**Inequality in Quality:**

**Population Heterogeneity in Literacy Skills around the World**

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**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 – but is still 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, as well as one sub-group of a population from another. In traditional demographic analysis, it has become standard practice to sort the total population along the dimensions of age and sex. There is little debate that both of these characteristics serve as fundamental differentiation in human society and can be considered essential for studying the demographic processes of reproduction, mortality, and migration. More recently, it has been argued that education should also be routinely added to population analyses, given its substantive impact on progress in human development and its potential to alter population dynamics as fertility and mortality vary greatly and systematically by level of education (Lutz 2010; Lutz, Goujon, and Doblhammer-Reiter 1998).

So far, education in population distributions has been usually measured by highest level of educational attainment, i.e. the quantity of education. This has two main benefits: first, the educational attainment of a person can be rather unambiguously defined and easily measured (as it is nowadays done 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 and Lee 1993, 2001, 2013, 2015; Goujon et al. 2016; Lutz et al. 2005; Speringer et al. 2019). While this makes education easy to be integrated in population distributions, it also clouds the analysis as it completely disregards the quality dimension, i.e. the skills people actually have. This proves problematic for two main reasons: first, 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.

This demonstrates the need for incorporating a quality (or skills) dimension into existing population distributions by age, sex, and educational attainment, hence improving actual comparability between the state of human capital in different populations and sub-groups of populations. A high school graduation in one country does not necessarily provide for the same (or at least similar) skills and knowledge as a high school graduation in another country, and nature and quality of schooling may substantially change over time. In addition, skills of an individual might change considerably in the decades after graduation, while highest educational attainment remains unchanged. A skills adjustment, based on results of a growing number of international adult skills assessments, can largely dissolve 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 sub-populations, and thus deserve to be considered a relevant source of population heterogeneity?*

Drawing on large-scale adult skills assessment surveys, such as the OECD's Program for the International Assessment of Adult Competencies (PIAAC) 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 can also reveal important inter-cohort changes in literacy skills – allowing to better understand 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 transf

orm into knowledge societies, sophisticated comprehension and advanced skills of all kinds become essential for successful integration and participation in the labor market, in education and training, as well as in 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. <u>Relevance of skills (criterion i)</u>

There is little debate about human capital being 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 – mostly because of the lack of available data.

Only recently, a growing body of research has shown that skills matter equally – or even more – for many of the benefits of education. Hanushek & 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 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 poor health, even after controlling for educational attainment and income.

With the increasing availability of internationally comparable data on adult (literacy) skills, one can hence 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 2016).

## 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 less children, greater autonomy in reproductive decision-making, more knowledge about and access to contraception and use it more effectively (Bongaarts 2010; Cleland and 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 mostly (or at least partly) literacy skills that play a central role in fertility decline. Already in 1979, Cochraine (1979) concluded that increased 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, in a book by LeVine et al. (2012), the authors 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, Sobotka, and Zeman 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, Kelley, and Mason 1996; Anker and Knowles 1980; Caldwell 1979; Cochrane, O'Hara, and Leslie 1980; Kitagawa and Hauser 1973; Lutz and Kebede 2018). While there are hardly any studies particularly focusing 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 with high literacy scores, there is 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).

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

The reason why demographic analyses are almost exclusively done by educational attainment and hardly 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 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, thus being inadequate for demographic analyses of total populations.

Only recently, there have 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) 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 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 largest international assessment of adult skills. For developing countries, World Bank has developed a similar test, named 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 they are available for the largest number of countries. In addition, their relevance for many socio-economic outcomes (as highlighted in Section 1.2 and 1.3) as well as the fact that literacy skills are strongly correlated with other skill domains (e.g. numeracy) make them an interesting dimension for demographic analyses. What is important to mention is that measures of literacy skills, as used within this paper, go far beyond the mere ability to read. 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 albeit this 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 for example Hamilton & Barton 2000; Sticht 2001; or St. Clair 2012 for a summary of arguments). Here, I only want 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, being 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. Programme for the International Assesmment of Adult Competencies (PIAAC)

The 'Programme for the International Assessment of Adult Competencies' (PIAAC) is a cross-national assessment 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 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 9 additional countries. Finally, in 2017-2018 five new countries participated in the survey and USA conducted the survey once again. In each participating country, a nationally representative sample of around 5,000 respondents were selected who were asked to do a computer-based assessment (with a pencil-and-paper option for respondents who did not have 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 by combining the 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 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. 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 socio-economic 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 as well as the evaluation of complex text. In order to get a better understanding of how literacy is conceptualized in PIAAC, links to examples of literacy items are presented in the Appendix.

3.2. Skills towards Employment and Productivity Survey (STEP)

The ‘Skills toward Employment and Productivity Survey’ (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, with a special focus on low- and middle-income country contexts. Three broad types of skills are measured within STEP: cognitive skills, socio-economic, and job-relevant skills (World Bank 2014). Data were collected between 2012 and 2017 in 12 low- and middle-income countries, with each sample consisting of around 3,000 individuals, representative of the urban adult population between the ages of 16 and 65.

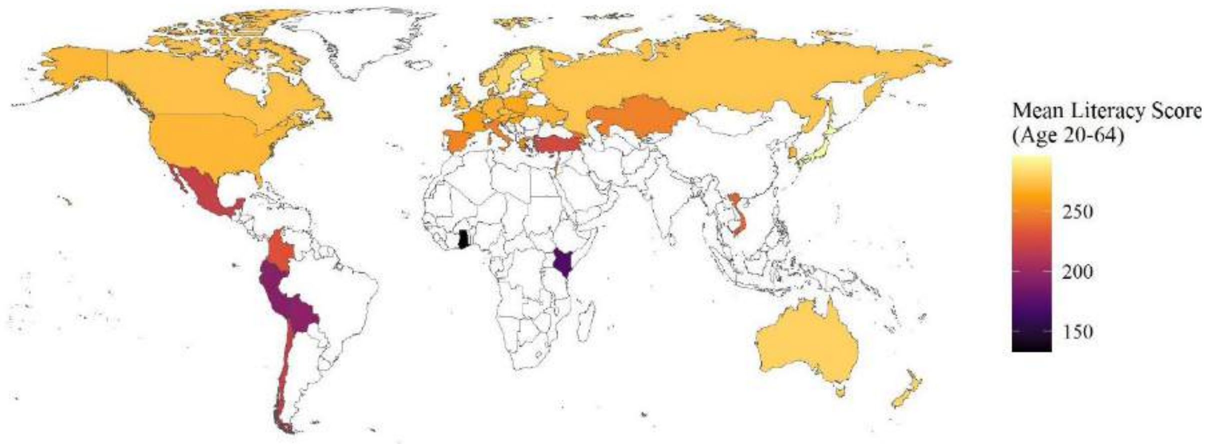
The measurement of cognitive skills, which is used within the analyses of this paper, includes a direct assessment of reading literacy designed to identify respondent’s levels of competence at accessing, identifying, integrating, interpreting, and evaluating information. A primary goal for the design 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, thus allowing for results to be reported on a common scale – making the two assessment 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.

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 reading core test, consisting of 8 short items and thus 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, sample items presented in the Appendix also apply to the STEP literacy assessment.

It is important to mention that although STEP and PIAAC use very 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. Second, STEP uses only paper-based instruments, while the PIAAC assessment was designed to be primarily administered on a computer. However, differences in the delivery mode were shown to not significantly affect the comparability of result (OECD 2019). Finally, 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 it is the case in some of the STEP countries. Despite these notable limitations, I still decided to include STEP data in the analysis. 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 which is more diverse in terms of social and economic development. 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 & Paccagnella 2020), suggesting that – given the matched psychometric methods – results are still largely comparable. Nevertheless, it is important to be transparent about these differences so that readers can read and interpret the results with adequate caution.

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 skill 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, which is 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. Wittgenstein Centre (WIC) Human Capital Data Explorer

For the population data by age, sex, and educational attainment, I rely on data from the Wittgenstein Centre 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 have traditionally been geographic regions (Rogers 1980), but could as well be educational attainment categories or levels of skills. Since 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[1] OECD mean PIAAC literacy test score, calculated separately for each age-, sex-, and education group as presented in Table 1. In this way, despite notable differences and advances of OECD countries in terms of age structure and educational attainment distribution, the performance threshold is still 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.

