OECD Education Working Papers No. 178

Can we close gaps
in literacy by social
background over the life
course? Evidence from
synthetic 1950-1980 birth
cohorts

Anna K. Chmielewski

<https://dx.doi.org/10.1787/c105422d-en>

CAN WE CLOSE GAPS IN LITERACY BY SOCIAL BACKGROUND OVER THE LIFE COURSE? EVIDENCE FROM SYNTHETIC 1950-1980 BIRTH COHORTS

OECD Education Working Paper No. 178

Anna K. Chmielewski, OECD

This working paper has been authorised by Andreas Schleicher, Director of the Directorate for Education and Skills, OECD

Michael Ward, michael.ward@oecd.org

JT03435548

OECD EDUCATION WORKING PAPERS SERIES

OECD Working Papers should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and arguments employed herein are those of the author(s).

Working Papers describe preliminary results or research in progress by the author(s) and are published to stimulate discussion on a broad range of issues on which the OECD works. Comments on Working Papers are welcome, and may be sent to the Directorate for Education and Skills, OECD, 2 rue André-Pascal, 75775 Paris Cedex 16, France.

This document, as well as any data and map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

You can copy, download or print OECD content for your own use, and you can include excerpts from OECD publications, databases and multimedia products in your own documents, presentations, blogs, websites and teaching materials, provided that suitable acknowledgement of OECD as source and copyright owner is given. All requests for public or commercial use and translation rights should be submitted to rights@oecd.org.

Comment on the series is welcome, and should be sent to edu.contact@oecd.org.

This working paper has been authorised by Andreas Schleicher, Director of the Directorate for Education and Skills, OECD.

www.oecd.org/edu/workingpapers

© OECD 2018

Acknowledgements

Anna Katyn Chmielewski acknowledges funding from the OECD Thomas J. Alexander Fellowship Programme for carrying out this work.

Abstract

It is well-known that there are large disparities in academic achievement between children of different socio-economic status (SES) backgrounds. This study examines the evolution of disparities in literacy skills between *adults* of different SES backgrounds. It compares countries' patterns in the evolution of disparities in literacy by SES background as cohorts age and asks which patterns of educational and labour force participation predict a narrowing rather than a widening of these disparities. Since there is no international longitudinal study of skills across the entire adult life span, this study uses three cross-sectional international adult studies (International Adult Literacy Survey, Adult Literacy and Lifeskills and Programme for the International Assessment of Adult Competencies) and matches birth years to create synthetic cohorts. Results indicate that there is large cross-national variation in the evolution of skills disparities associated with SES background. Disparities in literacy proficiency tend to widen when SES disparities in high school completion, professional and blue-collar employment increase. Disparities narrow when workers exit the labour force, a finding that is explained by the large inequalities in the employment experiences of individuals from different SES backgrounds, measured by differences in use of literacy skills at work. These results help to explain cross-national variation in the evolution of skills disparities by SES background, which has implications for policies aimed at closing skills gaps over the life course.

Résumé

Il est bien connu qu'il existe des écarts importants dans l'achèvement académique des enfants issus de différents milieux économiques et sociaux.

Cette étude examine l'évolution des disparités en matière d'alphabétisation entre *adultes* d'origine socioéconomiques différentes. Elle compare dans les différents pays les modèles d'évolution des disparités en matière d'alphabétisation selon le milieu socio-économique à mesure que les cohortes vieillissent et pose la question suivante : quels modèles de participation à l'éducation et au marché du travail prévoient une réduction plutôt qu'une aggravation de ces disparités. Puisqu'il n'existe pas d'étude internationale longitudinale des compétences au cours de la vie adulte, cette étude examine trois échantillons issus d'études internationales (l'Enquête internationale sur l'alphabétisation des adultes, l'Enquête sur la littératie et les compétences des adultes et le Programme pour l'évaluation internationale des compétences des adultes) et associe les années de naissance afin de créer des cohortes synthétiques. Les résultats indiquent qu'il existe de grandes variations transnationales dans l'évolution des disparités de compétences associées au milieu socioéconomique. Les disparités en matière de compétence en littératie tendent à s'accroître lorsqu'on observe une augmentation des disparités de milieu socioéconomique au niveau de l'achèvement du cycle secondaire, de l'emploi professionnel et de l'emploi des cols bleus. Ces disparités tendent à se réduire lorsque les travailleurs quittent la population active, ce qui s'explique par les grandes inégalités dans les expériences d'emploi des personnes d'origines socioéconomiques différentes, mesurées par les différences de niveau d'alphabétisation requis dans leur travail. Ces résultats contribuent à expliquer les variations transnationales dans l'évolution des disparités de compétences selon l'origine socioéconomique, ce qui a des implications pour les politiques visant à combler les déficits de compétences tout au long de la vie.

Table of contents

Acknowledgements	3
Abstract	4
Résumé	5
Introduction	9
1. Why do skills gaps based on SES background change over the life course?	12
2. “Differential uptake” versus “Differential impact”	13
3. Evidence on the evolution of skills gaps based on SES background over the life course.....	15
4. Research questions	18
5. Empirical approach.....	19
6. Data.....	21
Variables	21
7. Methods	27
8. Results.....	30
Descriptive Results	30
Gap Models	43
Interaction Models	47
9. Discussion	53
References	56
Annexe A.	58

Tables

Table 1. Birth year bands for creating synthetic cohorts	19
Table 2. Coefficients from mixed-effects models predicting literacy skills gaps by SES background from SES differences in covariates	45
Table 3. Coefficients from mixed-effects models predicting literacy skills from covariates and SES background group interactions	48
Table A A.1. Coefficients on high-SES background from regressions predicting age when individual completed education, by country and education level.....	73
Table A A.2. Coefficients on high-SES background from logistic regressions predicting that job involves long periods of physical work at least weekly	73

Figures

Figure 1. Gaps in literacy skills by SES background, PIAAC 2011	10
Figure 2. Stylized illustrations of stable, widening or narrowing skills gaps based on SES background over life course	11
Figure 3. Distribution of parent education across countries 1946-1956 birth cohort	22
Figure 4. Distribution of parent education across countries, 1957-1966 birth cohort	23
Figure 5. Distribution of parent education across countries, 1967-1976 birth cohort	24
Figure 6. Distribution of parent education across countries, 1977-1986 birth cohort	25
Figure 7. Gaps in literacy skills by SES background, by age, Belgium-Flanders	31
Figure 8. Gaps in literacy skills by SES background, by age, Canada	32
Figure 9. Gaps in literacy skills by SES background, by age, Czech Republic	33
Figure 10. Gaps in literacy skills by SES background, by age, Denmark	34
Figure 11. Gaps in literacy skills by SES background, by age, England (UK)	35
Figure 12. Gaps in literacy skills by SES background, by age, Finland	36
Figure 13. Gaps in literacy skills by SES background, by age, Germany	37
Figure 14. Gaps in literacy skills by SES background, by age, Ireland	38
Figure 15. Gaps in literacy skills by SES background, by age, Netherlands	39
Figure 16. Gaps in literacy skills by SES background, by age, Northern Ireland (UK)	40
Figure 17. Gaps in literacy skills by SES background, by age, Norway	41
Figure 18. Gaps in literacy skills by SES background, by age, Sweden	42
Figure 19. Gaps in literacy skills by SES background, by age, United States	43
Figure 20. Difference between high and low-SES background employment by age and country	52
Figure A A.1. Nationally standardized gaps in literacy skills by SES background	58
Figure A A.2. Raw and adjusted gaps in literacy skills by SES background, by age, Belgium-Flanders	59
Figure A A.3. Raw and adjusted SES in literacy skills by SES background, by age, Canada	60
Figure A A.4. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Czech Republic	61
Figure A A.5. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Denmark	62
Figure A A.6. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, England (UK)	63
Figure A A.7. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Finland	64
Figure A A.8. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Germany	65
Figure A A.9. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Ireland	66
Figure A A.10. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Netherlands	67
Figure A A.11. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Northern Ireland (UK)	68
Figure A A.12. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Norway	69
Figure A A.13. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Sweden	70
Figure A A.14. Raw and adjusted SES origin gaps by social origin in literacy skills by SES background, by age, United States	71

Figure A A.15. Difference in proportion of high-SES and low-SES background who completed high school or more, by country, birth cohort and age.....	72
---	----

Introduction

It is well-known that there are disparities in academic achievement between children of different socio-economic status (SES) backgrounds. These disparities are often referred to as the “SES achievement gap”, where the “gap” describes the difference in achievement between children from high-SES backgrounds and their low-SES counterparts (Chmielewski and Reardon 2016). International large-scale assessments document that these gaps exist in every participating country (e.g., Mullis et al. 2012; OECD 2013b). Achievement gaps based on SES background are due both to disparities in the quality of primary and secondary education experienced by children from different SES backgrounds and to differences in out-of-school experiences in homes and neighbourhoods (Baker, Goesling and LeTendre 2002; Bradbury et al. 2015; Downey and Condon 2016; Downey, von Hippel and Broh 2004; Merry 2013). What has been studied less is how skills gaps by SES background persist into adulthood, whether cumulative advantage and disadvantage cause skills gaps to widen over the life course or whether they narrow over time. This study looks at this question, using data from three international surveys of adult skills, the Programme for the International Assessment of Adult Competencies (PIAAC), conducted in 2011; the Adult Literacy and Life Skills Survey (ALL), conducted between 2003 and 2008; and the International Adult Literacy Study (IALS), conducted between 1994 and 1998. The international design of these surveys allows a cross-national comparison of how skills gaps evolve with age, in order to understand how variation in adults’ educational and labour force experiences shapes the evolution of skills gaps over the life course.

