37	4.87	2.22
167	Gambia	0.56	0.16	0.70	0.20	0.93	0.27	1.20	0.36	1.63	0.51	2.01	0.65	2.42	0.82	2.96	1.11	3.62	1.32	4.38	2.02
168	Central African Republic	0.60	0.18	0.94	0.28	1.36	0.43	1.87	0.63	2.29	0.78	2.72	0.96	3.50	1.35	4.30	1.80	5.09	1.70	5.85	1.93
169	Somalia	0.90	0.25	1.04	0.44	1.25	0.54	1.51	0.68	1.77	0.83	2.02	0.94	2.18	1.09	2.36	1.18	2.82	1.48	3.31	1.82
170	Senegal	1.05	0.31	1.37	0.41	1.62	0.49	1.87	0.58	2.14	0.68	2.43	0.78	2.70	0.92	3.21	0.99	3.74	1.26	4.26	1.77
171	Cote d'Ivoire	0.87	0.26	1.19	0.37	1.57	0.50	2.00	0.67	2.44	0.83	2.84	0.93	3.20	1.21	3.59	1.50	4.04	1.62	4.64	1.77
172	Guinea-Bissau	0.40	0.12	0.60	0.18	0.88	0.26	1.23	0.37	1.63	0.52	2.06	0.67	2.50	0.89	2.98	1.15	3.53	1.34	4.07	1.76
173	Angola	0.66	0.24	0.82	0.30	1.05	0.42	1.32	0.54	1.63	0.73	1.89	0.82	2.09	1.00	2.25	1.13	2.47	1.20	2.91	1.66
174	Benin	0.85	0.24	1.10	0.32	1.40	0.42	1.77	0.54	2.08	0.64	2.32	0.76	2.58	0.77	3.02	1.04	3.63	1.42	4.30	1.54
175	Sierra Leone	1.14	0.36	1.41	0.45	1.70	0.56	2.03	0.68	2.36	0.83	2.71	0.97	3.02	0.99	3.37	1.27	3.87	1.11	4.30	1.47
176	Ethiopia	0.43	0.13	0.54	0.16	0.69	0.21	0.88	0.28	1.12	0.35	1.37	0.45	1.69	0.54	2.05	0.75	2.61	1.11	3.18	1.43
177	Guinea	0.60	0.19	0.90	0.28	1.18	0.38	1.43	0.47	1.65	0.57	1.90	0.52	2.26	0.69	2.86	0.73	3.55	1.12	4.23	1.32
178	Mozambique	0.42	0.13	0.56	0.18	0.75	0.24	0.90	0.29	0.99	0.34	1.18	0.40	1.43	0.53	1.75	0.75	2.30	1.01	2.93	1.20
179	Yemen	0.01	0.00	0.02	0.01	0.04	0.01	0.08	0.03	0.18	0.07	0.32	0.12	0.67	0.29	1.10	0.48	1.61	0.78	2.38	1.02
180	South Sudan	0.54	0.20	0.61	0.23	0.69	0.28	0.81	0.33	1.06	0.47	1.31	0.59	1.57	0.76	1.86	0.58	2.22	1.24	2.63	0.91
181	Chad	0.28	0.08	0.44	0.13	0.63	0.18	0.83	0.25	1.06	0.27	1.32	0.44	1.63	0.49	1.99	0.39	2.42	1.05	2.93	0.90
182	Afghanistan	0.56	0.17	0.74	0.23	0.96	0.29	1.20	0.37	1.39	0.45	1.55	0.51	1.72	0.61	2.03	0.77	2.51	0.82	3.17	0.84
183	Burkina Faso	0.26	0.07	0.38	0.10	0.52	0.14	0.68	0.18	0.89	0.23	1.14	0.28	1.36	0.37	1.52	0.30	2.04	0.50	2.58	0.63
184	Mali	0.37	0.10	0.50	0.13	0.68	0.19	0.86	0.25	1.02	0.32	1.17	0.31	1.32	0.26	1.54	0.35	1.88	0.45	2.25	0.57
185	Niger	0.14	0.04	0.23	0.06	0.34	0.09	0.49	0.12	0.68	0.17	0.82	0.21	1.00	0.25	1.20	0.20	1.50	0.33	1.95	0.56

Table S3. Mean Years of Schooling (MYS) and Skills in Literacy Adjusted Mean Years of Schooling (SLAMYS) for 185 countries (1970-2015) ranked by their 2015 SLAMYS score.

		1970	1975	1980	1985	1990	1995	2000	2005	2010	2015	TOTAL
AFRICA	PIAAC/STEP	2	2	2	2	2	2	2	2	2	2	**20**
	DHS	0	0	0	0	0	0	9	27	28	27	**82**
	Predicted	48	48	48	48	48	48	39	21	20	21	**389**
ASIA	PIAAC/STEP	10	10	10	10	10	10	10	10	10	10	**100**
	DHS	0	0	0	0	0	0	4	6	7	13	**30**
	Predicted	39	39	39	39	39	39	35	33	32	26	**360**
EUROPE	PIAAC/STEP	23	23	23	23	23	23	23	23	23	23	**230**
	DHS	0	0	0	0	0	0	1	1	1	1	**4**
	Predicted	16	16	16	16	16	16	15	15	15	15	**390**
LATIN AMERICA	PIAAC/STEP	6	6	6	6	6	6	6	6	6	6	**60**
	DHS	0	0	0	0	0	0	3	3	3	3	**12**
	Predicted	28	28	28	28	28	28	25	25	25	25	**268**
NORTH AMERICA	PIAAC/STEP	2	2	2	2	2	2	2	2	2	2	**20**
	DHS	0	0	0	0	0	0	0	0	0	0	**0**
	Predicted	0	0	0	0	0	0	0	0	0	0	**0**
OCEANIA	PIAAC/STEP	1	1	1	1	1	1	1	1	1	1	**10**
	DHS	0	0	0	0	0	0	0	0	0	0	**0**
	Predicted	10	10	10	10	10	10	10	10	10	10	**100**
TOTAL	PIAAC/STEP	**44**	**44**	**44**	**44**	**44**	**44**	**44**	**44**	**44**	**44**	**440**
	DHS	**0**	**0**	**0**	**0**	**0**	**0**	**17**	**37**	**39**	**44**	**137**
	Predicted	**141**	**141**	**141**	**141**	**141**	**141**	**124**	**104**	**102**	**97**	**1273**

Table S4. Quantitative assessment of data quality. Numbers represent how many of the SLAMYS scores were calculated using which data source/method, by year and continent.

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2.3. Inequality in Quality: Population Heterogeneity in Literacy Skills around the World

The third paper was submitted to *Population Research and Policy Review*. I received an acknowledgment of receipt on March 12, 2022.

Abstract: Education is a recognized source of demographic heterogeneity, with educational attainment (measuring the quantity of human capital) increasingly entering demographic analyses as an explicit dimension. However, the quality dimension of human capital (i.e., the skills people actually have) also matters greatly for many of the benefits of education and serves as an additional relevant source of demographic heterogeneity; nonetheless it is largely disregarded in demographic analyses. This research aims to accommodate this by incorporating a skills dimension into existing population distributions. Drawing on large-scale adult skills assessment surveys, I combine measures of literacy skills with population distributions by age, sex, and educational attainment for 45 countries. The resulting skills-adjusted education pyramids capture the "inequality in quality", revealing considerable population heterogeneity in literacy skills between countries—with significant differences even within same age-, sex- and education-groups. This paper extends the literature on education as a demographic variable, stressing the need to additionally incorporate a skills dimension and providing empirical evidence for large heterogeneity in literacy skills among otherwise similar sub-populations. Pointing at gender, generational, and geographical gaps in skills-adjusted educational attainment, this research provides new insights into distributional aspects of human capital, with clear relevance for progress towards development goals.

1. Introduction

Human beings have many observable and measurable characteristics that distinguish one individual from another and one population subgroup from another. In traditional demographic analysis, it has become standard practice to sort the total population along the dimensions of age and sex. Both these characteristics serve as fundamental differentiation in human society and there is little debate that each is considered an essential input to studies of the demographic processes of reproduction, mortality, and migration. More recently, it has been argued that education should also be routinely added to population analyses, partly because of its substantive impact on progress in human development and partly because of its potential to alter population dynamics, given that fertility and mortality vary greatly and systematically by level of education (Lutz, 2010; Lutz et al., 1998).

To date, education in population distributions has usually been measured by highest level of educational attainment (i.e., the quantity of education). This has two main benefits: firstly, the educational attainment of a person can be defined quite unambiguously and information on it can be easily collected (as done nowadays in most national censuses); and second, it is unidirectional and usually remains invariant after a certain age. Global harmonized datasets on educational attainment distributions, disaggregated by age and sex, are now readily available for almost all countries of the world (Barro & Lee, 1993, 2001, 2013, 2015; Goujon et al., 2016; Lutz et al., 2005; Speringer et al., 2019). While this makes education easy to integrate into population distributions, it also clouds the analysis as it completely disregards the quality dimension (i.e., the skills people actually have). This is problematical for two main reasons: firstly, attainment does not necessarily guarantee learning or the acquisition of skills; and second, any changes in skills beyond the age when highest formal education is attained are not considered at all.

There is thus a need to incorporate a quality (or skills) dimension into existing population distributions by age, sex, and educational attainment, and hence improve actual comparability between the state of human capital in different populations and subgroups of populations. A high school graduate in one country does not necessarily attain the same (or at least similar) skills and knowledge as a high school graduate in another country. Moreover, the nature and quality of schooling may substantially change over time. In addition, an individual's skills might change considerably in the decades after graduation, while highest educational attainment might remain unchanged. A skills adjustment, based on the results of a growing number of international adult skills assessments, can largely dissipate these issues, allowing for a more holistic analysis of the many benefits of education.

This paper builds on the hypothesis that the highest level of educational attainment alone cannot fully capture human capital as a relevant source of heterogeneity. As shown by previous research, countries with similar levels of educational attainment do not necessarily show similar levels of skills (Angrist et al., 2021; Lutz et al., 2021). Consequently, one can expect significant differences in skills-adjusted human capital between (sub)populations—even within same age-, sex- and educational attainment-groups. Based on this hypothesis, this research aims to answer the following research question: *Do literacy skills differ substantially between otherwise similar subpopulations, and thus deserve to be considered a relevant source of population heterogeneity?*

Drawing on large-scale adult skills assessment surveys, such as the Programme for the International Assessment of Adult Competencies (PIAAC) of the Organization for Economic Co-operation and Development (OECD) or the World Bank's STEP Skills Measurement Program (STEP), I attempt to answer this research question by combining measures of literacy skills with population distributions by age, sex, and educational attainment for 45 countries. The resulting skills-adjusted education pyramids have the potential to not only capture the "inequality in quality", but to also reveal important inter-cohort changes in literacy skills—allowing a better understanding of the impact of rising human capital on societal development and economic growth.

The remainder of this paper is structured as follows. Section 2 summarizes existing findings on the relevance of literacy skills as a demographic dimension. In Section 3, I present the data sources used to develop the skills-adjusted educational attainment distribution, followed by a detailed explanation of the methodology in Section 4. Finally, I present and discuss the results in Section 5, and Section 6 concludes and discusses potential limitations.

2. Literacy skills as a demographic dimension

As our societies transform into knowledge societies, sophisticated comprehension and advanced skills of all kinds become essential for successful integration and participation in the labor market, education and training, and social and civic life. But do skills (and in particular literacy skills) also deserve to be included in population analyses as a demographic dimension, equal in status to age, sex, and educational attainment? Lutz et al. (1998) have defined the following three criteria governing the choice of dimensions in demographic analyses, on which grounds I will base my discussion:

i. The dimension needs to be interesting and therefore desirable as explicit output parameter.
ii. The dimension needs to be a relevant source of heterogeneity with an impact on overall population dynamics.
iii. It needs to be feasible in terms of data and methodology to consider the dimension explicitly

2.1. Relevance of skills (criterion i)

There is little debate that human capital is of overwhelming social, economic, and cultural importance. This statement, however, largely draws on empirical evidence using educational attainment as sole indicator for human capital. The impact of the quality dimension (i.e., the skills people actually have) is much less investigated, mainly because of the lack of available data.

Only recently, has a growing body of research shown that skills matter equally—or even more—for many of the benefits of education. Hanushek and Woessmann (2008), for example, found strong evidence that the cognitive skills of a population—rather than mere school attainment—are powerfully related to individual earnings, to the distribution of income, and to economic growth. In a more recent paper, Schwerdt and Wiederhold (2018) used PIAAC literacy test scores to analyze the relationship between literacy and growth and concluded that quality-based measures of human capital (i.e., literacy) are a much better predictor of a country's growth experience than quantity-based measures (i.e., years of schooling). In addition, they found an equally strong association between labor productivity and literacy skills. In terms of social outcomes, literacy skills have been found to be strongly associated with both physical health (Kakarmath et al., 2018; Smith-Greenaway, 2015) and mental well-being (Falzon, 2019). Relatedly, by using PIAAC literacy test results, Encinas-Martin (2018) showed that there is a strong and consistent association between literacy skills and self-rated health, even after controlling for educational attainment and income.

Drawing on findings that make use of the increased availability of internationally comparable data on adult literacy skills, one can conclude that skills are positively linked to a number of important economic and social outcomes, reflecting aspects of human capital that are identified and valued separately from other aspects related to education or personal characteristics. Consequently, investing in school quality and programs for adults with poor literacy and other cognitive skills may result in significant economic and social returns both for individuals and for society as a whole (OECD, 2016a).