[1] Population estimates by age, sex, and educational attainment come from the Wittgenstein Centre 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

In order 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[2,3]. 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) sub-groups, I was able to disaggregate the population for each country by 5-year age groups, sex, and eight skills-adjusted educational attainment categories (with skills-adjusted human capital only available for the age groups 16-20 to 60-64). 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. However, these sub-groups usually do not

[2] 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.

[3] 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.

From 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 2, 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). In order to account for these peculiarities, the R packages *intsvy* and *BIFIEsurvey* were used which provide tools and analyses specifically designed to work with international assessment data[4].

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[5]. 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 hence 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. Results & 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

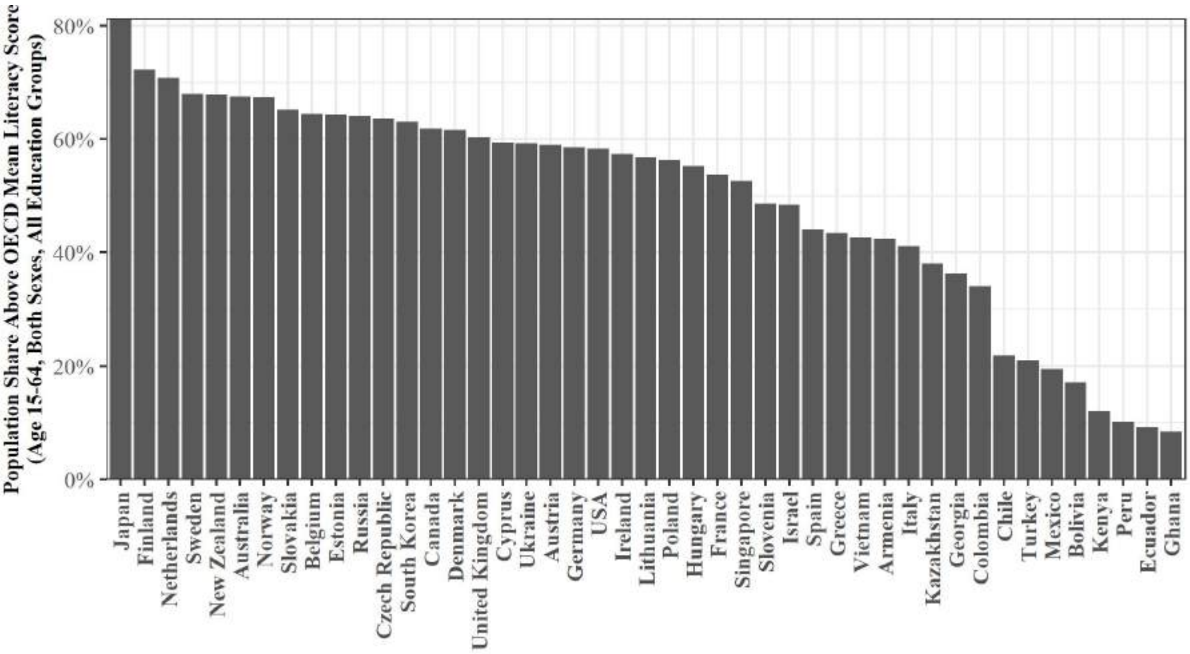
[4] For further information on the packages, see https://cran.r-project.org/web/packages/intsvy/intsvy.pdf and https://cran.r-project.org/web/packages/BIFIEsurvey/BIFIEsurvey.pdf

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

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, 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. Figure 2 depicts for each of the 45 countries the proportion of the population aged 15-64 which have 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 are leading 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 looking at distributional aspects of skills.

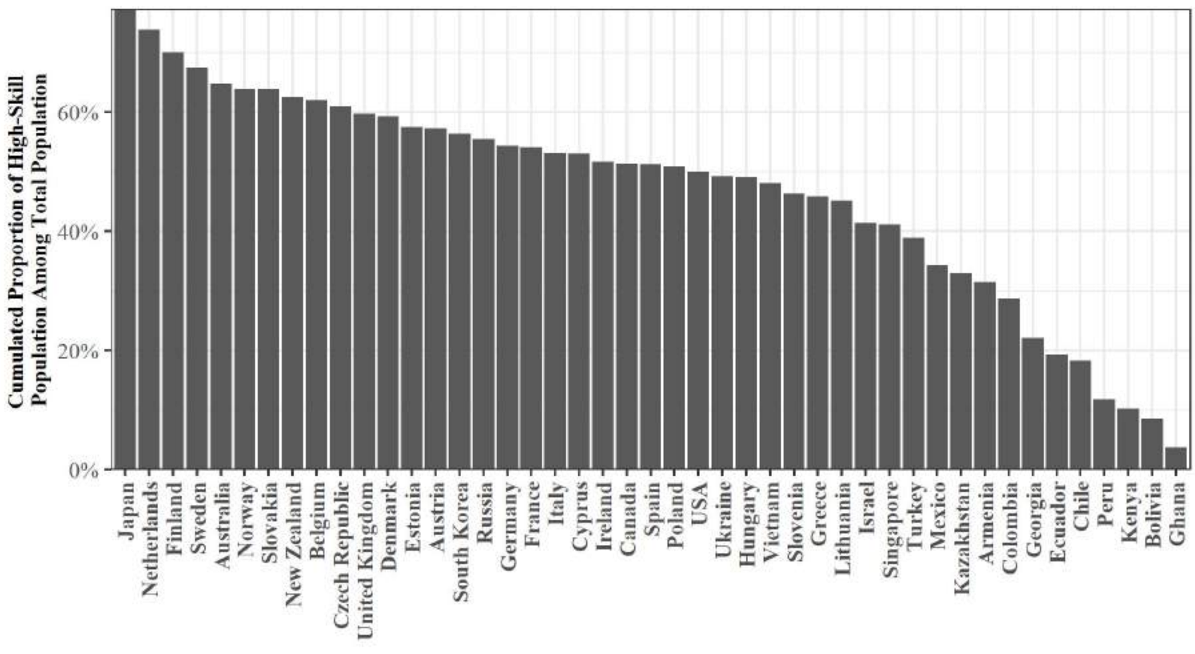
Figure 2. Proportion of population (age 15-64, both sexes, all educational attainment groups) above OECD mean literacy score, by country, 2015




Source: Author’s calculations

While this is certainly relevant when assessing the human capital in a population based on a summary measure, 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 OECD average in 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 as compared to Figure 2. This can be explained by the fact that countries such as Japan or Finland are doing so well in literacy assessments also because they have large shares of the population with post-secondary education, who have, on average, higher skills than the overall OECD mean. However, when comparing their performance to the OECD mean of their respective age-sex-education group, the supremacy of these countries in terms of the share of the population above the OECD mean is decreasing a little bit. 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.