The gaps in adults’ skills based on SES background are quite large. This can be seen in PIAAC using parental educational attainment as a proxy for SES. Across participating countries that participated in PIAAC, the gap in literacy skills between adults whose parents did not complete tertiary education and adults with at least one parent who completed tertiary education averages around half of a standard deviation on the PIAAC international scale. This is equivalent to the difference between Level 2 on the PIAAC scale (a level at which individuals can normally successfully complete items that require them to paraphrase texts and make low-level inferences), and Level 3 (a level at which individuals can understand denser texts and make higher level inferences) (OECD 2013a). However, the size of the skills gap based on SES background varies considerably across countries. Figure 1 shows the difference in literacy proficiency between a respondent whose parents did not complete tertiary education and those with at least one parent completing tertiary education for 15 countries participating in PIAAC, sorted by decreasing size. The gaps range from about 33 points (more than two thirds of a standard deviation) in Italy to only about 14 points (less than one third of a standard deviation) in England (United Kingdom).¹

Figure 1. Gaps in literacy skills by SES background, PIAAC 2011

Source: Author's own calculations from PIAAC dataset, www.oecd.org/site/piaac/publicdataandanalysis.htm.
 Note: Countries sorted from the largest to the smallest literacy gap.

Gaps in literacy skills based on SES background among adults are concerning because they suggest that the disadvantages of low-SES in childhood persist into adulthood and are difficult to overcome. Persistent skills gaps may be an important mechanism that impedes social mobility. Beyond economic chances, access to a minimum level of literacy skills is also important to civic and democratic participation in society. The striking cross-national variation in skills gaps by SES background seen in Figure 1 raises the question of which policy differences between countries may explain why some countries exhibit greater equity in the distribution of literacy skills than others. For example, countries with smaller skills gaps by SES background may have higher quality and/or more equitable school systems; more open access or lower-cost higher education and skills training, and/or higher levels of health and wellbeing.

However, attempting to adjudicate between these explanations simply by comparing the country-level associations between such policies and the size of skills gaps by SES background cross-sectionally is complicated by unobserved differences between countries. Thus, it is preferable to compare changes in skills gaps by SES background *within* countries as individuals age. A particular policy—such as expansion of adult education and training for mid-career workers—may cause skills gaps by SES background to narrow between the ages of 40 and 50, for example. By comparing the skills gap by SES background over time within the same country, we can control for unobserved characteristics that determined the size of the skills gap by SES background

up until the age of 40, in this example. Therefore, rather than comparing total skills gaps by SES background across countries at a single point in time, this paper compares the *trajectories* of skills gaps as cohorts age. The comparison, then, is not between countries with smaller or larger skills gaps by SES background but between countries with stable, widening or narrowing skills gaps, as illustrated by the hypothetical stylized graphs in Figure 2.²

Figure 2. Stylized illustrations of stable, widening or narrowing skills gaps based on SES background over life course

Source: Author's own calculations using PIAAC dataset,
www.oecd.org/site/piaac/publicdataandanalysis.htm.

1. Why do skills gaps based on SES background change over the life course?

Little prior research has directly studied the evolution of skills gaps based on SES background over the life course. The exception is one recent paper by Borgonovi et al. (2017), which matches country birth cohorts that participated in PISA 2000 and 2003 (age 15) and PIAAC (age 24 or 27). The authors find that gaps in literacy and numeracy skills based on two measures of SES (parental education and the number of books in their home) widened between age 15 and young adulthood in the majority of countries. They point to high-SES young adults' greater likelihood of participation in higher education, in the labour-market and in high-skilled jobs in particular as explanations for these growing disparities.

The mechanisms behind widening SES disparities in skills in young adulthood are likely driven by both the direct and the indirect effects of parental SES on skills development. First, the skills gaps by SES background that are already present in childhood appear to lead to greater educational opportunities and to higher-skilled work (Jackson 2013). These opportunities may lead to further skill development. This "skill begets skill" process constitutes the indirect effect of SES background on adult skills via childhood skills. Net of skills, students from high-SES backgrounds are still more likely to attend higher education (Jackson 2013), giving them perhaps their most important opportunity to further develop skills in young adulthood. Furthermore, a greater likelihood of attending higher education gives high-SES young adults greater access to high-skilled professional jobs, which may provide further opportunities for on-the-job skill development. This constitutes the indirect effect of SES background on adult skills via adults' own educational attainment. But SES background may also affect adults' skills in more direct ways via financial support. Having high-SES parents may enable a student to attend a more expensive institution that may be higher-quality, or to be a full-time student without needing to work, allowing more time for studying and skills development. Recent graduates from high-SES backgrounds may be less pressed to find work quickly due to parental financial support, allowing them to be choosier in the job search; and parental social connections may also help them to find better jobs that are closely matched with their education level. Both factors could make adults from high-SES backgrounds more likely to get highly-skilled work that allows them to continue developing skills on-the-job.

Considering middle and later adulthood, many of these direct and indirect processes may continue. At the same time, though, inheritance or parental financial support may give adults from high-SES backgrounds the freedom to exit the formal labour force, and instead perform family or household duties, unpaid internships, creative pursuits, volunteering or charity work, or to take early retirement. Some of these activities may actually allow skills to deteriorate.

2. “Differential uptake” versus “Differential impact”

In understanding how educational and labour force experiences can shape gaps in literacy skills by SES background, it is important to distinguish between two different processes, which are analogous to the concepts of “differential uptake” versus “differential impact” in health policy research. Different SES groups can have “differential uptake” or access to educational and labour force experiences (e.g., low-SES background individuals attend higher education at lower rates than high-SES background individuals). In addition, educational and labour force experiences can have “differential impact” on the literacy skills of high- and low-SES background individuals (e.g., low-SES background individuals’ literacy skills could increase more than those of high-SES background individuals while in higher education).

For half a century, the sociological literature on achievement gaps related to SES background in childhood has examined the differential impact of time at school versus time at home for children of different SES backgrounds as a strategy to understand the relative contribution of school effects versus home or family effects to SES achievement gaps (Downey and Condron 2016). US research finds that SES achievement gaps narrow when students are in school and widen when they are out of school, such as during early childhood and summer vacations, suggesting that school environments are more equal than home environments (Downey, von Hippel and Broh 2004; Merry 2013). There is also evidence that this pattern may vary cross-nationally, both due to factors as simple as the length of summer vacation and as generalized as the relative inequality of school and home environments for children of different SES backgrounds (Baker, Goesling and LeTendre 2002; Bradbury et al. 2015; Davies and Aurini 2013; Heyneman and Loxley 1983; Merry 2013). For adults, education and labour force experiences may also affect those of different SES backgrounds differently; for example, further education and opportunities for skills use and development at work may have compensatory effects on those of low-SES backgrounds because they enter adulthood with lower skills, or education and labour force participation may have weaker or even negative effects on those of low-SES backgrounds because they systematically have access to lower-quality education or less skill-intensive occupations. One goal of the current study is to investigate how adulthood fits into this sociological framework. Does further education play an equalising role and home environments a dis-equalising role? How does time in the labour force fit into the picture?

In childhood models of school year and summer effects, it is necessary only to take “differential impact” into account. “Differential uptake” can be ignored, since schooling is compulsory at this age, and thus all children experience school enrolment and summer vacations during the same months, regardless of SES background. However, adults of different SES backgrounds may have educational and labour force experiences asynchronously. For example, low-SES background individuals may complete higher education at older ages after an interruption, and high-SES background individuals may enter the labour force at older ages after being supported by their parents as full-time students in young adulthood. These differences in timing may be another explanation for

the differential impact of adults' educational and labour force experiences (e.g., if low-SES individuals experience some skill deterioration during an interruption between secondary and higher education).