2.2. Skills as a relevant source of demographic heterogeneity (criterion ii)

Consistent patterns of fertility differentials by mothers' education have been found from medieval times to the present in virtually all countries and at very different stages of economic developments (Skirbekk, 2008). Almost universally, higher-educated women have fewer children, greater autonomy in reproductive decision-making, more knowledge about and access to contraception and more effective use of it (Bongaarts, 2010; Cleland & Rodriguez, 1988). Yet, the processes and channels through which education can affect fertility outcomes are still not completely clear.

A growing body of literature suggests that it is mainly (or at least partly) literacy skills that play a central role in fertility decline. In 1979, Cochraine (1979, p. 29) was already concluding that "literacy gives people access to more sources of information and a wider perspective on their own culture", whereas the time spent in school mainly affects fertility outcomes through exposure to social networks. Other studies found that literacy skills may reinforce fertility effects of educational attainment. Jejeebhoy (1995), for example, concluded that in developing countries, where women's literacy is high, primary education is more likely to push fertility down, and the negative effect of secondary education is particularly sharp. More recently, LeVine et al. (2012), suggest that literacy skills constitute a causal link between schooling and maternal behavior, contributing to the decline in birth rates in developing countries. In richer countries, educational fertility differentials also exist, although the differences are less pervasive and more ambiguous (Basten et al., 2014). While there are hardly any empirical studies for developed countries on whether it is the actual cognitive skills that matter for reproductive behavior or the time spent in education, it is most likely a combination of both.

In addition to fertility, numerous studies have also shown that mortality differentials by education consistently exist for both men and women in both developed and developing countries (Ahlburg et al., 1996; Anker & Knowles, 1980; Caldwell, 1979; Cochrane et al., 1980; Kitagawa & Hauser, 1973; Lutz & Kebede, 2018). While there are hardly any studies that particularly focus on the relationship between literacy skills and mortality, it is fair to assume that cognitive skills play a central role in reducing mortality, as they allow for better planning and self-control throughout the entire life. Relatedly, higher scores on intelligence tests have been found to be associated with lower risk of mortality ascribed to all major causes of death (Calvin et al., 2017). In a study analyzing the health and social dimensions of adult skills in Canada, findings reveal that high literacy scores indicate a strong likelihood of reporting positive health outcome—even for those who have only low levels of formal education—suggesting that literacy skills may help to mitigate some of the negative outcomes that accompany lower educational attainment, including increased mortality. Conversely, a higher level of educational attainment is not strongly associated with positive health outcomes, when skills are low (Council of Ministers of Education, 2018).

Consequently, existing studies very much support that literacy skills may have an important impact on overall population dynamics, hence also fulfilling criteria ii. Nevertheless, more empirical research is needed to fully understand the impact of literacy skills on demographic behavior, including fertility, mortality, and even migration.

2.3. Feasibility in terms of data availability (criterion iii)

The reason why demographic analyses are almost exclusively carried out by educational attainment but hardly at all by qualitative measures of human capital is first and foremost related to data availability. Consistent data for comparing learning outcomes in different countries and over time are only available since the late 1990s and early 2000s, when surveys such as 'Trends in Mathematics and Science Study' (TIMSS), 'Progress in International Reading Literacy Study' (PIRLS) (both coordinated by the International Association for the Evaluation of Educational Achievement (IEA)), or the 'Programme for International Students Assessment' (PISA, coordinated by the OECD) started to collect data on a regular basis for a large number of countries around the globe. These tests, however, focus exclusively on the school-age population, and are thus inadequate for demographic analyses of total populations.

Only recently, have there been initiatives to test the skills of adults at an international level. The Educational Testing Service (ETS) (in partnership with a number of agencies and international organizations including the OECD) started to collect international large-scale data on adult skills since 1994. Between 2011 and 2017, OECD implemented the 'Programme for the International Assessment of Adult Competencies' (PIAAC), where the skills of numeracy, literacy, and problem-solving in technology-rich environments of adults aged between 16 and 65 were tested in a total of 37 countries—the largest international assessment of adult skills to date. For developing countries, the World Bank has developed a similar test, the 'Skills toward Employment and Productivity Survey' (STEP) which includes a literacy test with items that are linked to the literacy scale used in PIAAC.

Here, I focus exclusively on literacy skills, as these are available for the largest number of countries. Moreover, their relevance for many socioeconomic outcomes (as highlighted in Section 2.1 and 2.2) and the fact that literacy skills are strongly correlated with other skill domains (e.g., numeracy or problem-solving skills) make them an interesting dimension for demographic analyses. It is important to mention that measures of literacy skills, as used within this paper, go far beyond the mere ability to read and/or write. Drawing on the definition of PIAAC, literacy skills are described as the "ability to understand, evaluate, use and engage with written texts to participate in society, achieve one's goals, and develop one's knowledge and potential" (OECD, 2013, p. 4).

Finally, it is important to highlight that this paper rests on the implicit assumption that literacy skills reflect a universal set of cognitive characteristics that can be reliably assessed through tests. This is a strong assumption and although not the topic of this paper, it is worth referring to the broad body of literature questioning the premises, constructs, and outcomes of literacy and other skills assessments (see for example Hamilton & Barton, 2000; St. Clair, 2012; or Sticht, 2001 for a summary of arguments). Here, I wish only to acknowledge that literacy as measured in large-scale surveys is a very particular construct that certainly does not represent a complete measure of human capital. Nevertheless, I argue that literacy skills can serve as a relevant additional source of demographic heterogeneity, as it is much more than a corollary of educational attainment.

3. Data sources

The estimated population distributions by age, sex, and skills-adjusted educational attainment for 45 countries are based on three main data sources: the Programme for the International Assessment of Adult Competencies (PIAAC), the Skills towards Employment and Productivity Survey (STEP), and the Wittgenstein Centre (WIC) Human Capital Data Explorer. In the following, each of these data sources will be described in more detail.

3.1. PIAAC

PIAAC is a cross-national assessment of adult skills, coordinated by the OECD. The main survey conducted as part of PIAAC is the Survey of Adult Skills, which assesses proficiency of adults (aged 16-65) in three information-processing skills considered essential for successful participation in the information-rich economies and societies of the 21st century: literacy, numeracy, and problem solving in technology-rich environments.

So far, 37 countries have participated in PIAAC. The first round of the survey collected data from around 166,000 adults aged 16 to 65 in 23 countries in 2011 and 2012. In 2014, the second round of the survey was conducted, with data collection in nine additional countries. Finally, in 2017-2018 five new countries participated in the survey and the United States conducted the survey once again. In each participating country, a nationally representative sample of around 5,000 respondents were selected and asked to perform a computer-based assessment (with a pencil-and-paper option for respondents without sufficient computer skills to take the assessment in computer-based mode). It is planned to repeat the survey every ten years, with preparations for the second wave of data collection currently in process.

The PIAAC survey design is based on item response theory (IRT), with proficiency scores scaled between 0 and 500. To increase the accuracy of the cognitive measurement, PIAAC uses plausible values (PVs)—which are multiple imputations drawn from a posteriori distribution. For each survey participant, a set of ten PVs for all proficiency domains was estimated to replicate a probable score distribution that summarizes how well each respondent answered a small subset of the assessment items and how well other respondents from a similar background performed on the rest of the assessment item pool. This makes the Survey of Adult Skills particularly useful for studying adult skills in populations and subgroups of populations, rather than at the level of individuals. Further details on the statistical test design of PIAAC can be found in the Survey of Adult Skills Technical Report (OECD, 2016b). In addition to the module on the direct assessment of skills, PIAAC also includes a detailed background questionnaire that collects information about demographic and socioeconomic characteristics, use of skills in daily life, and characteristics of working life.

Analyses throughout this paper exclusively focus on literacy skills, as these are available for the largest number of countries. In PIAAC, literacy encompasses both prose literacy (using continuous text) and document literacy (using noncontinuous text) and is defined as the "ability to understand, evaluate, use and engage with written texts to participate in society, achieve one's goals, and develop one's knowledge and potential" (OECD 2013, p.4). The assessment includes a wide range of tasks, including decoding of written words and sentences, comprehension interpretation, and the evaluation of complex text. To gain a better understanding of how literacy is conceptualized in PIAAC, links to examples of literacy items are presented in the Appendix (see A.2).

3.2. STEP

STEP was developed by the World Bank to improve understanding how skills are related to employability and productivity in low- and middle-income country contexts. Three broad types of skills are measured within STEP: cognitive, socioeconomic, and job-relevant skills (World Bank, 2014). Data were collected between 2012 and 2017 in twelve low- and middle-income countries; each sample consisted of around 3,000 individuals, who were representative of the urban adult population between the ages of 16 and 65.

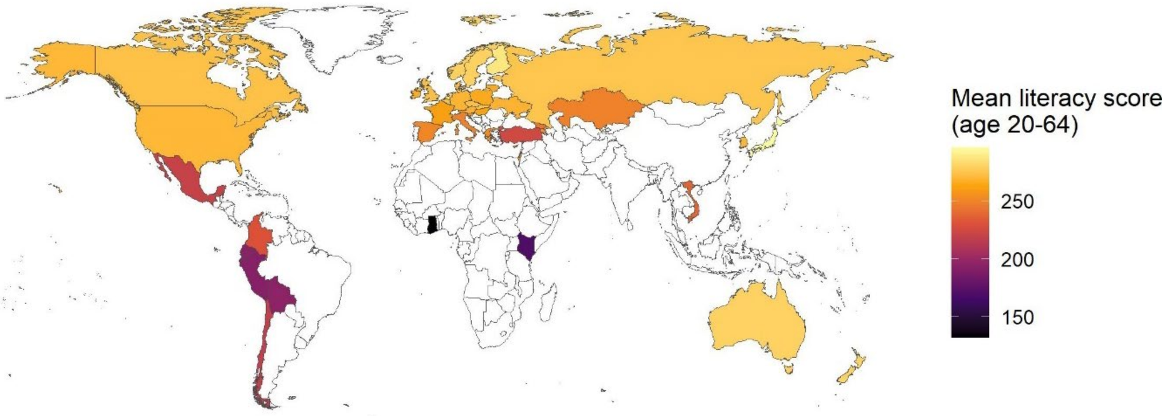
Analyses within this paper draw on cognitive skills results, that is, on a direct literacy assessment designed to identify respondents' levels of competence at accessing, identifying, integrating, interpreting, and evaluating information. The STEP literacy assessment is designed in such a way that it can be linked to the PIAAC Survey of Adult Skills: both literacy tests are capitalized on the same item pool and results are reported on a common scale, making them directly comparable. Just like PIAAC, STEP is based on IRT and thus allows unbiased estimation of the plausible range and location of literacy proficiency for populations and subgroups of populations. Given that STEP literacy items are derived from the literacy framework of PIAAC, sample items presented in the Appendix also apply to the STEP literacy assessment.

The STEP literacy assessment was administered in a total of twelve countries. However, only eight of them, namely Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam, conducted the full literacy assessment. The remaining countries only implemented a reading core test, the results of which are not relatable to PIAAC literacy scores. Thus, only data from the above-mentioned eight countries are included in the analyses. It is, however, important to mention that although STEP and PIAAC use very similar psychometric methods to estimate the literacy proficiency of participating adults, there are also some differences between the two surveys. Most importantly, the target population in STEP is limited to adults living in urban areas, while PIAAC is representative of all adults living in a country[1].

[1] A detailed comparison between PIAAC and STEP can be found in Keslair & Paccagnella (2020).

Figure 1 highlights all 45 countries with large-scale literacy assessment data available. The color shading on the map represents the mean literacy score, revealing a considerable skills gap between the rich Global North and the poorer Global South. More specifically, Japan—the country with the highest mean literacy score (296) —has a 2.2 times higher score than Ghana, the country with the least literate population of all 45 countries (133).

Figure 1. Data availability and mean literacy score by country.



Source: Author's calculations based on PIAAC and STEP data

3.3. WIC Human Capital Data Explorer

For the population data by age, sex, and educational attainment, I rely on data from the WIC Human Capital Data Explorer (Wittgenstein Centre for Demography and Global Human Capital, 2018), which includes the reconstruction of populations by level of educational attainment from 1950 to 2015 as well as a set of different scenarios of future population and human capital trends until 2100.

The databank contains detailed population data for 201 countries by 5-year age groups, sex, and educational attainment. Six education categories ('no education', 'incomplete primary', 'primary', 'lower secondary', 'upper secondary', and 'post-secondary') are available for all countries; eight education categories (further decomposition of 'post-secondary' into 'short post-secondary', 'Bachelor', and 'Master and higher') are available for 60 countries. Further details and features on the methodology of the data can be found in Lutz et al. (2018) and

Lutz, Butz, and KC (2014) for the global population projections, and in Speringer et al. (2019) for the reconstruction.

4. Methodology

When conducting multi-dimensional demographic analyses, the population to be studied is divided into any number of "states", which, traditionally, were geographic regions (Rogers, 1980), but could also be educational attainment categories or levels of skills. As the goal of this paper is to provide distributional information on skills for different levels of educational attainment (which would per se differ in expectable skills), I decided to use the mean proficiency of the OECD population, disaggregated by age, sex, and educational attainment as a benchmark threshold. More specifically, the threshold equals the 2015 population-weighted[2] OECD mean PIAAC literacy test score, calculated separately for each age-, sex-, and education-group as presented in Table 1. Despite notable differences and advances of OECD countries in terms of age structure or educational attainment distribution, the performance threshold is nonetheless a valid and accessible standard of comparison, as individual performances are solely evaluated on grounds of reaching the OECD mean literacy score in their specific age-, sex-, and education-group.