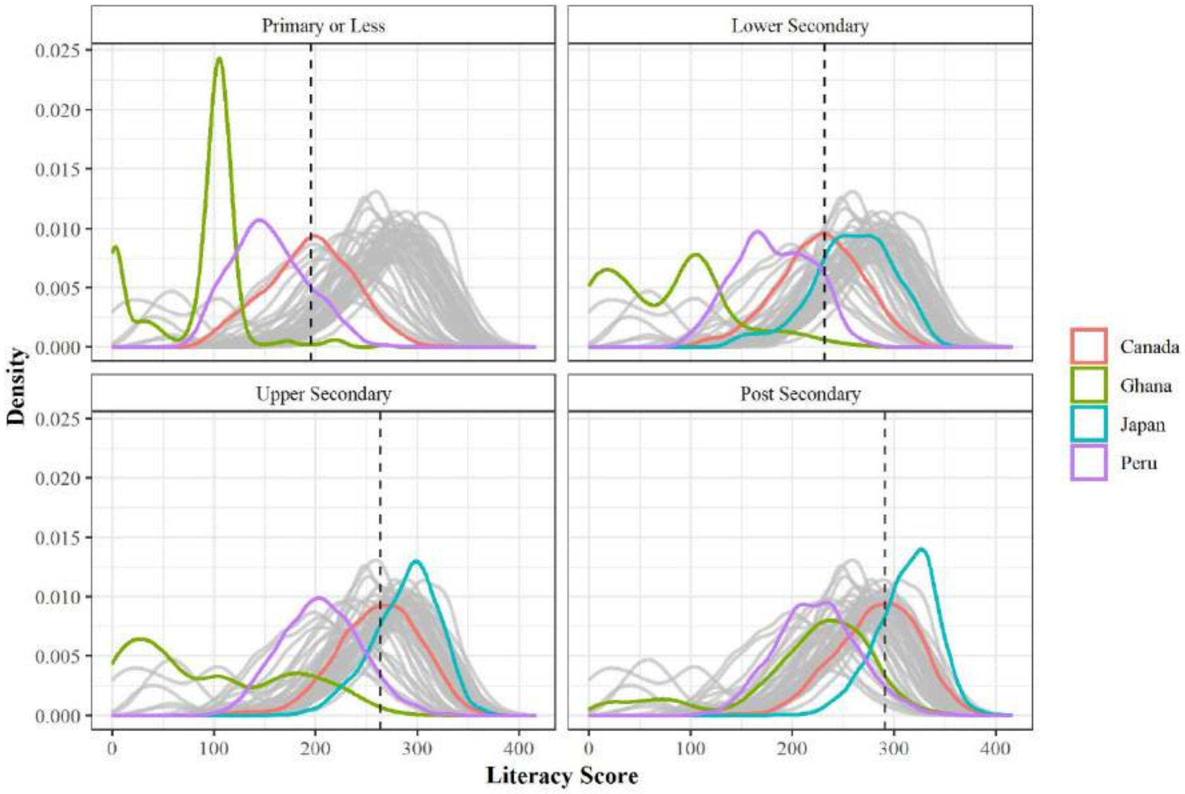
Figure 3. Cumulated proportion of population above OECD mean literacy score in their respective age-sex-education group, by country, 2015




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 – of course also due to the fact that in Ghana still roughly one quarter of the population aged 20-64 never experienced any formal education. 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 shows the weakness of previous analyses, where everyone with the same degree (and same age and sex) was treated equally 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 2064); selected countries are highlighted

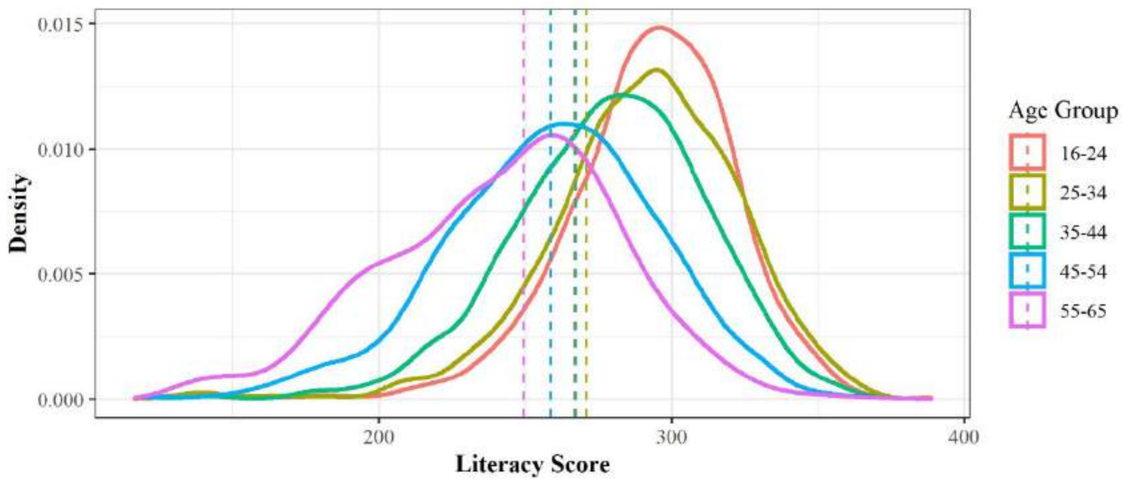



Source: Author’s calculations

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

Besides 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 of skills when people get older) and cohort effects (i.e. generational changes such as a different educational attainment distribution and different quality of schooling between younger and older people). Consider the case of South Korea, 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, 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 (Hertzog et al. 2008; Desjardins and Warnke 2012; Skirbekk et al. 2012; Green and Riddell 2013; Barrett and Riddell 2016; Paccagnella 2016). 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 – in contrast to other countries – to massively increase the quantity of education, without sacrificing quality. As can be seen on the plot, improvements in literacy skills by birth cohort are much larger in South Korea than for the OECD average (depicted by the dashed vertical line).

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

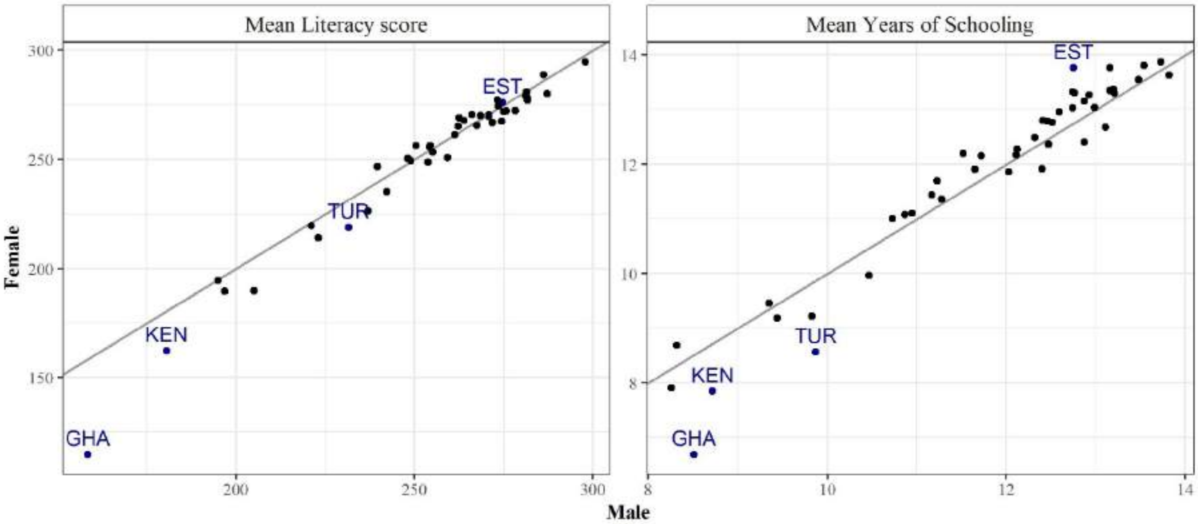



Source: Author's calculations

*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), i.e. 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 in terms of both being in school and 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, e.g. for numeracy skills (OECD 2016).