3. Evidence on the evolution of skills gaps based on SES background over the life course

While previous research has not directly explored the evolution of skills gaps by SES background in adulthood, prior studies do reveal how literacy skills typically evolve over the life course and how these trajectories can be altered by individuals' educational and labour force experiences at particular ages. Published research has also examined the differential impact of ageing, educational and labour force experiences according to individual characteristics, such as skill level, educational attainment or, in a small number of studies, SES background. In reviewing the literature, we examine differential impact of ageing according to all of these characteristics. Although skill and education level are not the same as SES background, the results nevertheless provide some suggestion of what we might find for differential impact according to SES background, as cumulative disadvantage since childhood makes adults of lower SES background more likely to be among the lower-skilled and less educated.

Evidence on the age-skills profile typically shows a curvilinear relationship, with increasing skills in young adulthood, followed by a peak and accelerating declines in older adulthood (Desjardins and Warnke 2012; Paccagnella 2016a; Schaie 1994). The precise age of this peak appears to depend on the type of skills tested and on whether the age-skills profile is modelled using cross-sectional or longitudinal data. Research using the international surveys of adult literacy skills tends to locate the peak around age 30 (Green and Riddell 2013; Paccagnella 2016a). In terms of differential impact of ageing on individuals of different SES backgrounds, a longitudinal study of individuals age 65 and older in France showed that those with more highly educated parents may experience slightly faster rates of skills decline, but only for some cognitive domains (Glymour, Tzourio and Dufouil 2012). Studies examining the differential impact of ageing based on individuals' own education level also appear to find mixed or weak effects. Both in the longitudinal French sample (Glymour, Tzourio and Dufouil 2012) and in cross-sectional PIAAC data (Paccagnella 2016a), more educated individuals experienced slightly faster skills decline. In contrast, a study using longitudinal Dutch data on individuals between ages 24 and 81 found that more educated adults experienced slower skills decline (De Grip et al. 2008). In terms of the skills distribution more generally, Paccagnella (2016a) observes that the dispersion of scores tends to increase with age in most countries in cross-sectional PIAAC data. This suggests that high-skilled individuals' skills decline more slowly with age than do those of low-skilled individuals, though it is not possible to know this with certainty without longitudinal data.

That the peak in literacy skills occurs at the relatively young age of 30 suggests that formal education is the strongest determinant of cognitive skills (Paccagnella 2016a). Additionally, two studies using these data have demonstrated a large causal impact of schooling on skills. Green and Riddell (2013) came to this conclusion using ALL literacy data for Canada and variation in provincial compulsory schooling laws as an instrument for schooling, and Dinçer (2016) obtained similar findings using PIAAC literacy and numeracy data for 16 European countries and national variation in compulsory schooling

laws as an instrument for schooling. Additionally, both studies provide some evidence of differential impact of schooling reforms. In a correlational analysis, Green and Riddell (2013) observe that schooling is more strongly associated with skills at the tenth skills percentile in Canada, Norway and the US. In his Instrumental Variables (IV) analysis, Dinçer (2016) shows that the causal effect of additional schooling is greater at the lower end of the skills distribution. Both results imply that educational expansion promotes equity. However, it should again be noted that these authors examine differential impact according to individuals' own skill levels, rather than according their SES background, which is the main focus of the current paper. There is not a great deal of research on whether cognitive skills increase in higher education, although Arum and Roksa's (2011) US study shows that students' scores on a critical reasoning test increase relatively little in US universities. They do not find a strong differential impact by SES background (measured by parental education level), so skills gaps by SES background remain relatively constant as students move through university.

Moving beyond education, employment is an additional important setting where literacy skills may further develop or deteriorate. In a longitudinal study of individuals between ages 32 and 62 in France, those whose survey responses indicated greater cognitive stimulation at work experienced greater improvements in cognitive functioning at the 10-year follow-up, and those who indicated lower stimulation at work experienced declines in cognitive functioning, associations that held for both younger and older workers, and after statistically controlling for education, gender and health factors (Marquié et al. 2010). The Dutch longitudinal study mentioned previously showed that job-worker mismatch was a factor in age-related cognitive decline; undereducated workers experienced significantly less cognitive decline in several domains, though overeducated workers experienced only slightly and non-significantly greater skills decline (De Grip et al. 2008).

Furthermore, time outside the labour-market also appears related to skill depreciation. Using a longitudinal follow-up to the Swedish IALS sample, Edin and Gustavsson (2008) show that time out of work is associated with a decline in literacy skills. The authors excluded retired individuals from their analysis but included those out of work due to unemployment, long-term illness, household duties and other reasons (they did not separate these various reasons for being out of work in their models). Edin and Gustavsson find evidence for a dosing effect, where more time out of work predicts more extreme skills depreciation, an association that is approximately linear. In terms of differential impact, the authors find slightly (though not statistically significantly) greater skills loss among individuals lower in the skill distribution.

Lastly, there is evidence that retirement from the labour force causes skill decline. Using comparable cross-sectional surveys from the US, UK and 11 European countries and national pension policies as an instrument to correct for the endogeneity of a person's decision to retire, Rohwedder and Willis (2010) find that retirement has a statistically significant negative impact on cognitive ability. They reason that this effect occurs through two mechanisms: that retirement is a less stimulating environment than work and that impending retirement gives workers less incentive to invest in human capital development on-the-job. An interesting differential impact was found in a recent study by Mazzonna and Peracchi (2016), who use longitudinal data for 11 European countries and estimate that retirement accelerates cognitive (as well as health) declines in most workers, but that retirement appears to have a *positive* cognitive and health effects for workers leaving jobs with a high level of physical burden.

The current paper attempts to connect the adult skills literature with the research on children's in-school and out-of-school development. In particular, which are equalising and which are dis-equalising: time in higher education, in the labour force or at home? Many of the studies reviewed above—particularly Mazzonna and Peracchi's (2016) surprising recent findings on the positive impact of retirement for workers in physically burdensome jobs—suggest that, to the extent that low-SES background individuals are more likely to work in manual jobs, time in the labour force may be more inequality-promoting than time at home.

4. Research questions

This study addresses two policy-relevant questions regarding cross-national differences in the evolution of differences in literacy proficiency associated with SES background:

1. In which countries and cohorts do literacy skills gaps based on SES background narrow as individuals age, and in which countries and cohorts do gaps widen?
2. How is the evolution of skills gaps by SES background associated with SES disparities in education and labour force participation and skills use (“differential uptake”)?

Lastly, it addresses a question more relevant to sociological theory:

3. How are the literacy skills of adults from different SES backgrounds differentially impacted by education and labour force experiences (“differential impact”)?

5. Empirical approach

The OECD's PIAAC makes it possible to estimate differences in cognitive skills according to SES background at a range of ages throughout the lifespan. PIAAC sampled adults between the ages of 16 and 65 in 22 countries in 2011 and 2012, surveyed them on their educational and labour-market experiences and family SES background, and assessed their literacy and numeracy skills. However, simply comparing different age groups within the PIAAC study will yield estimates where cohort effects are confounded with age effects. For example, individuals between ages 55-65 in PIAAC were born between 1946-1956, while individuals between ages 25-34 in PIAAC were born between 1977-1986. The two different birth cohorts experienced different sets of educational and labour-market policies, institutions and conditions. Moreover, because of educational and occupational upgrading within societies over time, the distributions of SES backgrounds in recent birth cohorts are not necessarily comparable to those of earlier cohorts.

This problem is addressed in the present study by exploiting two previous international assessments of adult skills: IALS, conducted between 1994-1998, and ALL, conducted between 2003 and 2008. Like PIAAC, IALS and ALL assessed the skills of adults ages 16-65, and many of the same countries participated in more than one study. Although the three adult assessments did not follow the same individuals over time, each sample is nationally representative of the relevant age cohorts. Thus, subsamples of individuals can be matched by birth year across studies to form "synthetic cohorts," a strategy that has been used in a small number of other studies based on these international adult assessment data (Green and Riddell 2013; Paccagnella 2016a; Paccagnella 2016b). By comparing variation across age within country-cohorts, the synthetic cohort design accounts for unobserved differences between countries and cohorts (e.g., childhood experiences). This design also avoids the problem of different distributions of SES backgrounds in different countries and cohorts, which could artificially make skills gaps by SES background larger or smaller due to different selectivity of the high- and low-SES categories. The approximate ages at which each birth cohort is observed in each study are displayed in Table 1.