[2] Population estimates by age, sex, and educational attainment come from the WIC Human Capital Data Explorer.

Table 1. Population-weighted OECD mean in PIAAC literacy scores by age, sex, and educational attainment, 2015.

Age	WOMEN				MEN			
	Primary or less	Lower secondary	Upper secondary	Post-secondary	Primary or less	Lower secondary	Upper secondary	Post-secondary
15-19	235.3	259.4	273.8		231.3	257.5	276.9	
20-24	201.3	237.2	274.3	289.9	208.8	231.2	277.9	291.8
25-29	197.1	229.6	263.3	295.2	198.2	232.2	267.7	299.8
30-34	197.2	232.4	262.5	294.0	191.0	231.8	263.0	298.0
35-39	198.7	227.7	262.8	292.2	204.9	230.2	265.2	301.1
40-44	198.3	231.3	264.4	291.3	194.3	236.9	264.0	297.5
45-49	190.9	230.8	263.7	287.6	199.5	232.8	258.8	293.7
50-54	190.5	233.2	260.2	282.6	195.4	231.2	259.1	289.1
55-59	192.2	232.4	254.8	281.0	192.4	231.6	258.0	283.1
60-64	190.0	234.9	255.7	276.6	195.4	231.1	254.4	279.6
Total OECD population (aged 20-64, both sexes, all education groups): 262.8								

Source: Author's calculations

To avoid using too small PIAAC/STEP sample sizes in each country-age-sex-education group, I reduced the six education categories retrieved from the WIC Human Capital Data Explorer to only four broader education categories (i.e., 'primary or less', 'lower secondary', 'upper secondary', and 'post-secondary') [3,4]. By further splitting each of these four educational attainment categories into low-skill (below population-weighted OECD PIAAC literacy mean) and high-skill (above population-weighted OECD PIAAC literacy mean) subgroups, I was able to disaggregate the population for each country by 5-year age groups, by sex, and by eight skills-adjusted educational attainment categories (with skills-adjusted human capital only available for the age groups 16-20 to 60-64).

[3] Referring to the International Standard Classification of Education (ISCED), 'primary or less' corresponds to ISCED 0 or 1, 'lower secondary' corresponds to ISCED 2, 'upper secondary' corresponds to ISCED 3, and 'post-secondary' corresponds to ISCED 4, 5, 6, 7, or 8.

[4] Whenever the PIAAC or STEP sample size of a specific country in a specific age-sex-education group is below 20 (e.g. in highly developed countries there is usually hardly anyone with educational attainment lower than junior high school), I assume 50 percent to be below and 50 percent to be above the benchmark threshold. The impact of this assumption on results is, however, negligible since sub-groups with such low sample sizes usually also contribute a very minor (or even non-existent) proportion to the overall population distribution.

Of the 45 countries for which I can estimate the population by age, sex, and skills-adjusted educational attainment, PIAAC microdata is used for 37 countries. For eight countries, the analyses are based on STEP microdata. As mentioned in Section 3, both PIAAC and STEP are large-scale assessment surveys with a complex sample design (i.e., replicate weights in PIAAC, standardized sample weights and stratification in STEP) and rotated test forms (i.e., plausible achievement values). To account for these particularities, the R packages *intsvy* and *BIFIEsurvey* were used, which provide tools and analyses specifically designed to work with international assessment data.[5]

As highlighted previously, the target population of the STEP Skills Measurement Program includes only urban adults. Due to the lack of available country-wide data on literacy skills for countries participating in the STEP survey, these results are still used to estimate the skills-adjusted educational attainment distribution for the total population.[6] This selection bias affects eight countries (Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Ukraine, and Vietnam) but only concerns the skills adjustment; data on population size by age, sex, and educational attainment are retrieved from the WIC Data Explorer and account for the total population. Results for these countries must thus be interpreted with caution. Additional adjustments of urban STEP scores to achieve representativeness for the entire country needs to be subject to further research.

All estimates within this paper are based on 2015 population data. The reader should note, however, that skills adjustments originate from any round of data collection of PIAAC cycle 1 (2011-2017) or STEP data collection between 2012 and 2016. As interpolation of skills data in single-year intervals to obtain 2015 values is not possible due to the non-availability of more than one data points over time for most countries, PIAAC and STEP literacy test results provide the unmodified basis for the 2015 estimates despite small variations in time.

[5] For further information on the packages, see https://cran.r-project.org/web/packages/intsvy/intsvy.pdf and https://cran.r-project.org/web/packages/BIFIEsurvey/BIFIEsurvey.pdf.

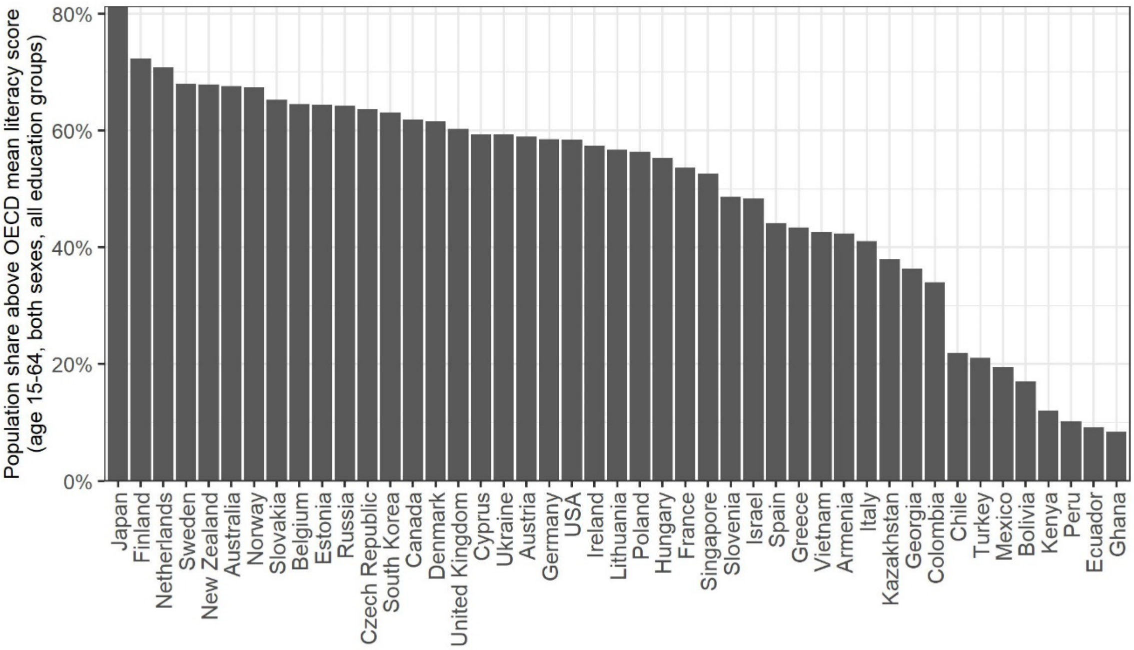
[6] Given that previous research has shown that literacy tends to be much higher in urban areas of developing countries (Roy & Mondal, 2015; Zhang, 2006), the estimates are likely to over-estimate literacy skills in the eight STEP countries.

5. Results and discussion

Based on the methodology described in Chapter 4, I was able to estimate population distributions by 5-year age groups, sex, and eight skills-adjusted educational attainment categories ('primary or less below OECD average', 'primary or less above OECD average', 'lower secondary below OECD average', 'lower secondary above OECD average', 'upper secondary below OECD average', 'upper secondary above OECD average', 'post-secondary below OECD average', and 'post-secondary above OECD average') for 45 countries for the year 2015.

Results reveal that there are significant differences in distributional aspects of skills between nations. For each of the 45 countries, Figure 2 depicts the proportion of the population aged 15-64 with skills above the population-weighted OECD mean literacy score (both sexes, all educational attainment groups combined). In line with previous findings, Japan, Finland, and the Netherlands lead the field, with the vast majority of the population having higher skills than the OECD average in these countries. In Japan, the share of the population with a literacy proficiency at least equivalent to the OECD average is even higher than 80%. On the other side of the ranking are developing countries such as Ghana, Ecuador, Peru, or Kenya, where only small parts of the population possess skills corresponding to the OECD average. Interestingly, Ecuador and Peru have a higher mean literacy score than Kenya, but are doing worse when distributional aspects of skills are taken into account.

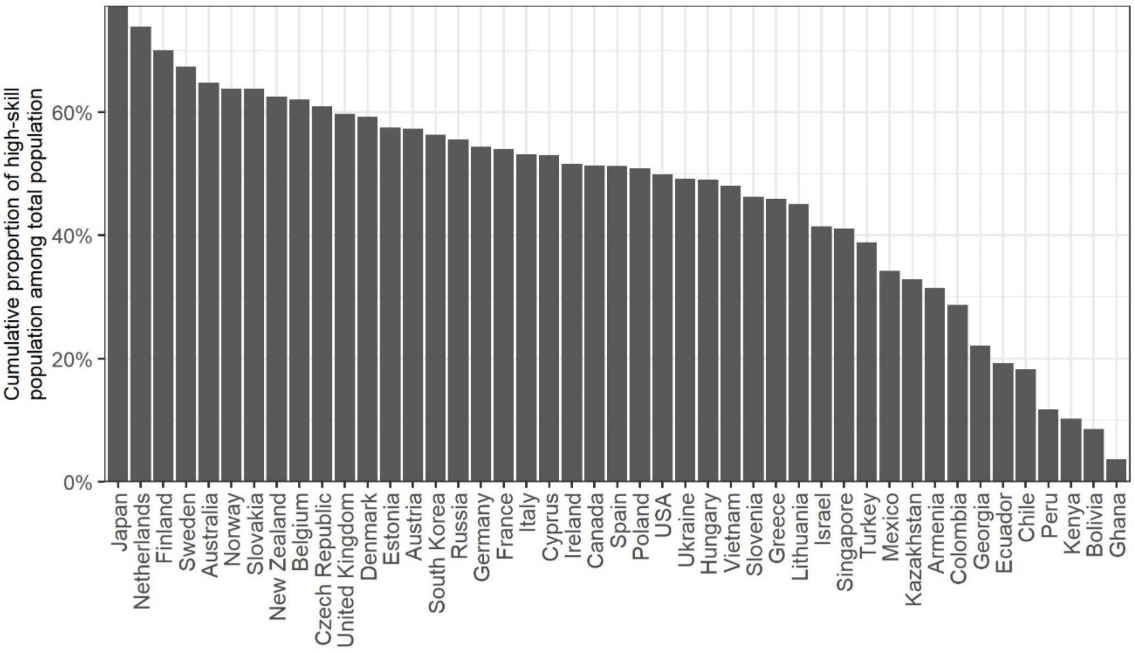
Figure 2. Proportion of population (age 15-64, both sexes, all educational attainment groups) above OECD mean literacy score, by country, 2015.



Source: Author's calculations

This is certainly relevant when assessing the human capital in a population based on a summary measure; however, compositional aspects of the population in terms of differences in age- and sex structure as well as in the educational attainment distribution are not considered in this analysis. To accommodate this, Figure 3 shows the cumulated share of population with skills classified as high (above the OECD average in the respective age-sex-education group) among the total population. More specifically, the percentage in the bar chart represents the sum of the population count with skills at least equal to the population-weighted OECD mean literacy score in their respective age-sex-education group (not the overall OECD average) divided by the total population aged 15-64. In this way, I can somehow correct for variations in skills solely due to a different educational composition or age/sex structure of the population. As shown in the graph, the proportion of the high-skill population when using age-, sex-, and education-specific benchmarks is lower for most countries compared with Figure 2. This can be explained by countries such as Japan or Finland doing so well in literacy assessments because they also have large shares of the population with post-secondary education with, on average, higher skills than the overall OECD mean. When comparing their performance to the OECD mean of their respective age-sex-education group, however, the supremacy of these countries in terms of the share of the population above the OECD mean decreases a little. Overall, the country ranking based on the above-mentioned criteria is, however, quite similar to the one shown in Figure 2 (where the overall OECD average was used as standard of comparison), with Japan, Netherlands, and Finland again leading the field.