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

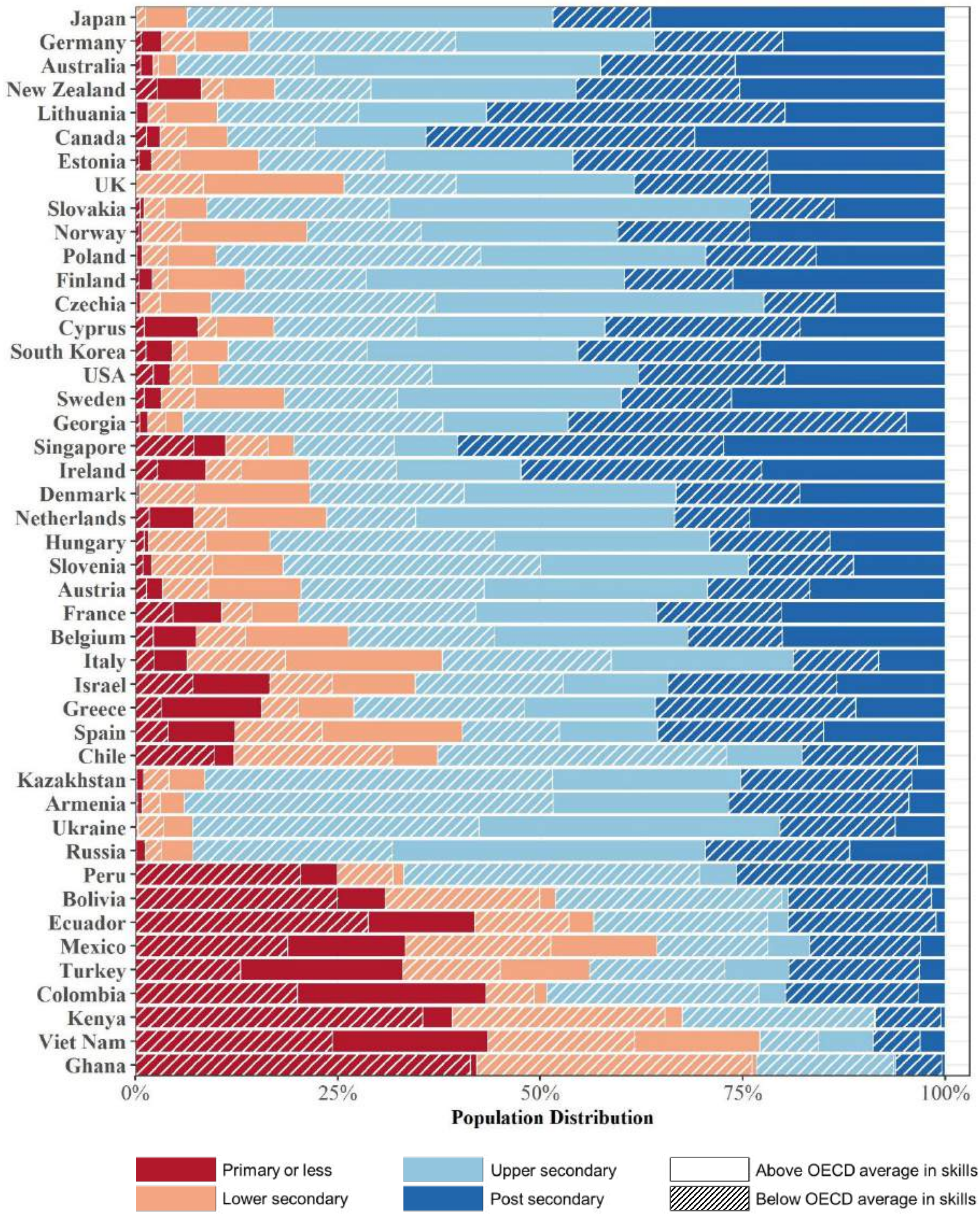



Source: Author's calculations

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

To get a better overview about 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 respective age-sex-education group) and a filled area (high-skill, i.e. above OECD mean in respective age-sex-education group). As can be seen on the plot, there are significant differences between 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, or 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 of 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

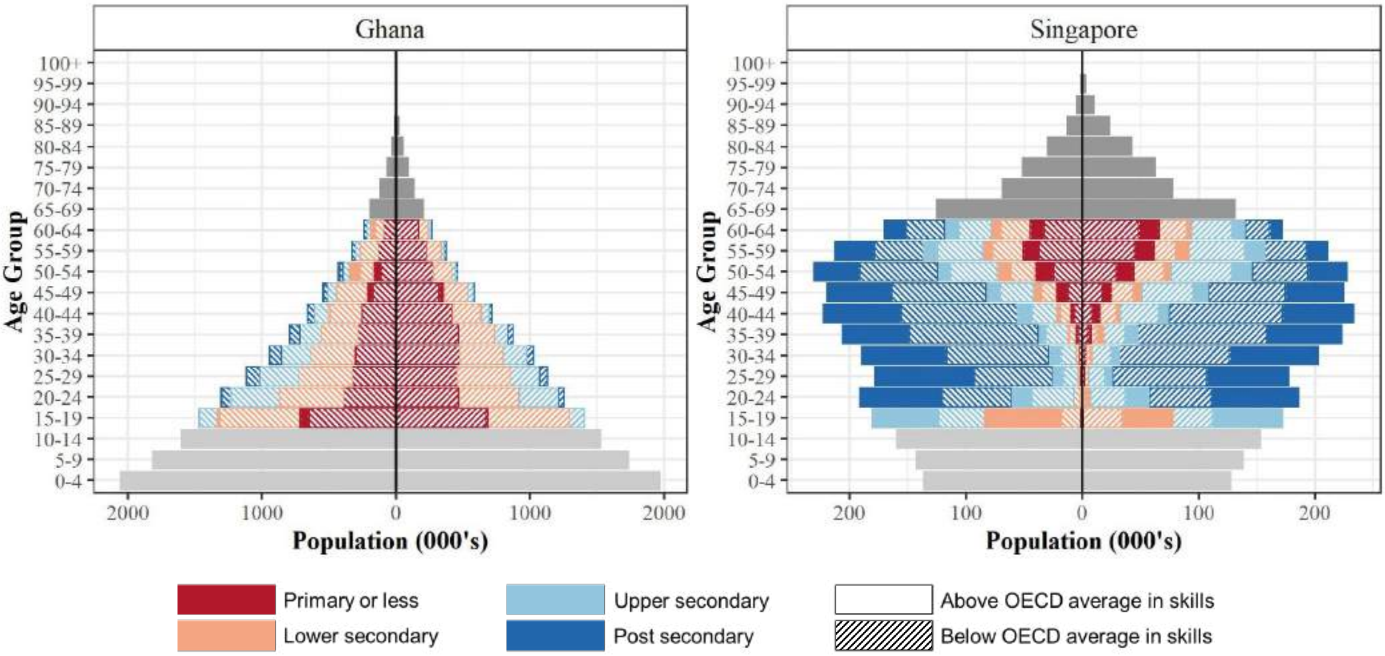
Other countries, such as Armenia, Chile, Georgia, or Kazakhstan, do have a solidly educated population, with the vast majority of people having attained at least upper secondary education. However, their skills are predominantly below the OECD average in the respective education group, suggesting again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

Among highly developed countries, results also reveal significant differences. While people in Japan, Finland, Netherlands, Norway, or Sweden both hold very high educational attainment and largely 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, or 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.

However, as mentioned previously, it needs the full distribution of the population by age, sex, and skills-adjusted educational attainment categories to not only capture the inequality in education and skills, but also reveal inter-cohort changes and gender differences. Therefore, Figure 8 presents multi-dimensional population pyramids for two exemplary 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, whereas the pattern indicates the level of skills6. 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.

[6] Skills-adjusted pyramids for the remaining 43 countries can be found in the Appendix (see Figure A.4).

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

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 number of students as well as potential insufficiency of school inputs and low government spending in 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 percent 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 OECD average.

## 6. Conclusion

Skilled human capital has been widely acknowledged as one of the key drivers of economic growth and social development. Given its overriding importance, particularly in modern knowledge societies, it is indeed a shortcoming of the statistical analysis of human capital that it almost exclusively focuses on the quantity of education, while quality and levels of skills matter at least equally. Likewise, in demographic studies, when analyzing (sub-)populations by their level of human capital, educational attainment is usually used – with the implicit but often unrealistic assumption that one can draw direct conclusions from the highest educational level people attained to 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, considering 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 likewise rise of skills. Rather, in some countries the increase in quantity of education may have come at the expanse of quality. 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 as well as immigration flows. More sophisticated analyses and explanations would therefore require country-specific case studies that could be 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, e.g. gender gaps in skills were shown to vary significantly with the domain of skills. The availability of more widespread and internationally comparable testing of adult skills beyond literacy would allow to validate results and further extend the analyses 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, results of this paper partly challenge this optimistic view and stress the importance of not losing sight on quality of education. Estimates presented here, however, only provide an important basis for analyzing human capital; future demographic analyses are needed, including – but not limited to – population projections (as well as reconstructions) by age, sex and skills-adjusted educational attainment.