Table 1. Birth year bands for creating synthetic cohorts

Cohort birth year	Age in IALS (1994)	Age in ALL (2003)	Age in PIAAC (2011)
1946-1956	38-48	47-57	55-65
1957-1966	28-37	37-46	45-54
1967-1976	18-27	27-36	35-44
1977-1986		17-26	25-34

Note: Actual age ranges observed in IALS and ALL differed slightly across countries, accounting for the fact that different countries participated in each study in slightly different years. Cohorts were defined by the same four birth year bands listed above, regardless of countries' years of participation in each survey. Therefore, the cohorts included are identical across all countries, but the spacing between time points varies across countries.

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

6. Data

Australia had to be excluded from the analysis because continuous age data were unavailable, two countries (Hungary and Switzerland) were excluded because rescaled literacy scores were unavailable for IALS and ALL, one country (New Zealand) was excluded because it participated in Round 2 of PIAAC and data were unavailable at the time of analysis and two countries (Italy and Poland) were excluded because coding inconsistencies have been reported in their IALS skills assessment data (Paccagnella 2016b)³. This results in a final sample of 13 countries⁴. In order to ensure data remain representative of the same cohort across years, individuals who immigrated after age 10 were excluded. Cohorts were constructed by 10-year bands (see Table 1), as narrower bands would have yielded very small sample sizes. The 10-year bands are defined by the four oldest age groups in the PIAAC survey; the youngest PIAAC age group (16-24) is excluded, as most of this birth cohort band is too young to have participated in the IALS or ALL surveys. Depending on which assessments a country participated in, either three or four different birth cohorts are available, and either two or three different years for each cohort. This yields a total of 98 observations (country-cohort-years), representing 125,779 individuals.

Variables

Literacy skills were assessed in domains of prose and document literacy. These domains form a single scale in PIAAC and two separate scales in IALS and ALL, but IALS and ALL have been rescaled to form a single literacy scale across the IALS, ALL and PIAAC tests. Numeracy skills have not been analysed because the ALL and PIAAC numeracy scores are not comparable to IALS quantitative literacy scores.

SES background is measured in terms of proxied by parental educational attainment, the only SES-related measure that is available in all three surveys of adult skills. Respondents reported mothers' and fathers' educational attainment, and the higher of the two is used. Educational attainment was reported in (or can be recoded to) three categories: (1) less than upper secondary (ISCED 1 and 2), (2) upper secondary (ISCED 3 and 4) and (3) tertiary (ISCED 5 and 6). Assuming that relatively few parents complete additional educational credentials after their children are already adults, the distributions of these variables should change little across years when a birth cohort is observed. This assumption can be checked by comparing data across IALS, ALL and PIAAC, as in Figures 3-6.

Figure 3. Distribution of parent education across countries 1946-1956 birth cohort

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 4. Distribution of parent education across countries, 1957-1966 birth cohort

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 5. Distribution of parent education across countries, 1967-1976 birth cohort

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 6. Distribution of parent education across countries, 1977-1986 birth cohort

Source: Author's own calculations from ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Although there is a great deal of cross-national and cross-cohort variation in the distribution of parental education, distributions across years for the same country-cohort are generally very similar, with four exceptions. In four countries (the Czech Republic, England (United Kingdom), Germany and Northern Ireland (United Kingdom)), a large number of observations appear to be miscoded as less than secondary rather than secondary education.⁵ Since correct parental education data cannot be recovered, the main analyses of this paper combine the lower two parental education categories, comparing the literacy skills of individuals with at least one parent with tertiary education (“High-SES background”) to those with neither parent with tertiary education (“Low-SES background”).

Proportion high-SES background. To account for the small remaining variation across years in the distribution of parental education, proportion high-SES background is added as a control to models. Two additional control variables are used to account for differences in samples across years, due to factors such as cohort attrition or sampling variation:

Proportion female should stay constant across years when a country-cohort is observed. If the proportion changes—for example, if the sample becomes more female because of attrition of males due to incarceration or premature death—literacy gaps by SES background may appear to decline because the remaining males are positively selected.

Mean birth year of the cohort is computed as the average birth year of all individuals in each 10-year band in each country-year. Like proportion high-SES and proportion female, mean birth year should also stay constant across years, as the same cohort birth year bands are used in each dataset to form synthetic cohorts. If mean birth year changes—for example, if it increases because of attrition of older individuals due to premature death—literacy gaps by SES background may appear to decline because the remaining individuals are positively selected.

Mean age is computed as the average age of all individuals in each 10-year band in each country-year. *Mean age* and *mean age*² of each cohort in each year are included as controls in some models to account for the typical curved trajectory of literacy skills by age. Note that, in models, mean age is not collinear with mean birth year because data come from multiple years.

Fourteen time-varying covariates having to do with (1) education, (2) labour force status, (3) occupation and (4) literacy skill use are included as explanatory independent variables. All variables are computed as proportions by aggregating (using survey weights) individual-level dummy variables to the country-cohort-year level:

Proportion with high school is the share of the country-cohort with at least a high school diploma (upper secondary, ISCED 3) or more in a given year. *Proportion with higher education* is the share of the country-cohort with a tertiary degree (ISCED 5 or more) in a given year. *Proportion in adult education* is the share of the country-cohort that reports participating in adult education or training in the past year. Following Gesthuizen et al. (2011), a portion of individuals classified with less than high school education in four IALS countries (the Czech Republic, England (United Kingdom), Germany and Northern Ireland (United Kingdom)) were recoded to high school completers using the continuous *Years of education* variable, in order to bring distributions in line with those reported in other national statistics from the 1990s.

Participants can have one of six mutually-exclusive labour force statuses: *employed, full-time student, unemployed, performing household duties, retired*, or *out of the labour force for other reasons*. In some models, the proportion of the country-cohort with each status is entered separately, and in other models, the last four statuses are combined to form *Proportion neither employed nor student*.

Employed participants can have one of three mutually-exclusive occupational categories: *Professional job* (managerial and professional – ISCO 1 and 2), *Lower white-collar job* (technicians, clerical and sales/service – ISCO 3, 4 and 5) and *Blue-collar job* (agricultural, skilled and unskilled manual occupations – ISCO 6, 7, 8 and 9).

Two variables describe the use of literacy skills: *Proportion reading at work* includes reading at least one of the following at least weekly: letters, memos or emails; articles or reports; manuals or reference books; bills or invoices; and diagrams, maps or schematics. Non-employed individuals are coded as 0 before aggregating. *Proportion reading at home* includes reading at least one of the following at least weekly: fiction or non-fiction books; and newspapers or magazines. Reading emails or letters was excluded in order to obtain some variation in the variable (otherwise nearly all years and countries were close to 100%). Reading at home excluded any reading for work or studies, except in PIAAC where studies were included. However, due to the synthetic cohort design of this study, the youngest age group with the heaviest representation of students (age 16-25) is excluded from PIAAC. Thus, the variable mostly represents recreational reading only.

7. Methods

Missing individual-level data are imputed using multiple imputations by iterated chained equations and creating ten imputed datasets. All aggregated measures used in the models are computed ten times and averaged. Standard errors incorporate uncertainty due to this imputation, as well as due to the ten plausible values of literacy scores and due to the complex sample design by the use of the jack-knife replicate procedure.

First, the evolution of gaps in literacy skills by SES background across the life course is summarized descriptively using 13 figures, one for each country. Gaps in literacy skills by SES background are computed as the difference in mean skills for each SES group in each country-cohort-year, and the corresponding standard error is computed according to the methods described above.

Next, two sets of mixed-effects models are used to estimate the relationships between gaps trajectories by age and variation in educational and labour force experiences. The models use country $\times$ cohort random effects to account for the nesting of years within country-cohorts; age-varying covariates are then entered (centred within country-cohort) in order to model changes by age in each country-cohort. The two types of models are intended to address the second research question regarding “differential uptake” and the third research question regarding “differential impact.”

The first set of “differential uptake” models uses as its outcome the literacy skills gaps by SES background in each country-cohort in each year from the initial descriptive figures, and predicts these gaps from differences between the two SES background groups in covariate values, as follows:

$$\widehat{Gap}_{tj} = \gamma_{00} + (\mathbf{D}_{tj} - \bar{\mathbf{D}}_j)\mathbf{B} + v_j + u_{tj} + \epsilon_{tj},$$

$$v_j \sim N(0, \tau_{00}); u_{tj} \sim N(0, \sigma^2); \epsilon_{tj} \sim N(0, \omega_{tj}),$$

[1]

where $\widehat{Gap}_{tj}$ is the estimated gap in year t in country-cohort j , $\mathbf{D}_{tj}$ is a vector of differences in time-varying covariates in year t , $\bar{\mathbf{D}}_j$ is the average of vector $\mathbf{D}_{tj}$ within country-cohort j , $\mathbf{B}$ is a vector of coefficients for the differences, τ_{00} is the between-country-cohort variance of the true gaps, σ^2 is the true within-group variance of the gaps, and $\omega_{tj} = [s.e.(\widehat{Gap}_{tj})]^2$ is the sampling variance of $\widehat{Gap}_{tj}$. ω_{tj} is estimated using a variance-known model in HLM 7, which uses the standard errors estimated for each skills gap to give greater weight to more precisely-estimated gaps.