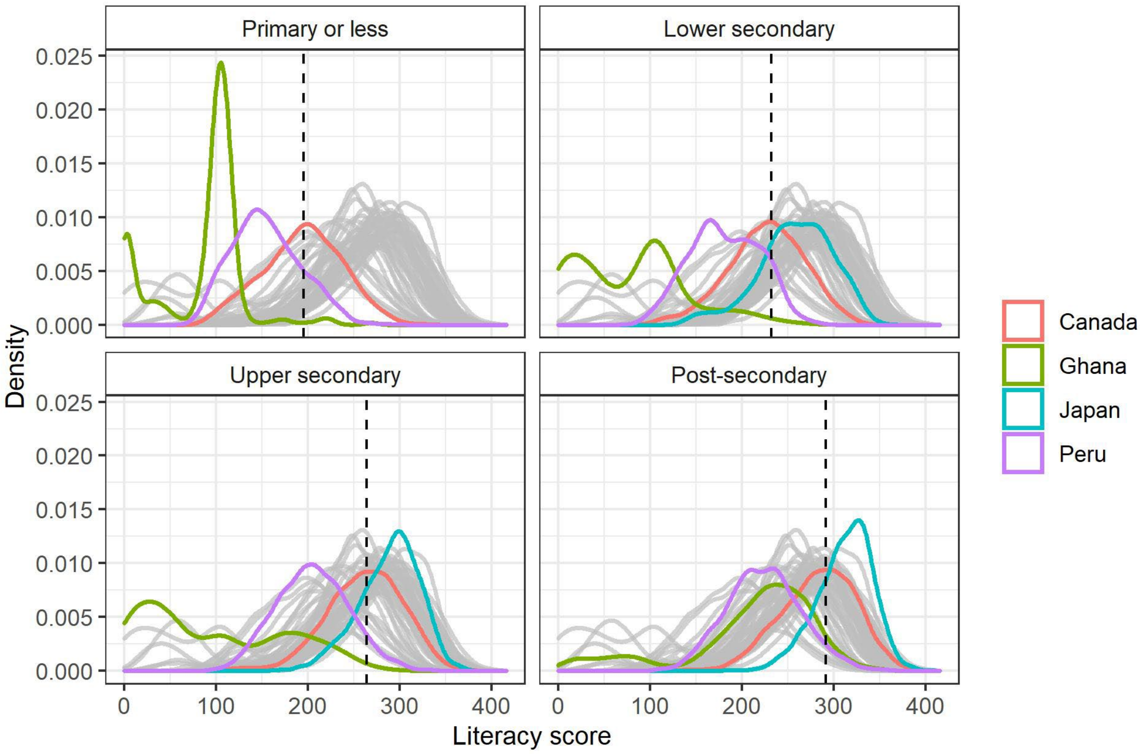
Figure 3. Cumulated proportion of population above OECD mean literacy score in their respective age-sex-education group, by country, 2015.



Source: Author's calculations

While the educational attainment distribution certainly plays a role in the distribution of literacy skills in a country, there is still considerable heterogeneity within each educational attainment level, demonstrating again the need for a quality dimension. Figure 4 depicts the density of literacy scores by educational attainment for all 45 countries (the dashed line represents the education-specific OECD mean literacy score) – with four exemplary countries highlighted, illustrating the wide spectrum of distribution patterns. In Ghana, for example, literacy skills in all education categories are concentrated at a much lower level compared to most other countries. This is particularly true for the least educated and also, of course, because roughly one quarter of the population aged 20-64 in Ghana have never had any formal education (Wittgenstein Centre for Demography and Global Human Capital, 2018). Similarly, the vast majority of people in Peru have literacy skills considerably below the population-weighted OECD average in their respective education group. While Canadians' literacy skills are normally distributed roughly around the OECD mean, literacy skills in Japan are concentrated on the upper end of the scale, with large shares of the population having particularly high scores—which is most noticeable in the higher education categories. The variety of the level of skills even within the same educational attainment category clearly illustrates the shortcoming of previous analyses, where everyone with the same degree (and same age and sex) is treated identically in terms of their demographic behavior, regardless of their actual level of skills.

Figure 4. Density of literacy scores by educational attainment and country (population aged 20-64); selected countries are highlighted.



Source: Author's calculations

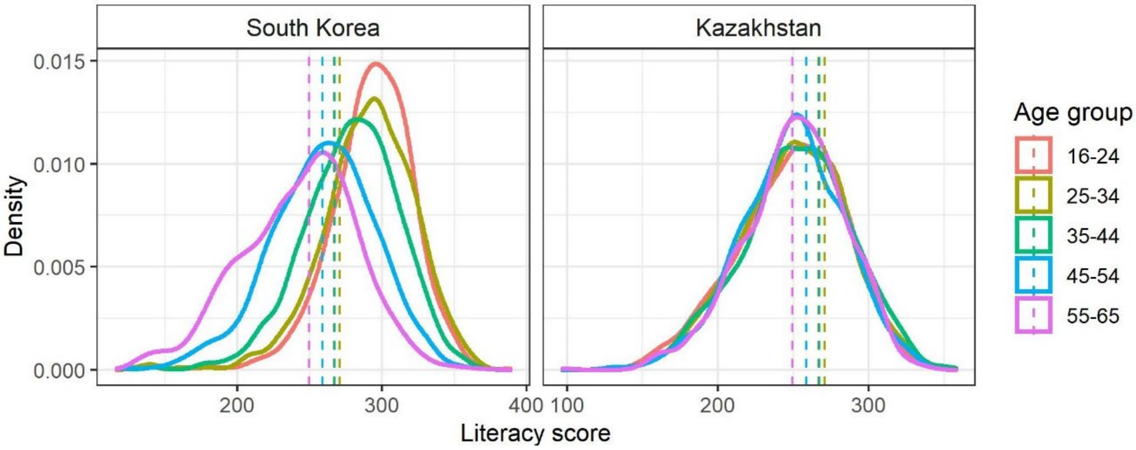
Notes: Density functions with less than 100 observations were removed from the graph.
Dashed line represents population-weighted OECD mean literacy score.

As well as differences between educational attainment levels, there is also significant heterogeneity in literacy skills among different age groups. In cross-sectional surveys, such as

PIAAC and STEP, these always reflect combinations of age effects (i.e., changes in skills as people get older) and cohort effects (i.e., generational changes such as a different educational attainment distribution or different quality of schooling between younger and older people). Consider the cases of South Korea and Kazakhstan, for which the distribution of PIAAC literacy scores by 10-year age group is depicted in Figure 5. As can be seen on the plot, in South Korea, younger people have consistently higher skills than older ones. Parts of these differences can be explained by age effects. Several studies have found a tendency for cognitive skills to rise in the early years and then eventually decline as adults age (Barrett & Riddell, 2016; Desjardins & Warnke, 2012; Green & Riddell, 2013; Hertzog et al., 2008; Paccagnella, 2016; Reiter, 2022; Skirbekk et al., 2012). But differences are additionally reinforced by cohort effects – particularly, in South Korea, which has experienced the most rapid education expansion in recent history. The country managed to massively increase the quantity of education, without sacrificing quality. Moreover, improvements in literacy skills by birth cohort are much larger in South Korea than for the OECD average (depicted by the dashed vertical line).

In Kazakhstan, on the other hand, the distribution of literacy skills is almost identical for all age groups—despite a significant increase in quantity of education among the younger generations (Wittgenstein Centre for Demography and Global Human Capital, 2018) as well as potential age effects. These findings suggest that Kazakhstan did not manage to translate the increased quantity of education among the younger cohorts to a corresponding rise in skills. Rather, quantity may have come at the expanse of quality.

Figure 5. Density of PIAAC literacy scores by 10-year age groups, South Korea and Kazakhstan.

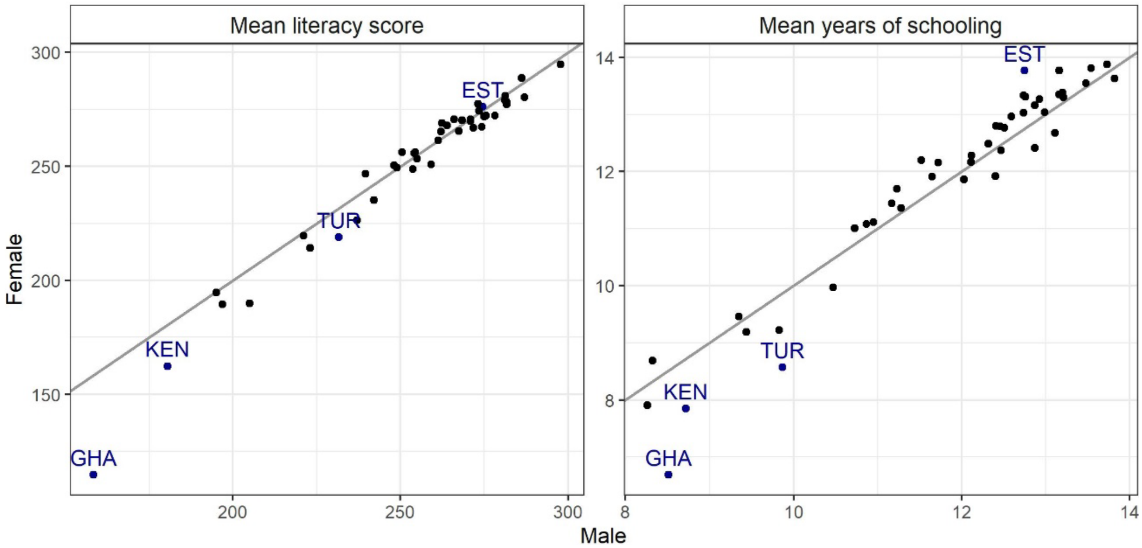


Source: Author's calculations

Notes: Dashed line represents population-weighted OECD mean literacy score.

In terms of gender differences, the gender gap in literacy skills is rather small in most of the 45 countries. However, while many highly developed countries currently experience the reversal of the gender gap in terms of educational attainment (De Hauw et al., 2017), namely women spending now more years in education than men, literacy skills among 20–-64-year-olds are still slightly higher for men than for women in most countries. This is depicted in Figure 6, with the left chart plotting male mean literacy scores (x-axis) against female mean literacy scores (y-axis), and the right chart plotting male mean years of schooling (x-axis) against female mean years of schooling (y-axis): the grey diagonal line represents any combination where male and female human capital is equally high. A few notable exceptions are highlighted in blue: Ghana and – to a slightly lower extent – Kenya and Turkey are countries where the gender gap for both quantity and quality of human capital is particularly high, with women still being discriminated both in terms of being in school and in terms of learning. On the other side of the spectrum is Estonia – the country, where women, on average, have the highest advantage in educational attainment compared to men from all countries in the sample; their supremacy in terms of literacy skills, however, is much smaller (or almost non-existent). Overall, gender differences in literacy skills are typically small in developed countries. It has been shown, however, that differences in mean scores between men and women are greater for other skill domains, for example, for numeracy skills (OECD, 2016a).

Figure 6. Mean literacy score and mean years of schooling (population aged 20-64), by country and gender.

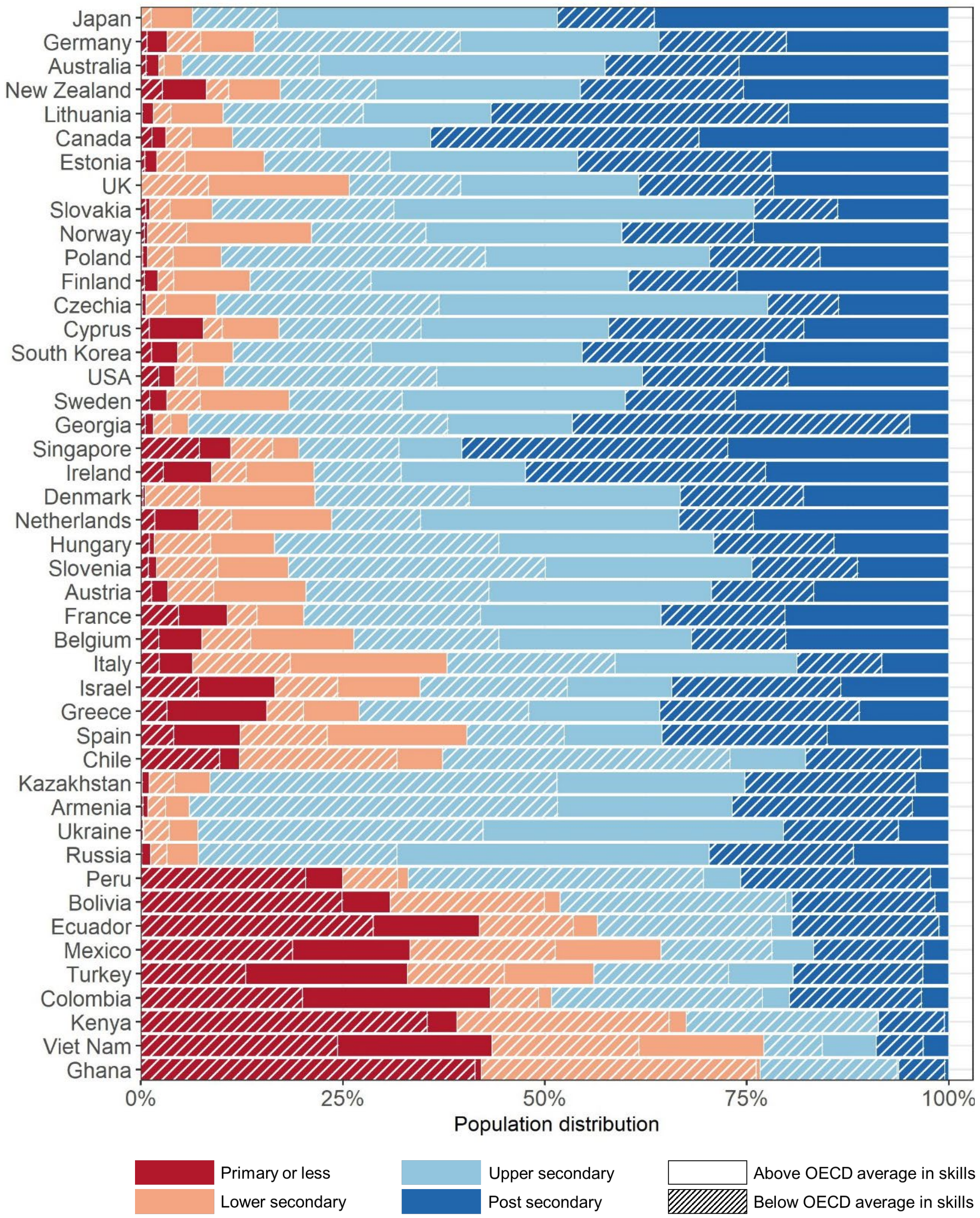


Source: Author's calculations

Note: Diagonal line represents equal literacy scores / mean years of schooling for men and women.