**Acknowledgments**

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

**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

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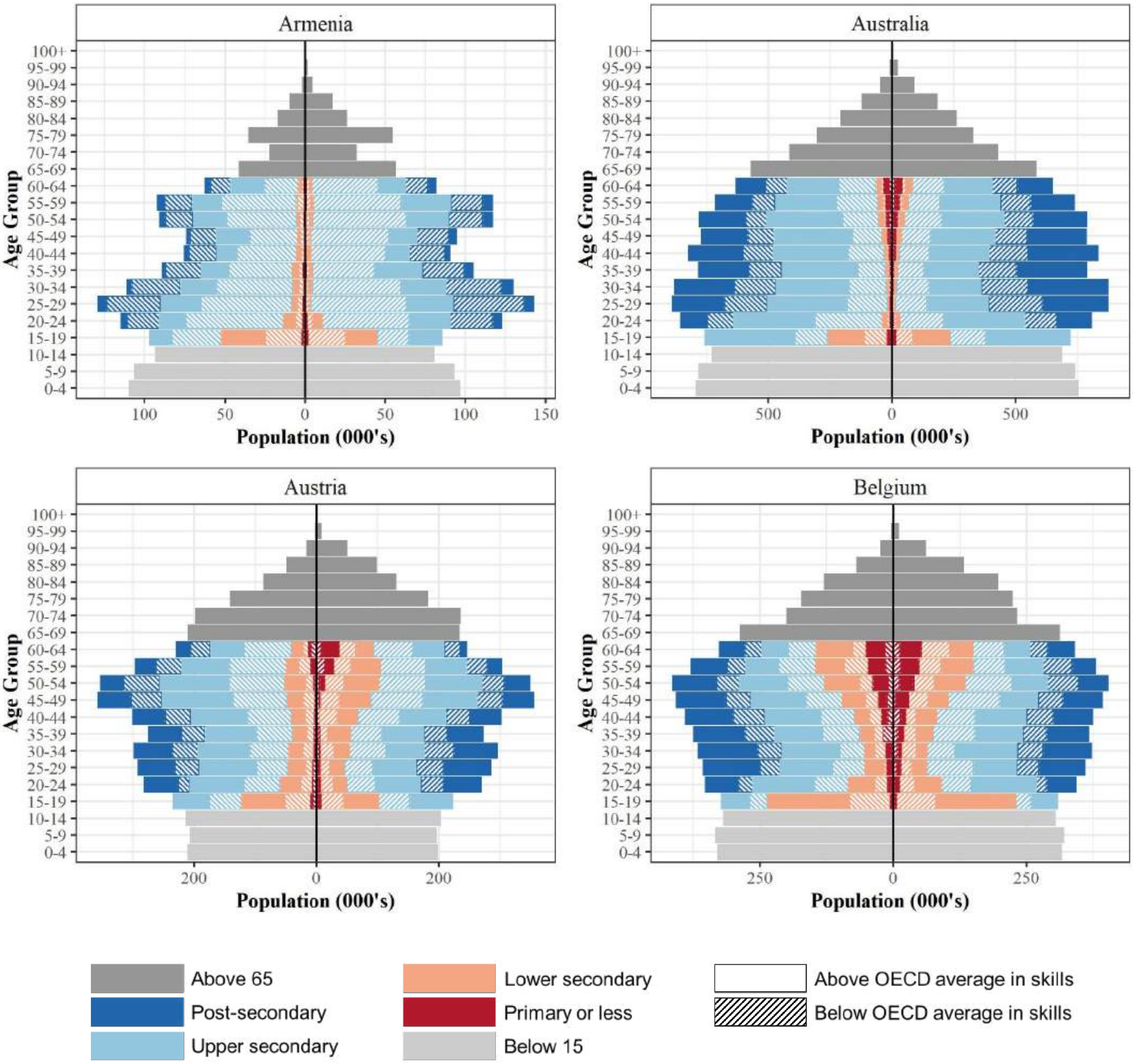
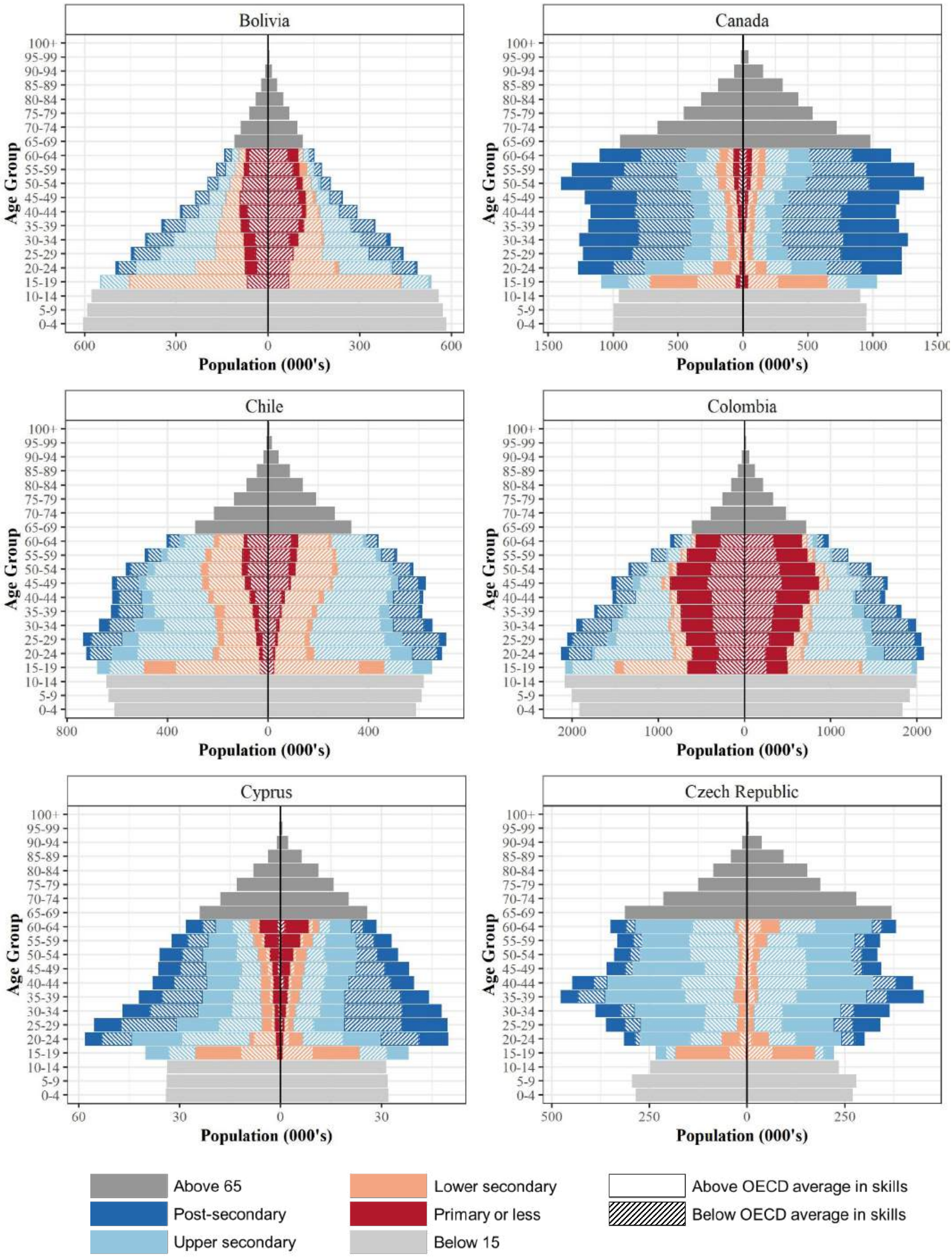
**Appendix**