The second set of “differential impact” models uses as its outcome the average literacy skills of each SES background group in each country-cohort in each year, and predicts literacy skills from interactions between a dummy variable indicating SES background group and time-varying covariates, as follows:

$$\begin{aligned} \widehat{MeanSkills}_{ti} = & \gamma_{00} + \gamma_{10}(Age_{ti}) + \gamma_{20}(Age_{ti}^2) + \gamma_{01}(HiSES_i) + (\mathbf{X}_{ti} - \bar{\mathbf{X}}_i)\mathbf{B} \\ & + (HiSES_i)(\mathbf{X}_{ti} - \bar{\mathbf{X}}_i)\mathbf{\Gamma} + v_i + u_{ti} + \epsilon_{ti}, \\ & v_i \sim N(0, \tau_{00}); u_{ti} \sim N(0, \sigma^2); \epsilon_{ti} \sim N(0, \omega_{ti}), \end{aligned}$$

[2]

where $\widehat{MeanSkills}_{ti}$ is mean literacy score in year t in country-cohort-SES group i , Age_{ti} and Age_{ti}^2 are the mean age and squared mean age of country-cohort-SES group i , $HiSES_i$ is a dummy variable indicating whether country-cohort-SES group i is of high (1) or low (0) SES background, $\mathbf{X}_{ti}$ is a vector of time-varying covariates in year t , $\bar{\mathbf{X}}_i$ is the average of vector $\mathbf{X}_{ti}$ within country-cohort-SES group i , $\mathbf{B}$ is a vector of coefficients for the time-varying covariates, $(HiSES_i)(\mathbf{X}_{ti} - \bar{\mathbf{X}}_i)$ is a vector of interactions between the $HiSES_i$ dummy and the time-varying covariates, $\mathbf{\Gamma}$ is a vector of coefficients for the interactions, τ_{00} is the between-country-cohort-SES group variance of the true skills means, σ^2 is the true within-group variance of the skills means, and $\omega_{ti} = [s.e.(\widehat{MeanSkills}_{ti})]^2$ is the sampling variance of $\widehat{MeanSkills}_{ti}$. ω_{ti} is estimated using a variance-known model in HLM 7, which uses the standard errors estimated for each skills mean to give greater weight to more precisely-estimated means.

Another modelling option that is more frequently used in the literature would be to pool the microdata from all three datasets, including country $\times$ cohort random effects as above, rather than running models on aggregated estimates. But it is important to note that a pooled microdata model would not increase the statistical power of the analysis, as the only variability of interest in this analysis is between the years when a cohort is observed rather than among individuals within years. For example, in 2011, the difference in skills between an individual with a tertiary degree and one without is endogenous, but if the share of a birth cohort with tertiary degrees has increased from 20 to 40 percent between 2003 and 2011, we can more plausibly attribute changes in skills in the cohort to the rising education level of the cohort. Thus, a pooled microdata model would still need to use either aggregated year-level covariates or interactions between covariates and year dummies in order to model only the variation across years. Such a model would be expected to yield very similar point estimates and standard errors to those reported here.

The strength of the synthetic cohorts design compared to a cross-sectional analysis is that it accounts for unobserved differences between countries and cohorts. However, the synthetic cohort estimates are still not truly causal, as they are based on observational data. Thus, even if increases in a covariate (e.g. labour force participation) are strongly associated with increases in skills, one cannot rule out that both are mutually determined by an unobserved factor, nor can one rule out reverse causality. That is, rather than labour force entry causing skills improvement, it could be that skills improvements cause individuals to decide to enter the labour force; these are impossible to disentangle in the models used here since both variables are observed simultaneously. One approach to address reverse causality is to use lagged independent variables. However, such an approach would not be possible to implement with the current data because most country-cohorts are observed at only two time points (IALS and PIAAC). If all independent variables were observed in the IALS data and the dependent variable in the PIAAC data, aside from the time lag being nearly 20 years, no over-time model could be implemented. Thus, the models in this paper do not make use of lagged covariates. However, one set of included variables do function similarly to lagged covariates: the educational degrees. While other included variables (labour force status, reading, adult education and training) describe respondents' current status, the high school and higher education degree

variables capture the proportion of a country-cohort that have *ever* completed such a degree at any point in their lifetimes (and they exclude individuals currently studying toward the degree in question). Thus, results for educational degrees are unlikely to be plagued by reverse causality, though results for other variables are subject to this issue.

A final limitation of synthetic cohorts designs compared to the ideal of truly longitudinal data is that conclusions are subject to the ecological fallacy. If the average educational level of a birth cohort increases and its average skills increase during the same time interval, we cannot know if it was the same individuals who completed further education whose skills also increased. It would also be possible that the skills of uneducated individuals increased, or that skills increased across the board for all members of the cohort, regardless of education—although it is difficult to imagine why either of these situations would occur. This aggregation problem is separate from the issue of causality, which would still be a problem, even using longitudinal non-experimental data (e.g., we cannot know if education caused skills to increase, even if we do know precisely which individuals obtained further education). Nevertheless, contrasting the results from the synthetic cohort design with those from cross-sectional data will provide evidence suggestive of what we would observe in truly longitudinal data.

8. Results

Descriptive Results

Figures 7-19 display age trajectories of the literacy skills gaps by SES background for each of the 13 countries of the sample. Each point in the figures is a gap—that is, a difference between the mean literacy skills of high-SES background individuals and their low-SES background counterparts, plotted at the average age of the birth cohort in the survey year (that is, the average age of individuals in the relevant 10-year cohort band, at the time when they were observed in the relevant survey). The grey vertical brackets are 95% confidence intervals. Gaps estimated at different ages for the same birth cohort are connected with quadratic or linear fit lines (quadratic for the countries that participated in all three study years, giving three observations per birth cohort—Canada, the Netherlands, Norway and the United States—and linear for all other countries, which have only two observations per cohort). Observations from different birth cohorts are not connected since different birth cohorts are not fully comparable. In some countries, estimates of the size of the gaps from different birth cohorts differ substantially, which is often due to large changes in the distribution of the SES background variable across birth cohorts, reflecting the upgrading of educational attainment across parents' generations over time. Nevertheless, examining age trajectories of all cohorts in each figure gives a general picture of how skills gaps by SES background evolve with age in each country, and reveals large variation in these trajectories across countries.⁶

Country descriptive figures will be discussed in clusters, grouping together countries that show similar gaps trajectories. First, Belgium-Flanders (Figure 7) is the only country with a pattern of declining and then increasing gaps, with a trough in middle age. The skills gap decreases slightly in size between approximately the mid-20s and age 40 for the 1976-1976 birth cohort, between when it is observed in IALS and later in PIAAC. For the 1957-1966 cohort, the skills gap increases between the mid-30s and age 50; and for the 1946-1956 cohort, the skills gap also increases between the mid-40s and age 60 (after starting at a lower level). In contrast, four countries show the reverse pattern: increasing skills gaps in young adulthood, a peak in middle age, and declining gaps thereafter. These countries are Canada, the Czech Republic, England (United Kingdom) and Finland (Figures 8, 9, 11 and 12). Four more countries show a pattern of skills gaps generally increasing over the entire life course: Denmark, Ireland, the Netherlands and Northern Ireland (United Kingdom) (Figures 10, 14, 15 and 16). The magnitude of these increases ranges substantially, from relatively small in Denmark, with gaps that remain essentially stable after age 40, to very large in Ireland and Northern Ireland (United Kingdom), with skills gaps that increase by more than 10 points (approximately 0.2 SD) over about 15 years for some birth cohorts. Two countries show the reverse pattern of skills gaps declining over the entire life course: Norway and the United States (Figures 17 and 19), although again the magnitude of these changes varies across countries. Germany (Figure 13) has a pattern of declining gaps in young adulthood, increasing gaps in middle age and declining gaps at older ages. Sweden (Figure 18) has the reverse pattern of increasing

gaps in young adulthood, declining gaps in middle age and increasing gaps at older ages. This large cross-national variation shows that persistent gaps across the lifespan in the literacy skills of individuals of different SES backgrounds are not inevitable. The first set of models will examine how these cross-national differences in the evolution of skills gaps are related to disparities in educational and labour force experiences.