To obtain a better overview of the distribution of human capital by country, Figure 7 depicts for all 45 countries (sorted after their mean years of schooling) the skills-adjusted educational attainment distribution for the working-age population (aged 20-64). The colors indicate the four different educational attainment groups, with each color being further split into a striped area (low-skill, i.e., below OECD mean in the respective education group) and a filled area (high-skill, i.e., above OECD mean in the respective education group). As can be seen on the plot, there are significant differences among countries, not only in terms of the educational attainment distribution, but also in terms of skills. Many of the less developed countries, such as Bolivia, Ghana, and Kenya, do not only have a considerably less educated population, but also the low-educated people in these countries have lower skills than the OECD average for this education group, resulting in a double disadvantage in human capital.

Figure 7. Distribution of skills-adjusted educational attainment, 2015, population aged 20-64.



Source: Author's calculations

Other countries, such as Armenia, Chile, Georgia, or Kazakhstan, do have a solidly educated population, with the vast majority of people having attained at least upper secondary education. However, their skills are predominantly below the OECD average in the respective education group, suggesting again poorer quality of schooling and the potential indication of a certain quantity–quality trade-off. This contrasts with Vietnam, a country where there are still quite a large number of people with lower secondary education or less, but larger shares of the population are above the OECD average in literacy skills.

Among highly developed countries, results also reveal significant differences. While people in Japan, Finland, Netherlands, Norway, and Sweden hold very high educational attainment and, on the whole, possess skills above the OECD average, the shares of the population above the OECD average in skills for each education category are considerably lower in countries such as Canada, France, Ireland, South Korea, and the United States – despite similar levels of educational attainment. Eastern and Southern European countries tend to have both slightly lower educational attainment and lower levels of skills.

As mentioned previously, however, the full distribution of the population by age, sex, and skills-adjusted educational attainment categories is needed not only to capture the inequality in education and skills, but also to reveal inter-cohort changes and gender differences. Figure 8 thus presents multi-dimensional population pyramids for two representative countries, with population size being depicted on the x-axis, and age groups being represented on the y-axis. Again, the colors indicate different educational attainment groups, while the pattern indicates the level of skills.[7] Ghana and Singapore are not only very different in terms of the age structure and educational attainment distribution, but also in terms of skills—even within the same age-sex-education group.

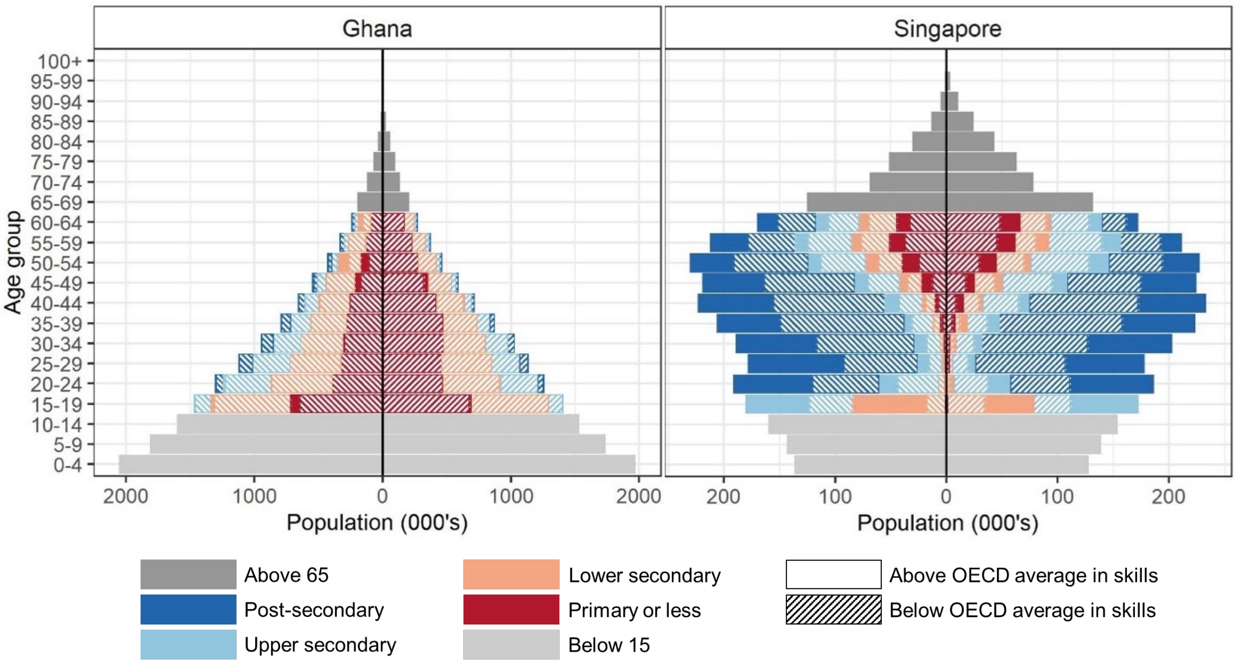
In Ghana, a country with a young and very low-educated population, hardly anyone manages to be above the age-, sex-, and education-specific OECD average in literacy skills. While younger age groups are better educated than older ones, the disadvantage in skills remains roughly constant over age groups, suggesting that the massive educational expansion that has been taking place recently did not necessarily translate in higher skills. This may be a result of the inability of the education system to cope with the increase in the

[7] Skills-adjusted pyramids for the remaining 43 countries can be found in the Appendix (see A.3).

number of students as well as the potential insufficiency of school inputs and low government spending on education.

Singapore, on the other hand, is a country where the skills-adjusted educational attainment distribution particularly differs between age groups and gender. While in 2015 more than 80% of the population aged 25-29 in 2015 have some kind of post-secondary education, over a third of women aged 60-64 in Singapore have only primary education or never attended any school. This is a result of a cohort effect: the cohort of women aged 60-64 in 2015 were 5-9 years old in 1960—at that time, Singapore was still a poor developing country without universal primary education. Similarly, while skills of most people over the age of 30 are still predominantly below the OECD average in their respective age-sex-education group, within the youngest cohorts, the filled areas tend to cover more than half of the bars, suggesting that while the quantity of education in Singapore increased rapidly, the quality of education improved even faster than the OECD average.

Figure 8. Population by 5-year age groups, sex, and skills-adjusted educational attainment (men on the left, women on the right), Ghana and Singapore, 2015.



Source: Author's calculations

6. Conclusion

Skilled human capital has been widely acknowledged as one of the key drivers of economic growth and social development. In view of the overriding importance of the statistical analysis of human capital, particularly in modern knowledge societies, its almost exclusive focus on the quantity of education is a notable shortcoming, given that quality and levels of skills matter at least equally. Likewise, in demographic studies, when (sub-) populations are being analyzed by their level of human capital, educational attainment is usually used, and there is the implicit but often unrealistic assumption that direct conclusions can be drawn from the highest educational level people have attained about the actual skills they have.

After establishing the relevance of literacy skills as a demographic dimension, the current paper presents estimates of population distributions by age-, sex-, and skills-adjusted educational attainment for 45 countries, providing for the first time a holistic depiction of the distribution of human capital that considers not only the quantity dimension of education, but also the qualitative element of actual skills. The resulting skills-adjusted education pyramids capture, on the one hand, the "inequality in quality", with poorer countries often experiencing the double burden of people being i) less educated and ii) having lower literacy skills than people with the same education in other countries. On the other hand, the skills-adjusted education pyramids also reveal important inter-cohort changes in literacy skills—indicating that not all countries managed to expand the quantity of education and simultaneously experience a concomitant rise in skills. Rather, in some countries the increase in quantity of education may have come at the expense of quality. The reasons for the specific patterns in the distribution of skills-adjusted educational attainment by age and sex are, without doubt, complex and depend on a variety of country-specific factors, including changes in school systems, demographic patterns, and immigration flows. More sophisticated analyses and explanations would therefore require country-specific case studies to be established, and this could be a subject for further research.

As with the majority of studies, the design of the current paper is also subject to some limitations. First and foremost, it covers a very specific set of countries, most of them rich OECD countries. While the use of STEP data in addition to PIAAC data allows for more diversity and the inclusion of more low- and middle-income countries, any direct comparison between the two skills assessments need to be treated with caution due to minor differences in survey design. Moreover, this paper analyzes a very specific domain of skills, namely literacy skills, and rests on the implicit assumption that they can be reliably assessed through tests. While literacy skills have been shown to be highly correlated with other cognitive skills, they may still vary in terms of distributional aspects. For example, gender gaps in skills were shown to vary significantly with the domain of skills (OECD, 2016a). The availability of more widespread and internationally comparable testing of adult skills beyond literacy would allow the results to be validated and the analyses to be further extended to additional skill domains.

Finally, skills-adjusted educational attainment distributions, as presented in this paper, can also be an important tool to monitor progress towards development goals. While progress was widely acknowledged after the rapid expansion of primary school enrollment rates in many developing countries starting around 2000, the results from this paper partly challenge this optimistic view and stress the importance of not losing sight of quality of education. The estimates presented here provide an important basis for analyzing human capital; however, future analyses are needed, including—but not limited to—population projections (as well as reconstructions) by age-, sex- and skills-adjusted educational attainment.

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Appendix

A.1. Replicability

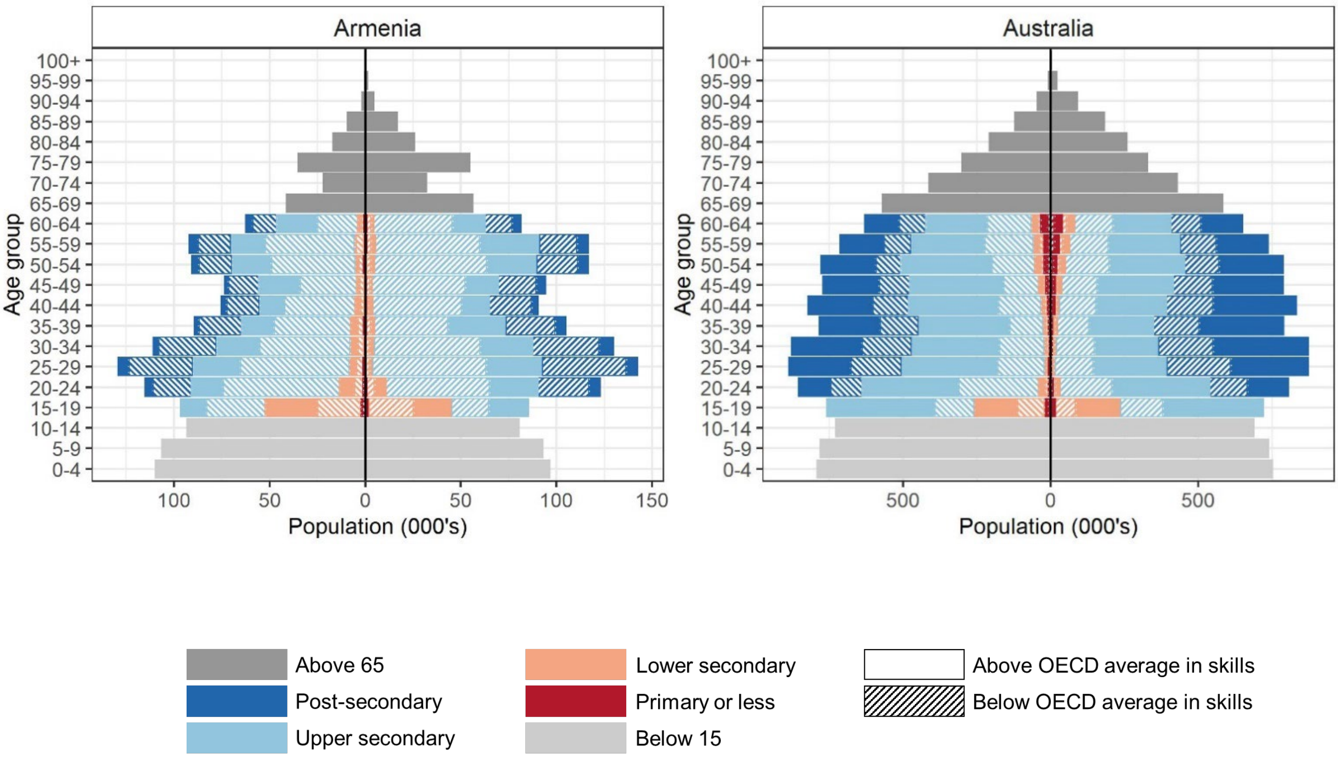
All results were generated using RStudio. Data and codes used to generate the results are available in the following GitHub repository:
https://github.com/clreiter/Skills-adjusted-education-pyramids