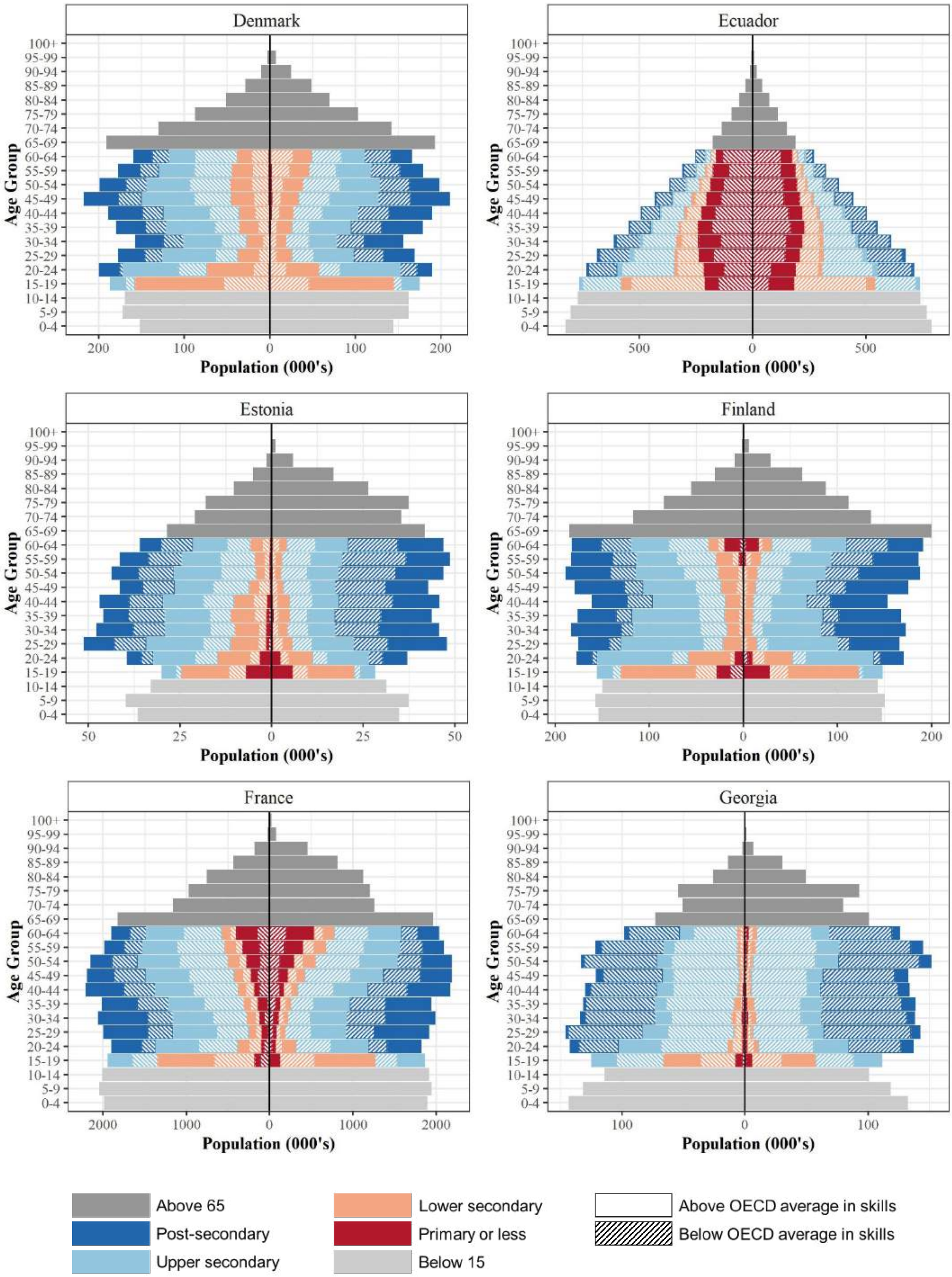
PIAAC Literacy Sample Items

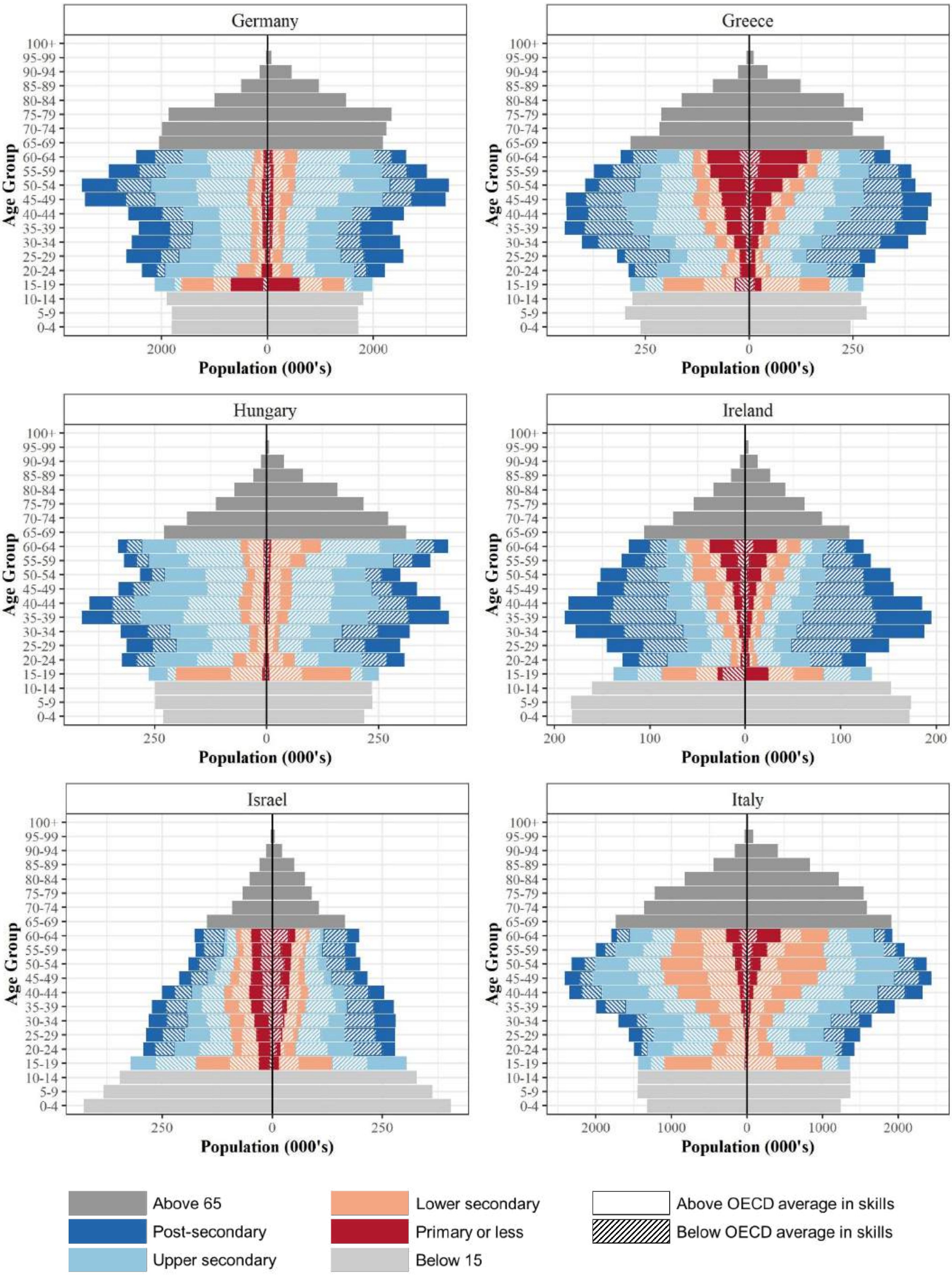
In order to get a better understanding of how literacy is conceptualized in PIAAC, examples of literacy items can be found under the following link:
https://nces.ed.gov/surveys/piaac/sample_lit.asp