Figure 7. Gaps in literacy skills by SES background, by age, Belgium-Flanders

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 8. Gaps in literacy skills by SES background, by age, Canada

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 9. Gaps in literacy skills by SES background, by age, Czech Republic

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 10. Gaps in literacy skills by SES background, by age, Denmark

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 11. Gaps in literacy skills by SES background, by age, England (UK)

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 12. Gaps in literacy skills by SES background, by age, Finland

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 13. Gaps in literacy skills by SES background, by age, Germany

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 14. Gaps in literacy skills by SES background, by age, Ireland

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 15. Gaps in literacy skills by SES background, by age, Netherlands

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 16. Gaps in literacy skills by SES background, by age, Northern Ireland (UK)

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 17. Gaps in literacy skills by SES background, by age, Norway

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 18. Gaps in literacy skills by SES background, by age, Sweden

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure 19. Gaps in literacy skills by SES background, by age, United States

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Gap Models

Table 2 reports models predicting skills gaps by SES background from disparities in the educational and labour force experiences of the two SES groups (Equation 1). Reflecting the large variation in the evolution of skills gaps across countries seen in Figures 7-19, no systematic international age trend could be found in the gaps, whether linear or quadratic, so age variables are omitted from the models. Model 1A includes only the three variables controlling for cohort attrition, *Proportion high-SES background*, *Proportion female* and *Mean birth year*. If the proportion of the cohort in the high-SES background group increases over time because of attrition from the low-SES background group due to incarceration or premature death, then literacy gaps are expected to decline because of positive selection of those remaining in the low-SES background sample. If the proportion of the cohort in the high-SES background group increases because additional parents attain tertiary degrees, then literacy gaps are also expected to decline because the marginal individuals moving to the high-SES background group may be relatively disadvantaged compared to other high-SES background individuals and relatively advantaged compared to the low-SES background group. As expected, an increasing proportion of the cohort in the high-SES background group is associated with declining gaps. It is not possible in this model of predicting gaps to determine which explanation fits the data better, but the interaction models will allow us to explore this finding further. The next two controls in Model 1A—and all of the covariates in subsequent models—are the differences obtained by subtracting each covariate value for the low-SES background

group from that for the high-SES group. When there is greater male attrition from the low-SES than the high-SES background group, gaps are expected to decline. This logic implies a positive association between the *Proportion female gap* and the *skills gap*, which is what is observed, although the association is not significant. When there is greater attrition from older birth years of a cohort for low-SES than high-SES background individuals, gaps are expected to decline, implying a positive association between the *Mean birth year gap* and the *skills gap*, which is also observed, although the association is also not statistically significant.

Table 2. Coefficients from mixed-effects models predicting literacy skills gaps by SES background from SES differences in covariates

	Model 1A			Model 1B			Model 1C			Model 1D		
Proportion High-SES background	-12.64	(18.02)		-2.54	(18.10)		-8.64	(13.07)		-6.52	(13.61)	
Difference between high- and low- SES:												
Proportion female	10.36	(12.20)		11.17	(10.28)		4.18	(10.22)		3.16	(9.72)	
Mean birth year	0.74	(2.42)		1.37	(2.18)		0.81	(1.77)		0.52	(1.69)	
Proportion with high school				23.62	(11.77)	*	24.65	(12.50)	*	25.58	(11.79)	*
Proportion with higher ed.				19.37	(6.21)	**	-8.56	(10.53)		-8.45	(11.04)	
Proportion adult ed.				7.55	(8.00)		0.01	(9.25)		-0.16	(8.50)	
Proportion neither employed nor student							-29.08	(17.01)	+	-26.16	(17.14)	
Proportion professional job							32.46	(13.22)	*	29.97	(14.53)	*
Proportion lower white-collar job							-6.44	(18.90)		-10.12	(20.04)	
Proportion blue collar job							-46.45	(18.48)	*	-46.54	(19.16)	*
Proportion reading at work										0.48	(13.13)	
Proportion reading at home										18.03	(10.16)	+
Intercept	19.04	(0.55)	***	18.96	(0.57)	***	18.89	(0.55)	***	18.84	(0.55)	***
Proportion Variance Explained (Years)	0.19			0.98			0.99			0.99		
Proportion Variance Explained (Country-Cohorts)	0.10			-0.44			0.16			0.13		
N (years)	98			98			98			98		
N (Country-Cohorts)	43			43			43			43		

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ ine.

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

The three variables added in Model 1B capture differences in high- and low-SES background groups' participation in education. When the high-SES background group's advantage in high school diplomas expands relative to the low-SES background group, skills gaps significantly increase ($p < 0.05$). A very similar pattern is observed for tertiary degrees ($p < 0.01$). Last, when the participation of high-SES background individuals in adult education and training expands relative to low-SES participation, skills gaps slightly increase, as expected, but the change is not statistically significant. It should be noted that the high school and higher education variables are measured differently from the adult education variable; while adult education indicates the share of the cohort who participated in adult education and training in the past year, high school and higher education are the shares of the cohort who have attained at least that level of education at any point in the past; thus, they represent net effects, and their associations with skills probably capture some combination of skills gained in education and subsequent career opportunities. The next model adds variables capturing these career experiences.

Model 1C adds the variables indicating occupation type (professional, lower white-collar or blue-collar), as well as the dummy variable "Proportion neither employed nor student," making full-time students the reference category. Relative to being a full-time student, as expected, when relatively more of the high-SES background group moves into professional occupations, literacy skills gaps significantly increase ($p < 0.05$), and when relatively more of the high-SES background group moves into blue-collar occupations, literacy gaps significantly decline ($p < 0.05$). Disproportionate employment in lower white-collar occupations is not strongly related to changes in literacy skills gaps. Last, when relatively more of the high-SES background group becomes unemployed or exits the labour force, literacy skills gaps decline, a change that is marginally significant ($p < 0.1$). After the occupational variables are added to the model, the higher education and adult education coefficients substantially decline; the coefficient for adult education is close to 0, that for higher education is *negative*, and neither is statistically significant. This suggests that the positive associations between disparities in these types of education observed in Model 1B were largely capturing the different career opportunities—and further skills development—available to those who complete further education. In contrast, the coefficient for disparities in high school attainment remains strongly positive after controlling for the occupational variables.

Finally, Model 1D attempts to capture the differences in everyday use of literacy skills among individuals in the same broad occupational and educational categories by including variables measuring disparities in reading habits at work and at home. After accounting for the educational and labour force variables, an increasing share of high- relative to low-SES background individuals reading at least weekly at work is associated with only a very small, non-significant increase in literacy skills gaps. This weak result suggests that differences in reading at work do not explain much of the skills gap by SES background beyond what is already explained by education and labour force variables. As expected, an increasing share of high- relative to low-SES background individuals reading at least weekly at home is associated with increasing skills gaps, a change that is marginally significant ($p < 0.1$).⁷

The "differential uptake" models in Table 2 assume that changes in literacy skills gaps by SES background are mainly related to disparities in the educational and labour force opportunities available to individuals of different SES backgrounds. However, it is also possible that educational and labour force experiences may have "differential impact" on

individuals of different SES backgrounds. The next set of models addresses this possibility.

Interaction Models

Table 3 shows the results of the interaction models (Equation 2), which examine differences between low- and high-SES background groups in how educational and labour force experiences are associated with changes in literacy skills. Model 2A includes only the High-SES dummy variable and the controls for age and cohort attrition. The coefficient on the High-SES dummy is 19.79, indicating that on average across all countries, cohorts and years, high-SES background individuals score about half of a standard deviation higher in literacy skills than their low-SES counterparts, which is consistent in magnitude with the intercepts of the models predicting gaps in Table 2. The linear and squared age terms are positive and negative, respectively. This age trajectory is consistent with other research using the international surveys of adult skills, which has found that literacy skills rise until about age 30 and decline thereafter (Green and Riddell 2013; Paccagnella 2016a). Interactions between the age terms and the High-SES dummy were not statistically significant, indicating that on average, the age trajectory in literacy does not differ for high- and low-SES background individuals, so the $SES \times age$ interactions are omitted from all models. SES interactions are included for the other three control variables in Model 2A (as well as all other covariates in subsequent models), along with a column reporting the outcome of a Wald general linear hypothesis test for the significance of each association for the high-SES background group. The results for the Proportion high-SES background control and its interaction with High-SES allow us to see which of the two explanations for results in Table 2 best fits the data. If the proportion of the cohort in the high-SES background group increases over time because of attrition from the low-SES background group, then literacy is expected to rise in the low-SES background group, and no change is expected for the high-SES background group. On the other hand, if the proportion of the cohort in the high-SES background group increases because more low-SES parents complete tertiary degrees after their children reach adulthood, then literacy proficiency may be expected to fall in both the high- and low-SES background groups. The latter pattern is found, with a negative coefficient on the main effect for Proportion high-SES, representing significantly falling skills for the low-SES background group ($p < 0.05$), and a negative interaction predicting an even more negative association for the high-SES background group, an association which a Wald test shows to be statistically significant ($p < 0.01$). Thus, the results suggest that the small changes in SES background distributions seen in Figures 3-6 are more due to educational upgrading later in life by parents than to attrition from the low-SES background group.⁸ Consistent with the results in Table 2, attrition of males and of older individuals within a cohort band is associated with rising literacy skills; and as expected, the interaction terms show that the associations are slightly less positive for the high-SES background group. All variables from Model 2A are retained in subsequent models as controls.