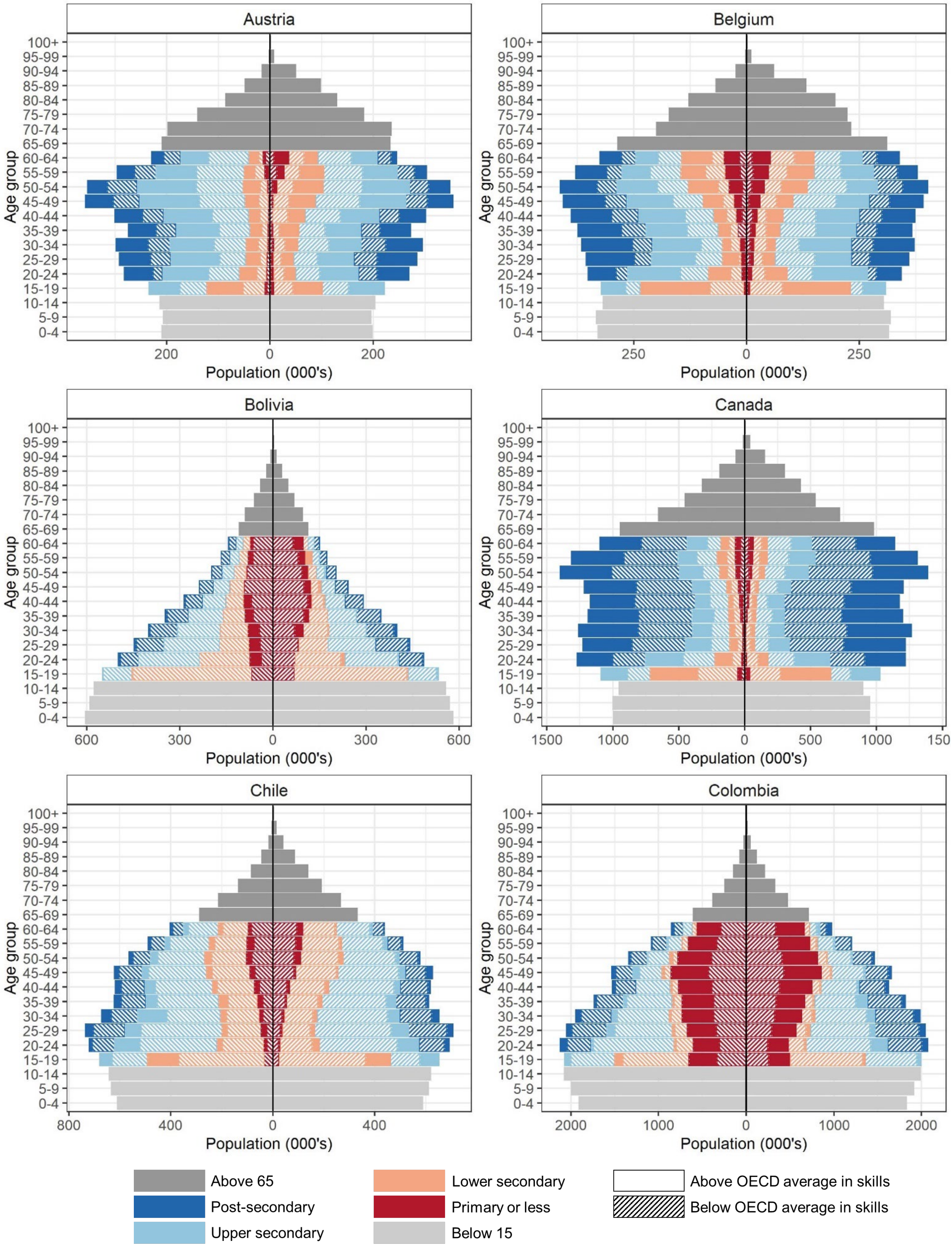
A.2. PIAAC literacy sample items

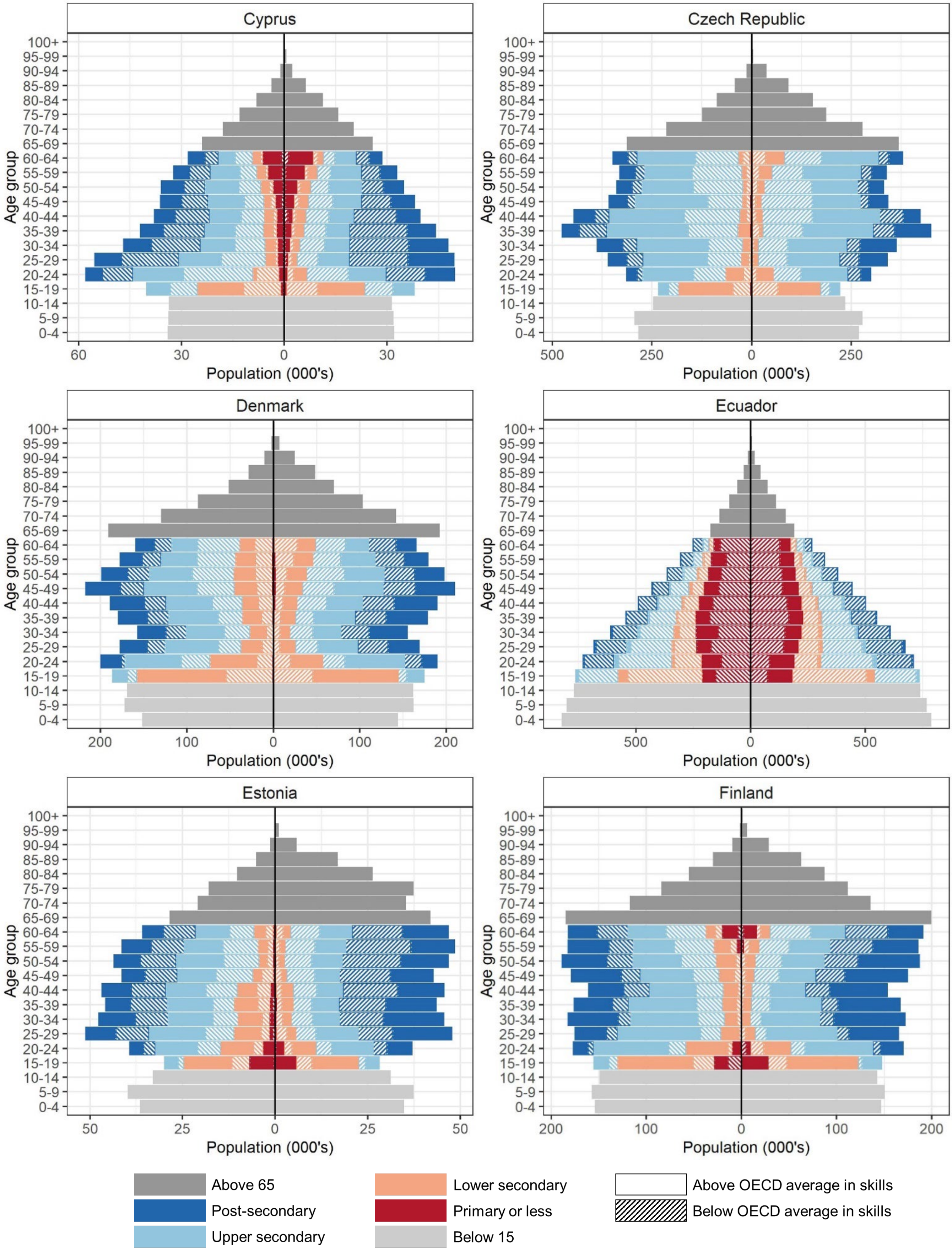
In order to get a better understanding of how literacy is conceptualized in PIAAC, examples of literacy items can be found under the following link:
https://nces.ed.gov/surveys/piaac/sample_lit.asp.