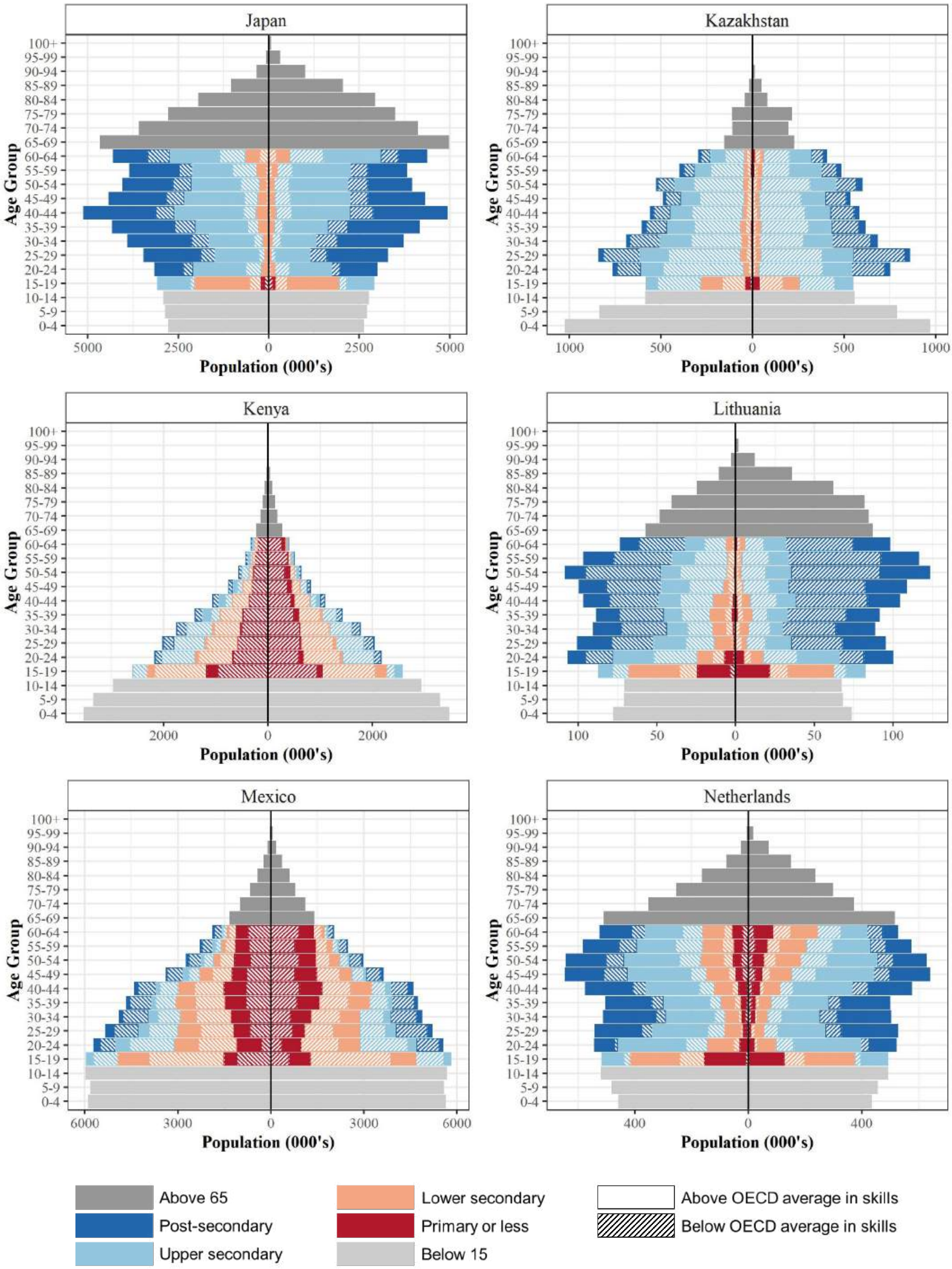
Figure A1. Population by 5-year age groups, sex, and skills-adjusted educational attainment (men on the left, women on the right), by country, 2015

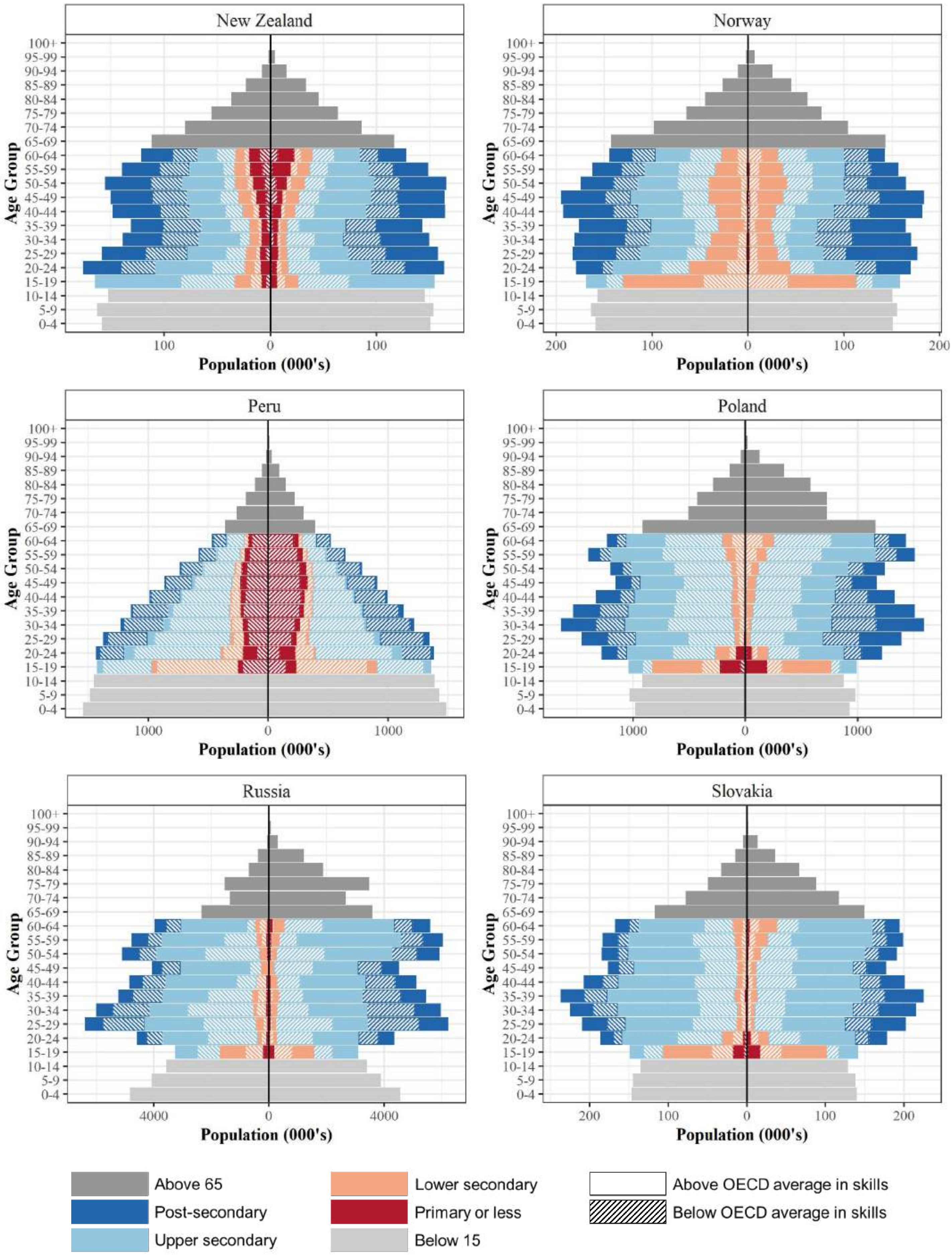



Bolivia
Canada
Chile
Colombia
Cyprus
Czech Republic
Age Group
100+
95-99
90-94
85-89
80-84
75-79
70-74
65-69
60-64
55-59
50-54
45-49
40-44
35-39
30-34
25-29
20-24
15-19
10-14
5-9
0-4
Population (000's)
600 300 0 300 600
1500 1000 500 0 500 1000 1500
800 400 0 400
2000 1000 0 1000 2000
60 30 0 30
500 250 0 250
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Denmark
Ecuador
Estonia
Finland
France
Georgia
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


Germany
Greece
Hungary
Ireland
Israel
Italy
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)
2000
0
2000
250
0
250
200
100
0
100
200
2000
1000
0
1000
2000
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Japan
Kazakhstan
Kenya
Lithuania
Mexico
Netherlands
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)
5000 2500 0 2500 5000
1000 500 0 500 1000
2000 0 2000
100 50 0 50 100
6000 3000 0 3000 6000
400 0 400
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