Table 3. Coefficients from mixed-effects models predicting literacy skills from covariates and SES background group interactions

	Model 2A			Model 2B			Model 2C			Model 2D			Model 2E		
	b	(se)	[Wald test]	b	(se)	[Wald test]	b	(se)	[Wald test]	b	(se)	[Wald test]	b	(se)	[Wald test]
High-SES background	19.79	(2.08)	***	19.63	(2.09)	***	20.00	(2.14)	***	20.31	(2.13)	***	20.05	(2.18)	***
Mean age	0.87	(0.33)	**	1.04	(0.46)	*	2.51	(0.71)	***	2.02	(0.77)	**	2.56	(0.68)	***
Mean age ²	-0.02	(0.00)	***	-0.02	(0.01)	***	-0.04	(0.01)	***	-0.04	(0.01)	***	-0.04	(0.01)	***
Proportion high-SES background	-33.58	(14.66)	*	-24.32	(17.79)		-21.35	(19.01)		6.15	(17.25)		-20.97	(14.93)	
Proportion high-SES background x high SES	-31.73	(28.77)		-49.35	(26.85)	+	-47.24	(29.82)		-88.35	(26.90)	**	-45.49	(28.42)	***
Proportion female	8.19	(32.27)		-18.01	(37.95)		-20.68	(31.73)		-22.12	(25.54)		-27.27	(27.73)	
Proportion female x High SES	-0.67	(41.68)		23.59	(46.91)		-7.74	(46.04)		-6.80	(37.79)		32.32	(38.91)	
Mean birth year	11.88	(4.60)	**	15.37	(5.10)	**	10.20	(4.87)	*	13.62	(4.49)	**	13.64	(4.55)	**
Mean birth year x High SES	-9.05	(5.29)	+	-13.80	(5.73)	*	-9.49	(5.80)		-13.39	(5.37)	*	-8.65	(5.63)	
Proportion with high school				15.20	(10.38)		16.72	(10.18)		9.24	(9.00)				
Proportion with high school x High SES				32.12	(17.83)	+	39.19	(21.76)	+	50.82	(19.20)	**			
Proportion with higher ed.				3.05	(10.62)		16.30	(15.45)		22.46	(15.33)				
Proportion with higher ed. X High SES				-18.10	(10.17)	+	-21.84	(18.59)		-32.48	(17.73)	+			
Proportion adult ed.				-18.13	(8.34)	*	-3.47	(8.51)		-4.26	(7.02)				
Proportion adult ed. X High SES				21.95	(11.91)	+	10.50	(12.50)		13.01	(11.44)				
Proportion neither employed nor student							-27.05	(16.78)		-22.41	(17.21)				
Proportion neither employed nor student x High SES							8.47	(22.90)		-1.27	(22.29)				
Proportion professional job							-71.86	(21.79)	***	-164.84	(29.37)	***			
Proportion professional job x High SES							39.09	(22.32)	+	155.12	(31.10)	***			
Proportion lower white-collar job							-34.80	(23.58)		-122.31	(33.17)	***			
Proportion lower white-collar job x High SES							33.07	(27.70)		143.33	(37.18)	***			
Proportion blue collar job							-64.08	(25.47)	*	-113.43	(27.23)	***			
Proportion blue collar job x High SES							-9.89	(50.47)		65.64	(45.93)				
Proportion reading at work										126.74	(25.03)	***			
Proportion reading at work x High SES										-152.70	(33.00)	***			
Proportion reading at home										-8.28	(5.36)				
Proportion reading at home x High SES										24.78	(7.54)	**			
Proportion full time student													49.92	(17.40)	**
Proportion full time student x High SES													-23.69	(14.40)	***
Proportion unemployed													-6.15	(37.22)	
Proportion unemployed x High SES													-32.18	(48.53)	
Proportion household duties													30.75	(27.18)	
Proportion household duties x High SES													-28.18	(36.15)	
Proportion retired													23.16	(13.19)	+
Proportion retired x High SES													-10.15	(17.94)	
Proportion out of LF-Other													48.21	(24.71)	+
Proportion out of LF-Other x High SES													-82.71	(32.90)	*
Intercept	284.18	(7.33)	***	280.04	(10.58)	***	252.83	(14.25)	***	262.15	(15.20)	***	251.41	(13.02)	***
Proportion Variance Explained (Years)	0.85			0.87			0.91			0.95			0.88		
Proportion Variance Explained (Country-Cohort-SES groups)	0.60			0.60			0.58			0.56			0.60		
N (Years)	196			196			196			196			196		
N (Country-Cohort-SES groups)	86			86			86			86			86		

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Model 2B adds the three variables (and their interactions with the High-SES dummy) that capture differences between SES background groups in how completion of further education is associated with changes in literacy skills. Several of the results do suggest differences between the SES groups. An increasing number of individuals obtaining high school diplomas is associated with rising literacy skills for both low- and high-SES background groups, as expected, although the relationship is stronger for high-SES background individuals and is statistically significant only for this group, according to a Wald test ($p < 0.01$). In contrast, after controlling for high school attainment, an increasing number of individuals obtaining higher education degrees is associated with a small and non-significant increase in literacy skills for the low-SES group and a significant *decline* in literacy skills for the high-SES group, according to a Wald test ($p < 0.05$). Last, the results for adult education and training imply, as with high school completion, that the low-SES background group benefits less than the high-SES group. In this case, however, increasing participation in adult education is associated with a significant *decline* in literacy skills for low-SES individuals ($p < 0.05$), while the association for high-SES individuals is close to 0 and not significant. The results for the educational variables suggest that some types of education (high school and adult education) may have a more positive impact on the literacy proficiency of high-SES than low-SES background individuals, while higher education appears to have a more positive impact on the literacy of low-SES background individuals, after controlling for other educational degrees. These will be elaborated further in the Discussion section. As with the gaps models, the high school and higher education variables capture net effects that include skills improvements in education as well as in subsequent years, when educated individuals are more likely to have professional jobs. The next model accounts for this possibility by controlling for occupational variables.

Model 2C adds variables indicating the types of employment individuals are engaged in, where jobs are classified in three broad categories: professional, lower white-collar or blue-collar. The dummy variable “Proportion neither employed nor student” is also included, making full-time student status the reference category. Relative to being a full-time student, increasing proportions in all other categories are associated with falling scores (being out of the labour force, in a blue or lower white-collar job and surprisingly, also a professional job). This is true for both low- and high-SES background individuals, but the associations tend to be weaker for high-SES background individuals, with positive interactions for being out of the labour force or in a professional or lower white-collar occupation, while the interaction is small and negative for blue-collar employment. Only the professional job $\times$ High-SES interaction is marginally significant ($p < 0.1$). Thus, different types of employment do not appear to have markedly different impacts on the literacy skills of low- and high-SES background individuals when they have access to the same occupation types. Adding the occupational variables to the model also does not substantially alter the educational coefficients, so the differential impact of education seen in Model 2B does not appear to be due to subsequent skill improvements during the working years. However, it is possible that the broad occupational categories in Model 2C do not sufficiently capture differences in skills use between occupations; the next model adds this consideration.