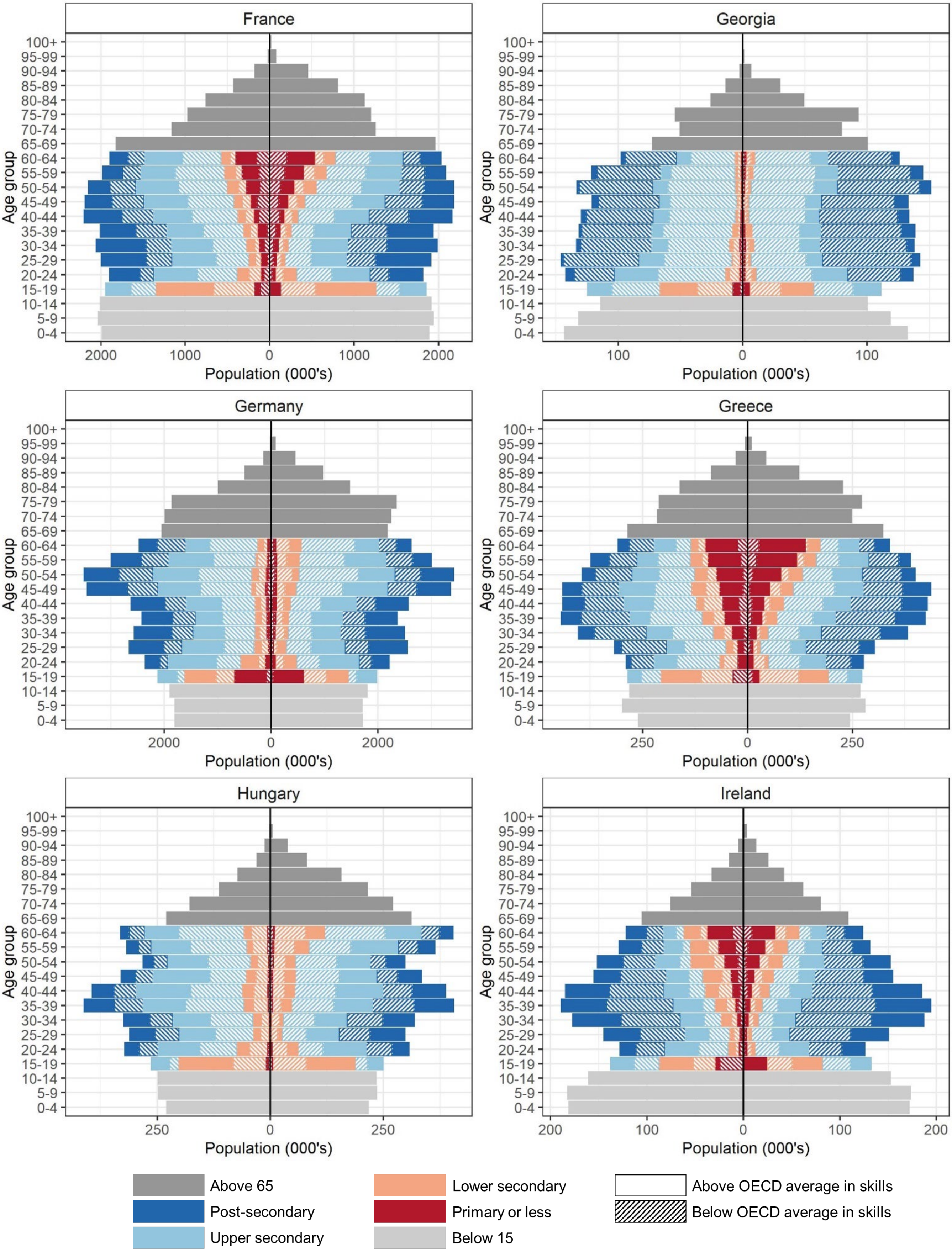
A.3. Skills-adjusted education pyramids

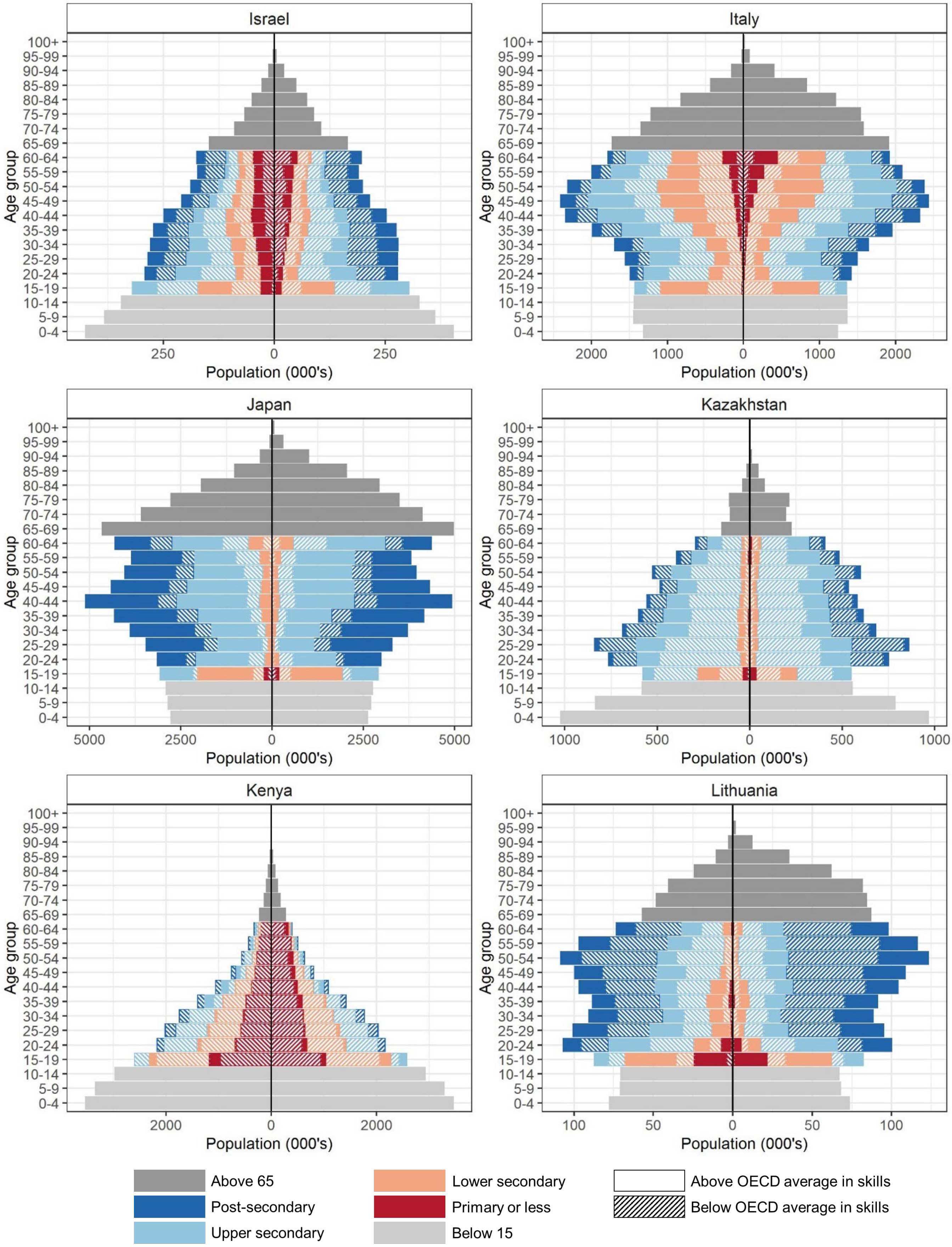
Population by 5-year age groups, sex, and skills-adjusted educational attainment (men on the left, women on the right), by country, 2015.

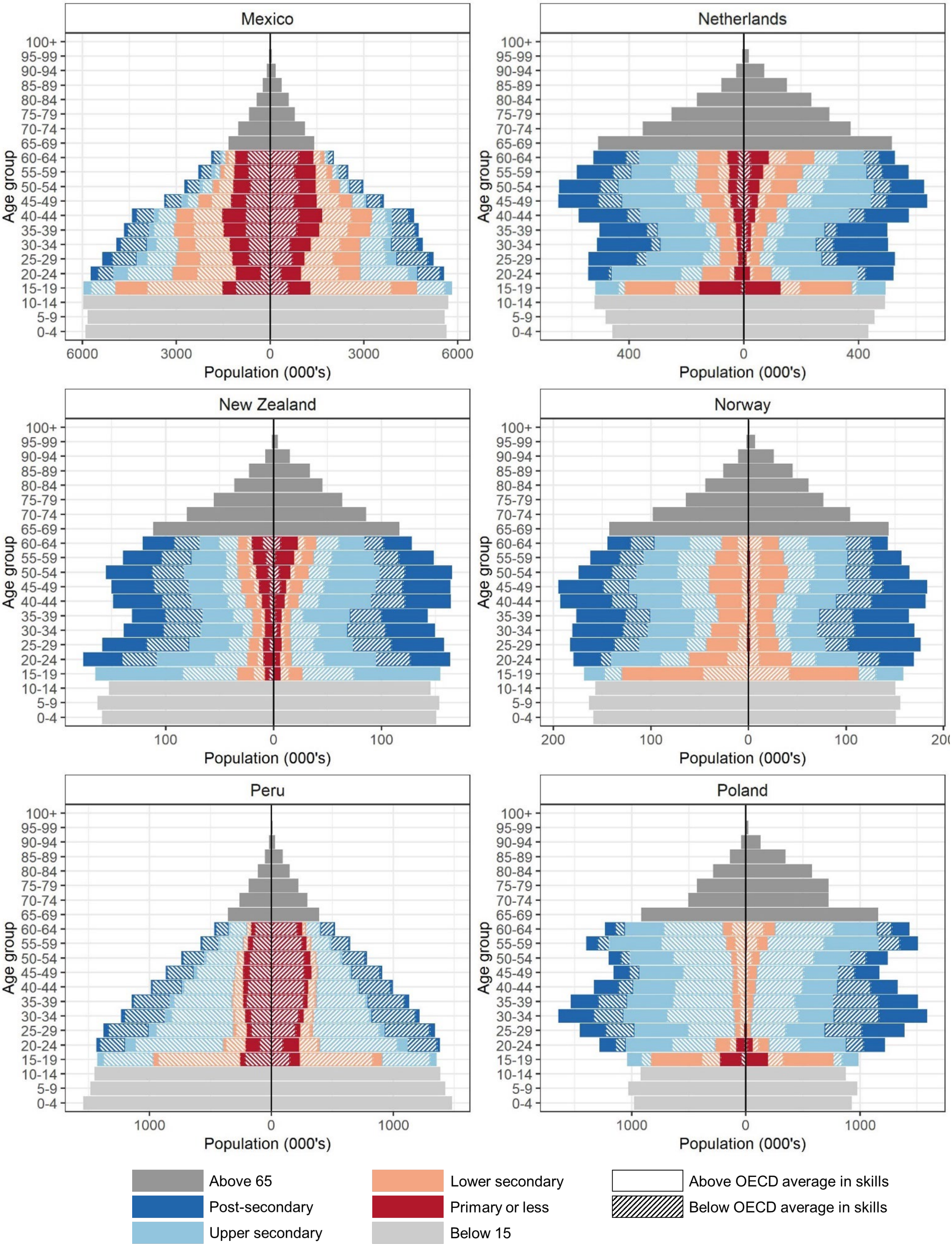


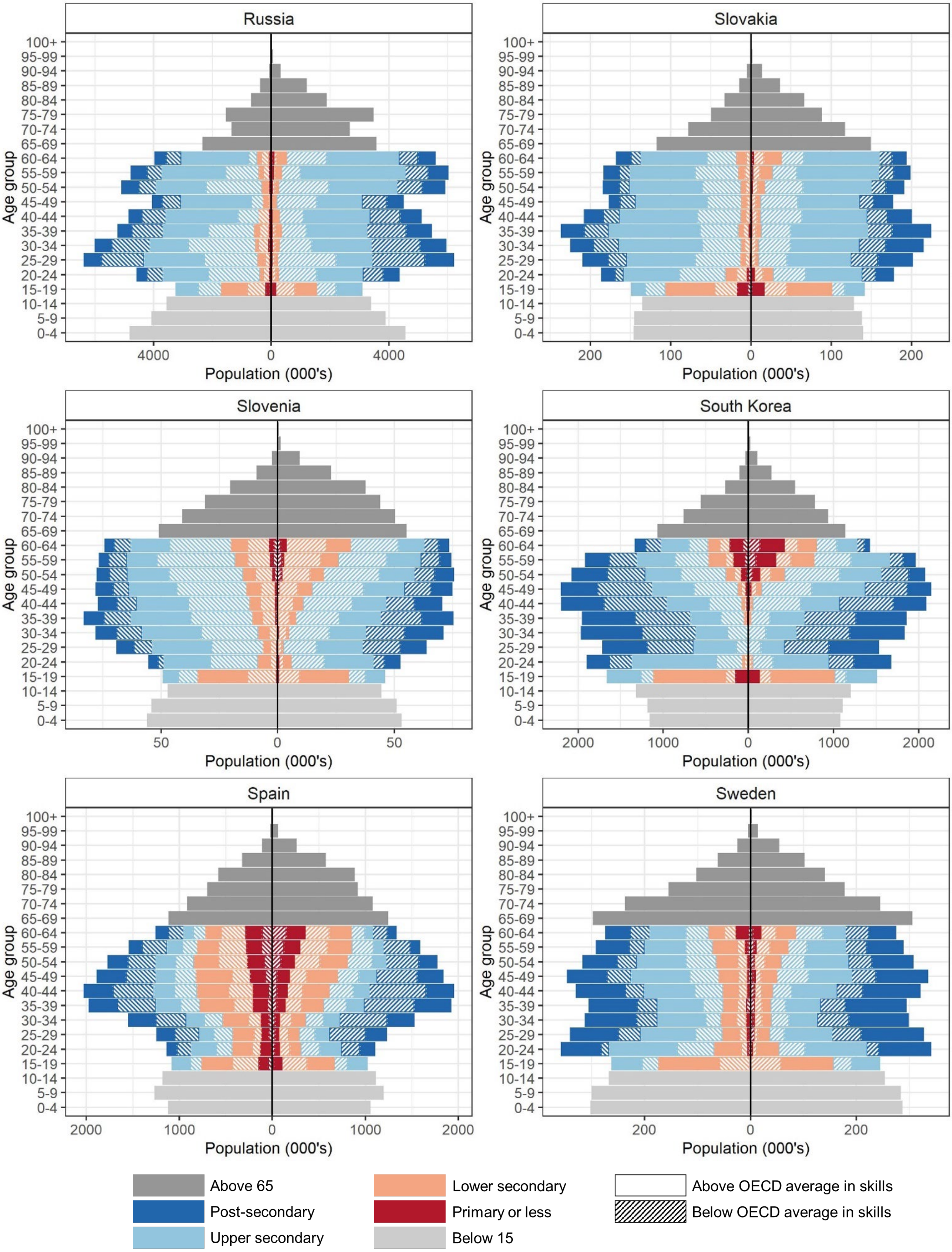

Austria
Belgium
Bolivia
Canada
Chile
Colombia
Age group
Population (000's)
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills

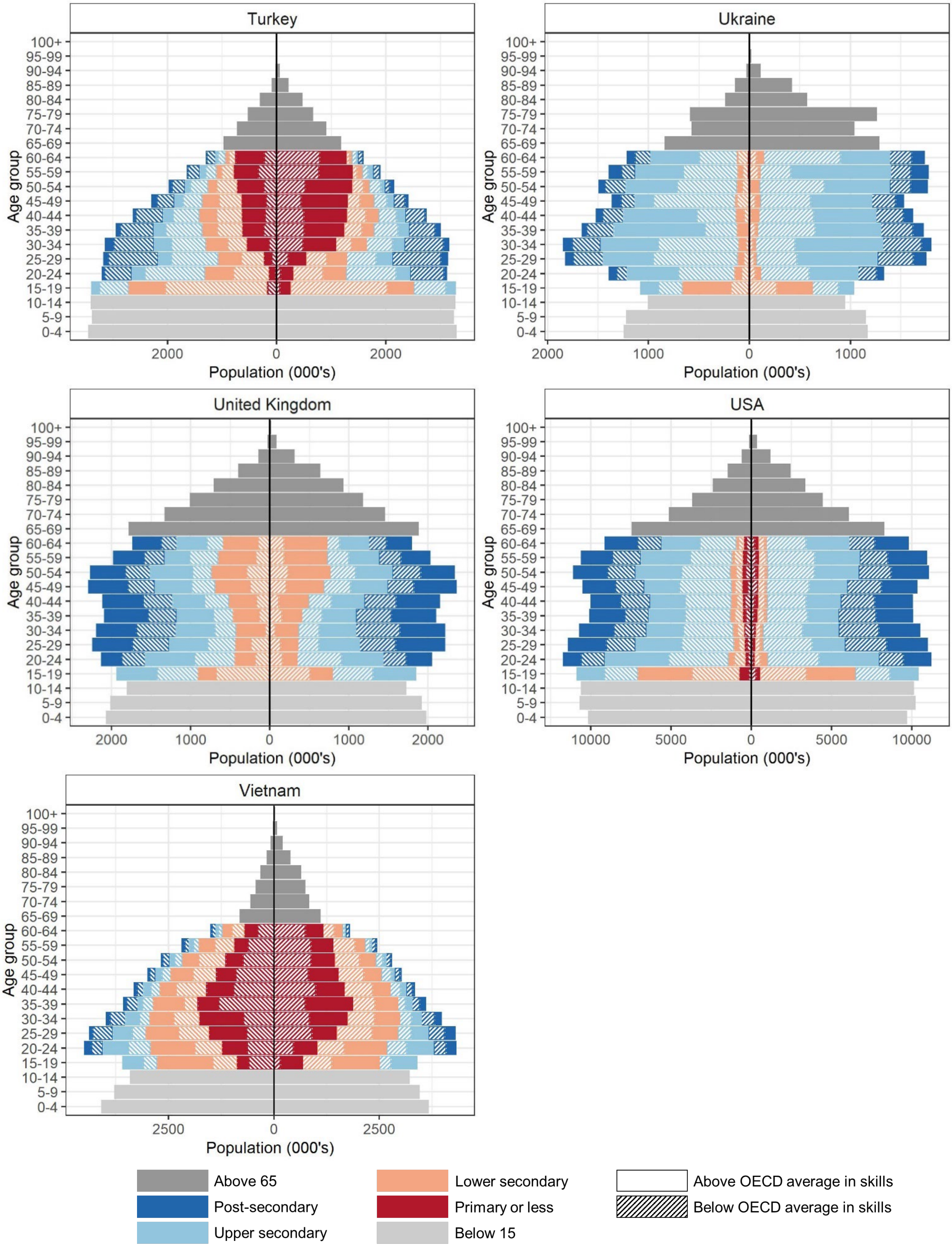

Cyprus
Czech Republic
Denmark
Ecuador
Estonia
Finland
Age group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


France
Georgia
Germany
Greece
Hungary
Ireland
Age group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
2000 1000 0 1000 2000
100 0 100
2000 0 2000
250 0 250
250 0 250
200 100 0 100 200
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Israel
Italy
Japan
Kazakhstan
Kenya
Lithuania
Age group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Mexico
Netherlands
New Zealand
Norway
Peru
Poland
Age group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
6000
3000
0
3000
6000
400
0
400
100
0
100
200
100
0
100
1000
0
1000
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Russia
Slovakia
Slovenia
South Korea
Spain
Sweden
Age group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Turkey
Ukraine
United Kingdom
USA
Vietnam
Age group
Population (000's)
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills

3. Conclusion

3.1. Main Findings

This thesis aims for a better understanding of the role of adult skills in human capital formation. More specifically, I wish to contribute to a better and more holistic measurement of human capital, paying special attention to skill levels, changes, and distribution in different populations around the world. The three publications have provided clear answers to the research questions stated in the introduction, which are now summarized in the following paragraphs.