New Zealand
Norway
Peru
Poland
Russia
Slovakia
Age Group
100+
95-99
90-94
85-89
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70-74
65-69
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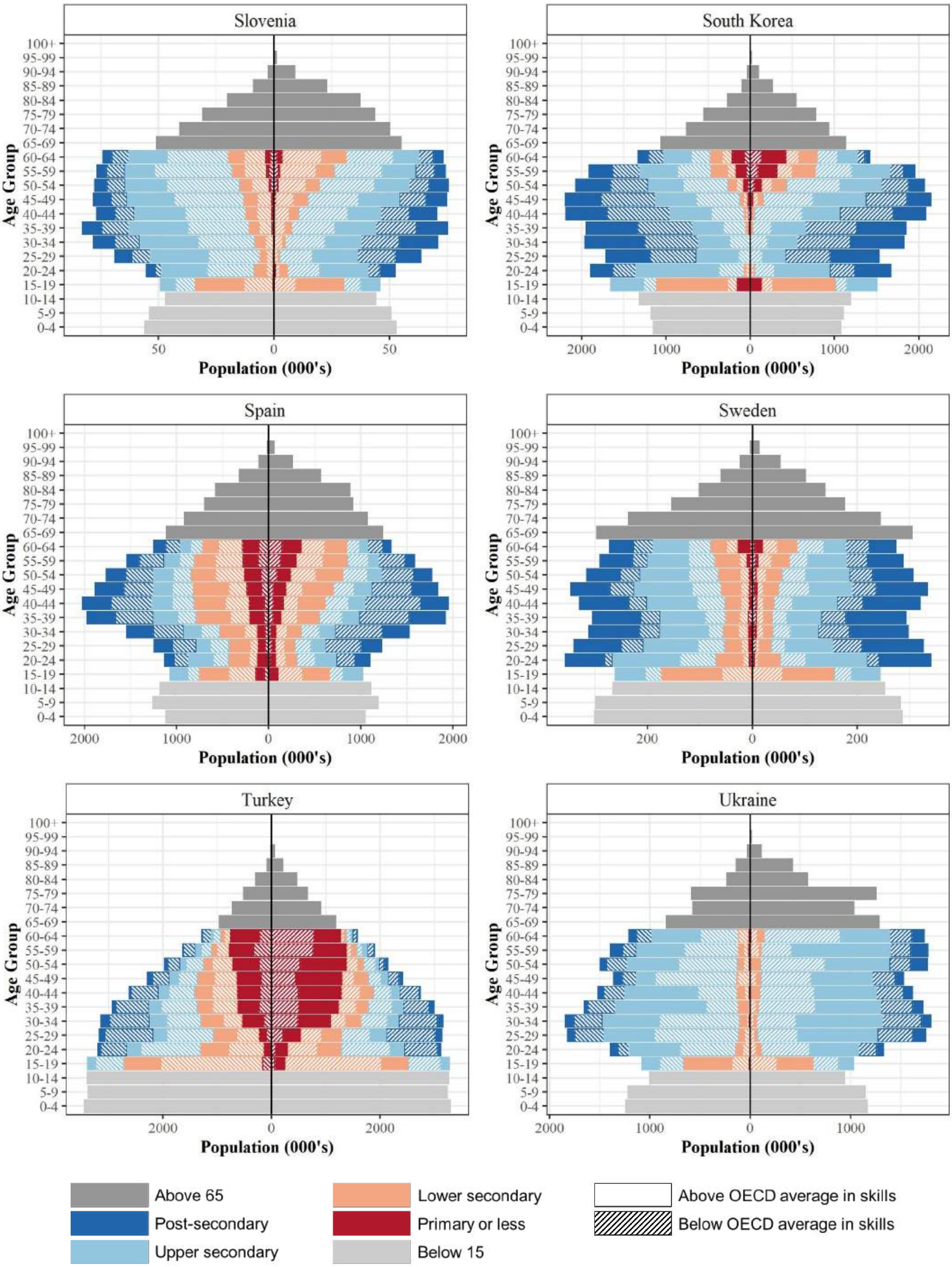
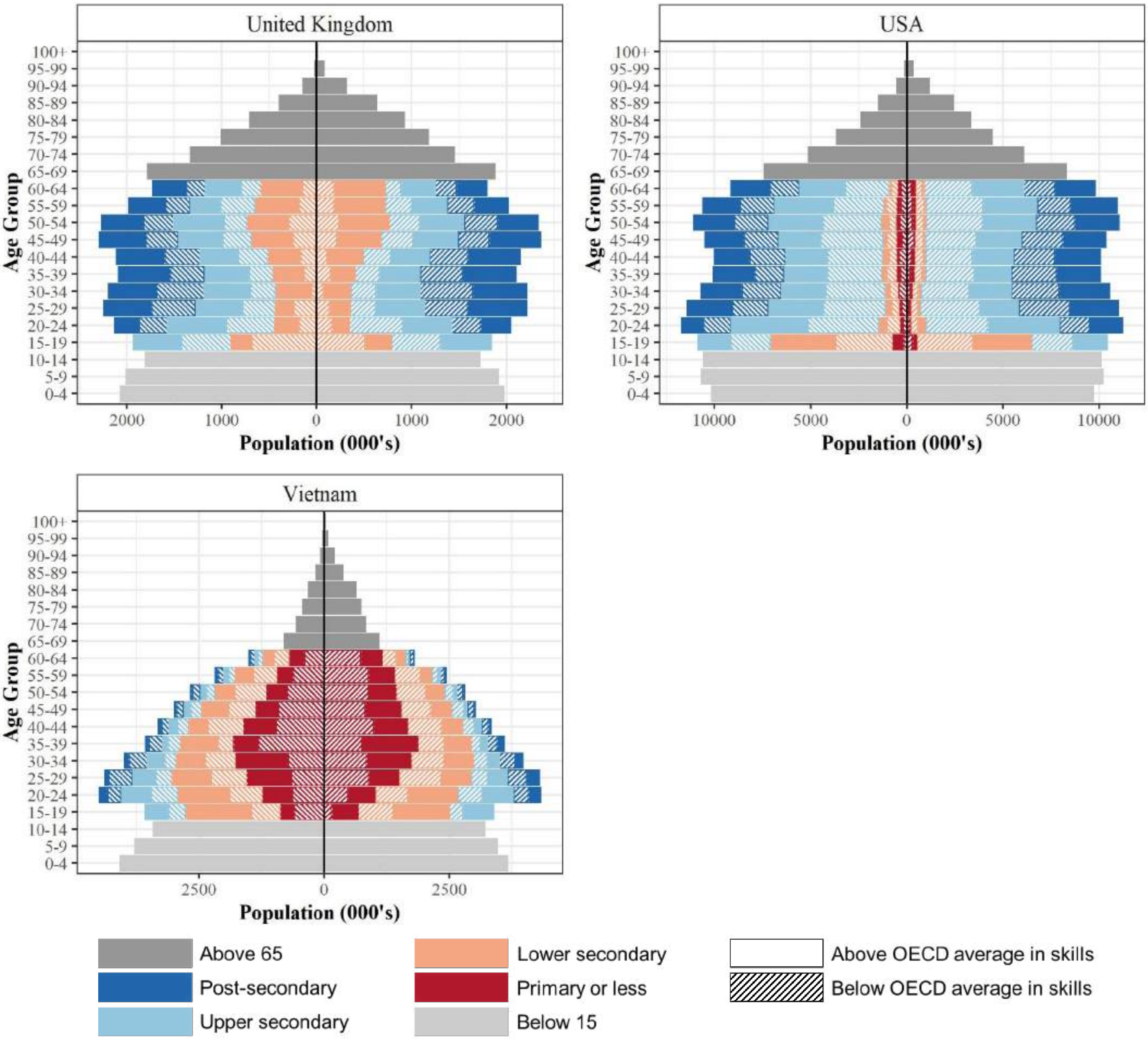
20-24
15-19
10-14
5-9
0-4
Population (000's)
Above 65
Post-secondary
Upper secondary
Lower secondary
Primary or less
Below 15
Above OECD average in skills
Below OECD average in skills


Slovenia
South Korea
Spain
Sweden
Turkey
Ukraine
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




Source: Author's calculations