The first publication investigated the changes of adult literacy skills over the life course and over time. The results show significant differences between countries for the period 1970–2015— regarding both the level of literacy skills and their development over time. While in the majority of countries included in the analysis, literacy skills have remained roughly constant or have even increased slightly over the last 45 years, populations in other countries (notably Ghana and the United Kingdom) have experienced minor skill loss. In addition, when the results are further disaggregated by age, sex, and educational attainment, it becomes clear that the changes in the level of skills in a country are also the consequence of a changing composition of its population. In most countries, older people were found to have consistently lower literacy skills during the whole 1970–2015 period, partly as a result of the skill loss that comes with the age effect, but also as a reflection of the lower educational attainment of the elderly. For Singapore, it was shown that the country's rise in skills is first and foremost driven by a growing group of highly educated individuals, whereas the literacy skills of the least educated have actually decreased over the last decades. When gender differences were assessed, most countries were found to have no significant gender gaps in literacy skills. However, there were a few exceptions: in Ghana, Kenya, and Turkey, men are still significantly higher skilled than women—even though the gap has slowly decreased over time.

For the life course development, I found considerable differences for specific subpopulations. Results show that those with lower education (i.e., people with lower secondary education or less) tend to lose the highest share of their literacy skills quite soon after leaving school. This can be explained by less educated people frequently taking jobs that have lower cognitive demands, meaning that they no longer practice the literacy skills they learned in school. On the other hand, higher-educated people (i.e., people with upper secondary education or higher) were found to still moderately gain literacy skills up to the age of 35, with these eventually starting to decline around the age of 45. Gender, on the other hand, was found to have hardly any effect on how literacy skills change over the life course. Results do, however, show a minor effect at the age of young adulthood: for lower-educated women up to the age of 35 the skills decline is a little bit steeper than for their male counterparts; similarly, the skill gain for higher-educated women is slightly flatter than for men. This may be explained by women being more likely to stay at home when they enter parenthood, thus facing lower cognitive demands than young fathers who tend to be continuously active in the labor market. For older age groups, no significant differences in the development of skills between men and women were found.

In the second dissertation publication (co-authored with Wolfgang Lutz, Caner Özdemir, Dilek Yildiz, Raquel Guimeraes, and Anne Goujon), we present a new indicator to comprehensively measure human capital, the Skills in Literacy Adjusted Mean Years of Schooling (SLAMYS). Drawing on international adult skills assessment data and using demographic back-projection and statistical estimation techniques, the paper presents the first demographically consistent human capital dataset that considers both educational attainment and literacy skills for 185 countries for the period 1970–2015. At the global level, it was found that SLAMYS increased from 3.7 in 1970 to 6.9 in 2015, whereas Mean Years of Schooling (MYS) increased from 4.8 to 8.5 during the same period. These global average trends do, however, hide considerable regional and national differences. The largest increase over time in terms of SLAMYS among the world regions was found for Eastern Asia: from 3.2 SLAMYS in 1970 to 8.4 in 2015. Sub-Saharan Africa, on the other hand, experienced an increase from the extremely low level of 0.8 SLAMYS in 1970 to 3.2 in 2015. This means that sub-Saharan Africa has currently about the same SLAMYS level as Eastern Asia in 1970. If skills are indeed a key driver of socioeconomic development, this implies that sub-Saharan Africa lags almost half a century behind Eastern Asia. Among the more industrialized countries, results reveal that Europe has been able to catch up over the last decades with North America, which still had a clear advantage in 1970.

Similarly, findings show great diversity among country-specific human capital trends. Japan, for example, already displayed a high level of SLAMYS in 1970 (fifth in the global ranking), but managed to increase SLAMYS even more than the observed rate for the conventional Mean Years of Schooling (MYS), reaching the top of the list with 15.6 SLAMYS in 2015. On the other end of the spectrum are many African and South Asian countries that were making good progress in terms of MYS, but much less so in terms of SLAMYS. At the very end of the list is Niger, with an estimated SLAMYS in 2015 as small as 0.6 and showing hardly any improvement over time. Nevertheless, there are also some positive exceptions in Africa. In Zimbabwe, for example, SLAMYS increased by almost a factor of four (from 2.2 in 1970 to 8.4 in 2015), reaching the same level of human capital as the average value in Eastern Asia. Overall, results challenge the view that the impressive recent gains in the expansion of schooling have led to a corresponding increase in human capital. While developing countries are rapidly catching up in terms of educational attainment, the gap between highly skilled and low-skilled populations continues to widen globally—it has even increased to the equivalent of over 10 years of schooling.

The final publication of this thesis studies population heterogeneity in literacy skills by incorporating a skills dimension into existing population distributions. Drawing on large-scale adult skills assessment surveys, I combine measures of literacy skills with population distributions by age, sex, and educational attainment for 45 countries, providing for the first time a holistic depiction of the distribution of human capital that considers not only the quantity dimension of education, but also the qualitative element of actual skills. On the one hand, the resulting skills-adjusted education pyramids capture the "inequality in quality," with poorer countries often experiencing the double burden of people being less educated and having lower literacy skills than people with the "same" education in other countries. While the educational attainment distribution certainly plays a role in the distribution of literacy skills in a country, results still show considerable heterogeneity within each educational attainment level, demonstrating again the weakness of conventional demographic analyses, where everyone with the same degree (and same age and sex) is treated equally in terms of their demographic behavior, regardless of their actual level of skills.

On the other hand, the skills-adjusted education pyramids also reveal important inter-cohort changes in literacy skills—again, with significant variation between countries. In South Korea, for example, results show that younger people have consistently higher skills than older people. Some of these differences can be explained by age effects, as cognitive skills tend to rise in the early years and then eventually decline as adults age. In addition, cohort effects are likely to play a role—particularly, in a country like South Korea which has experienced the most rapid education expansion in recent history. This cohort effect was, however, not found for all countries. In Kazakhstan, for example, the distribution of literacy skills was found to be almost identical for all age groups—although the country also experienced significant educational expansion in the past. These findings suggest that not all countries have managed to translate the increased quantity of education among the younger cohorts into a corresponding rise in skills. Rather, in some countries, quantity may have come at the expanse of quality. In terms of gender differences, the gender gap in literacy skills was found to be rather small in most of the 45 countries. However, considering that many highly developed countries currently experience the reversal of the gender gap in terms of educational attainment (i.e., women now spending more years in education than men), it is worth mentioning that literacy skills among 20–64-year-olds were found to be still slightly higher for men than for women in most countries included in the analysis.

A common finding in all three papers was that the widespread assumption—namely that direct conclusions can be drawn about the actual level of skills people possess based on the highest educational level people have attained—does not hold in most cases. Given that skills have been shown to matter greatly for many of the benefits of human capital, the prevailing use of indicators focusing only on the quantitative dimension of education may cloud the analysis and misguide assessments of the state of human capital around the world.

3.2. Contribution

This dissertation makes important contributions to the topics of human capital measurement and skills-adjusted education indicators, with crucial implications not only for scholars working with data on education and human capital but also for policy-makers concerned with development goals and policy evaluations. In the following, I highlight and specify the most important contributions.

The first key contribution of this dissertation is to give us new insights into the development of literacy skills over time and over the life course. Despite recent initiatives to consistently measure adult skills and make them comparable among countries, there is still little information as to how literacy skills have evolved over time within the same population and what the main drivers behind these changes are. This information is, however, crucial if we are to better understand skills-related effects on economic growth, sustainable development, and demographic changes. Due to the lack of longitudinal adult literacy skills data, there is also a lack of literature studying the complex interplay of age, cohort, and period effects—all potentially impacting skills development over the life course. The first paper of this dissertation fills that gap by applying demographic methods to estimate the changes in literacy skills as cohorts age. While the results are relevant in themselves, they are also an important contribution to future research, for example, for projecting skills-adjusted human capital into the future. While we know that educational attainment usually remains invariant after a certain age, accounting for potential depreciation of skills is also important for reliably predicting the future of human capital.

The second main contribution of this dissertation is related to the measurement of human capital. Although human capital is widely acknowledged as one of the key drivers of economic growth and social development, its measurement for working-age populations, on a global scale and over time, is still unsatisfactory. Existing indicators either only consider the quantity dimension of education and disregard the actual skills acquired, or they are demographically inconsistent because they apply the skills of the young cohorts in school to represent the skills of the working-age population- This assumption is particularly problematic in the case of rapidly expanding or changing school systems. To remedy this, a new indicator is suggested in this dissertation, the Skills in Literacy Adjusted Mean Years of Schooling (SLAMYS). Several features of this indicator advance the state of the art in the field of human capital measurement. First, it combines tests on adult skills with conventional educational attainment indicators, thus providing a fuller understanding of the level of human capital in a country. Secondly, it is estimated for a very large number of countries (185 countries representing 99% of the world's population) and for the period 1970–2015, presenting a broad picture of trends in global human capital. Finally, due to its reliance on adult skills assessment data and cohort analyses, it is demographically consistent, providing comparable data for skills-adjusted human capital for the working-age population over a 45-year period.

The development of a novel indicator to measure human capital can, however, only be a means to an end; it is the conclusions and implications drawn from its analysis that matter.

It is only when the indicator is correctly used and properly interpreted that it can help policy-makers better monitor progress and enhance policies. The widening global gap in human capital revealed by the analysis of the SLAMYS dataset is likely to have significant implications for disparities among countries in their economic development, health, and well-being, and this is of great relevance for policy-makers, particularly in the current transition to knowledge societies and the digital revolution.

The final dissertation publication extends the literature on education as a demographic variable. Education is increasingly entering demographic analyses as an explicit dimension due to its substantive impact on progress in human development and its potential to alter population dynamics (Lutz, 2010; Lutz et al., 1998). To date, however, this kind of analysis has been limited to the quantitative dimension of education (i.e., educational attainment). Here, for the first time, I investigate the importance of skills as a demographic dimension. My contribution is based on both a review of existing literature supporting the relevance of literacy skills as a demographic dimension and empirical analyses that provide evidence for large heterogeneity in literacy skills among otherwise similar subpopulations. By pointing out gender, generational, and geographical gaps in skills-adjusted educational attainment, I provide new insights into distributional aspects of human capital, with clear relevance for progress towards development goals.

3.3. Final Remarks

The value and importance of education is well recognized, as both a primary human right and a key driver of progress in economic development, health, and social empowerment. Education is also recognized as a key development priority by the international community. In the Millennium Development Goals (MDGs), defined in 2000 and pursued by a variety of global actors, the education-related targets focus largely on achieving universal primary education up to 2015, and great progress has been seen as a result (Friedman et al., 2020). This means little, however, if educational expansion does not come with a concomitant rise in skills. This lack of quality assessment was somewhat acknowledged by the Sustainable Development Goals (SDGs)—the follow-up to the MDGs with 2030 as target year— which emphasized the importance of education with a much broader scope, namely to "ensure inclusive and equitable *quality* education and promote lifelong learning opportunities for all" (United Nations, 2022). However, for the "quality turn" to be realized in practice, existing indicators also need to be rethought and refined (Sayed & Moriarty, 2020).

With this dissertation I hope to enhance the measurement and estimation of human capital, and also to provide arguments and evidence supporting a more holistic approach to education, in which skills are considered as equally important to the level of attainment. My empirical findings are very much based on literacy skills, which are increasingly becoming essential to enable individuals to thrive in contemporary societies (as highlighted in the introduction). Nevertheless, an individual's skill set is clearly not limited to their literacy level, but contains a much wider spectrum, with other skills likely to be of similar relevance. Therefore, in my concluding remarks, I also would like to stress the need for internationally comparable widespread testing of adult skills beyond literacy, which would enable researchers to further validate my findings and extend my analyses to additional skill domains.

Finally, at the end of this dissertation, which focuses so much on the measurement and estimation of human capital, it is important to return to the question as to why education and the acquisition of skills are so important for our lives. According to Sen (2005), through education, individuals can acquire the capabilities needed to enjoy freedoms and entitlement to fundamental human rights. When education is approached from this perspective, there is no doubt that quality education can empower human beings to better manage their lives. Hence, improving our measures of human capital, as I have attempted to do in this dissertation, can also ultimately help societies to better monitor progress and put forward policies to build a better future.

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