Model 2D attempts to capture the differences in use of literacy skills among individuals in the same broad occupational and educational categories by including variables measuring changes in SES groups’ reading habits at work and at home. Controlling for broad educational and labour-market status, an increasing proportion of low-SES

background individuals reading at least weekly at work is associated with a large and significant increase in literacy skills for this group ($p < .001$), while the same increase for high-SES background individuals is associated with a significantly more negative change, amounting to a *decline* in literacy skills, although the decline is not significant in a Wald test. In contrast with reading at work, an increasing proportion of the low-SES background group reading at least weekly at home is associated with a slight *decline* in literacy skills for this group, while the same increase in home reading for the high-SES group is associated with increasing literacy skills, an association that is significant in a Wald test ($p < 0.01$). The sharp contrast in home reading results for the different SES groups suggests that individuals from different SES backgrounds may have access to different kinds of materials for recreational reading. Further disaggregating the home reading variable into reading books versus newspapers or magazines (results not shown) reveals that this contrast is driven by reading news rather than books; increased newspaper and magazine reading is associated with declining literacy skills for the low-SES background group and increasing literacy skills for the high-SES background group, while increased book reading appears to have no differential impact on literacy skills by SES background. Thus, the SES background difference in home reading does seem to be at least partly attributable to the types of materials being read. After adding the reading variables to the model, the main effects for all of the occupational variables become dramatically more negative and the interaction effects more positive. Further exploration shows that this is primarily due to the addition of reading at work (rather than reading at home) to the model, and reflects the fact that the comparison is now between being a full-time student with no job (and therefore doing no reading for work) versus employment in a job in each occupational category with similarly infrequent reading. The results in Model 2D show that, for the low-SES background group, skill declines when moving from being a student into employment are highly dependent on the amount of reading involved in the job, while for the high-SES background group, the amount of reading for work does not affect the skill decline markedly.

Finally, Model 2E disaggregates the “Proportion neither employed nor student” dummy variable into its four (mutually-exclusive) component categories summarizing individuals’ labour force status. The omitted reference category is being employed (full- or part-time), which is compared with being a full-time student, unemployed, performing unpaid household duties, retired or out of the labour force for other reasons. Aside from the control variables, other covariates are omitted for parsimony due to the small sample size. Since chronologically, more individuals move from full-time student status into employment, it is more intuitive to interpret the Proportion full-time student coefficient in reverse. Consistent with the previous models, more low-SES background individuals moving from full-time student status into employment is associated with a significant decline in literacy skills for this group, while more high-SES background individuals moving into employment is associated with a smaller decline in literacy skills; both associations are significant ($p < 0.01$). The next four variables are those previously included in the “Proportion neither employed nor student” category. When comparing these combined categories with full-time student status in previous Models 2C and 2D, they were associated with a decline in literacy skills. However, now that the comparison is with being employed, the results are different. More individuals moving into these non-employed statuses is often associated with *rising* literacy skills among low-SES background individuals but with declining skills among high-SES individuals. Increasing rates of retirement and being out of the labour force for household duties or other reasons are all associated with rising literacy skills among low-SES background individuals, although only retirement and the “other reasons” category reach marginal statistical

significance ($p < 0.1$). Increasing unemployment is associated with a small and non-significant decline in literacy skills for low-SES background individuals. The High-SES interactions are negative for all of these categories, resulting in negative point estimates for unemployment and the “other” category and small positive point estimates for household duties and retirement, though none of these negative associations is significant in a Wald test. That leaving paid employment is associated with rising literacy among low-SES background individuals seems counterintuitive, but it is consistent with Mazzonna and Peracchi’s (2016) finding of a positive effect of retirement on health and cognitive abilities for those employed in jobs with a high level of physical burden, if we assume that low-SES background individuals are more likely to be employed in physically burdensome jobs.

One additional reason why employment may affect high- and low-SES background individuals differently is because it occurs asynchronously at different life stages. Figure 20 reports the proportion of each SES background group that is employed by age for the 15 countries in the sample (results are averaged across cohorts within countries for simplicity). In most countries, high-SES background individuals are less likely to be employed around age 20 because they are more likely to be full-time students; however, high-SES background individuals are more likely to be employed around age 60 in several countries (Denmark, Finland, Italy, Norway, and the United States), as low-SES background individuals appear to retire at younger ages. In some other countries, high-SES background individuals are less likely to be employed at every age (Germany, England (United Kingdom), Northern Ireland (United Kingdom) and the Republic of Ireland). These age-employment profiles not only help to explain the results of the differential impact models but also the cross-national variation in the evolution of literacy skills gaps that this paper set out to illuminate. For example, Ireland’s and Northern Ireland’s (United Kingdom) high-SES background groups are substantially less likely to be employed during young adulthood, gaps that gradually close with age, and both countries have increasing skills gaps by SES background throughout the life course. Germany has a pattern of large numbers of women returning to the workforce in middle age after performing household duties, and literacy skills gaps increase during this age range, likely due to inequalities in skills use at work for women of different SES backgrounds. Finland, England (United Kingdom) and particularly the Czech Republic have relatively young retirement ages, and skills gaps decrease during this age range, as workers leave unequal employment.

Figure 20. Difference between high and low-SES background employment by age and country

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

9. Discussion

In summary, literacy skills gaps by SES background change with age in most countries, and the direction of changes varies across countries. “Differential uptake” models reveal that the evolution of skills gaps is strongly related to disparities based on SES background in high school attainment, professional and blue-collar employment. Disparities in higher educational attainment do not have a positive or statistically significant independent association with skills gaps, after controlling for disparities in professional and blue-collar employment. Thus, it appears that higher education has an indirect effect on literacy skills through labour-market opportunities, particularly white-collar jobs that require individuals to continue using literacy skills frequently. The “differential uptake” models help to explain the large cross-national variation in the trajectory of skills gaps by SES background over the life course and suggest policy avenues for addressing and attempting to close skills gaps in adulthood. It appears very important that countries focus on closing disparities in opportunities for educational attainment between individuals of different SES backgrounds, thus indirectly closing disparities in access to professional employment.

The “differential impact” findings in this paper help to extend the sociological framework of childhood school effects and home effects across the life course. The “differential impact” results for the educational variables suggest that some types of education (high school and adult education) may have a more positive impact on the literacy proficiency of high-SES than low-SES background individuals, while higher education appears to have a more positive impact on the literacy of low-SES background individuals, after controlling for other educational degrees. These results suggest that in the case of high school and adult education, high-SES individuals may have access to higher-quality institutions and programs and/or be better prepared to take advantage of these learning opportunities. In the case of higher education, in contrast, individuals of low-SES backgrounds appear to experience a compensatory effect. That the effect of education on skills appears greater for high school than higher education (for both education groups) is consistent with the large causal effects found by Green and Riddell (2013) and Dinçer (2016) for high school and the small effects found by Arum and Roksa (2011) for US universities. One explanation could be that the basic literacy skills tested in the adult literacy surveys tend to be learned at lower levels of education. However, the differential effects by SES background seem inconsistent with those found in previous literature, where Green and Riddell (2013) and Dinçer (2016) found the largest effects of high school on the lowest-skilled individuals (granted, these are not the same as low-SES background individuals) and Arum and Roksa (2011) found no differences in university learning (or lack thereof) associated with SES background. One further possible explanation for the different results is that educational attainment occurs asynchronously for individuals of different SES backgrounds. On average across countries in PIAAC, low-SES background individuals age 35 and over who completed higher education report finishing their degree when they were about 1 year older than their high-SES background counterparts; this pattern also holds for high school degrees in some countries.⁹ Thus, the more positive effects of higher education for low-SES background individuals could

conceivably mean that higher education has a more positive effect on skills at an older age. In the case of high school, although high-SES background individuals tend to complete this level of education earlier in many countries, in several other countries in the sample, a large number of high-SES background individuals appear to have returned to school and completed high school degrees in middle age (Belgium-Flanders, Canada, Ireland and the Netherlands).¹⁰ These increases in high school attainment for high-SES background individuals correspond to large increases in skills gaps by SES background at these ages in these countries.

Regarding the labour-market variables, “differential impact” models reveal that employment is associated with larger literacy skill declines for low-SES than high-SES background individuals, an effect that appears to be due to differences in the types of employment that individuals from different SES backgrounds are likely to work in, and the opportunities for literacy skills use on-the-job. The negative effect of employment on literacy skills is so large for low-SES background individuals that exiting the labour force for retirement or “other” reasons is associated with marginally-significant *improvements* in skills. This is consistent with Mazzonna and Peracchi’s (2016) finding of a positive effect of retirement on health and cognitive abilities for those employed in jobs with a high level of physical burden, assuming that those from low-SES backgrounds are more likely to be employed on physically burdensome jobs. This does in fact appear to be the case, as PIAAC data show that individuals from low-SES backgrounds are about twice as likely as their high-SES counterparts to have a job that involves “working physically for a long period” at least weekly.¹¹ In contrast, for high-SES background individuals, exiting the labour force is generally associated with declining literacy skills. Thus, when both groups of individuals exit the labour force (such as in a country with a relatively a young retirement age like the Czech Republic), literacy skills gaps by SES background tend to narrow. This suggests that the experiences of individuals from different SES backgrounds are more similar when they are outside the labour force than when they are employed.

Thus, the “differential impact” findings for adults are, in a sense, the reverse of those for children, where skills gaps by SES narrow when children are in school and widen when children spend time at home, such as during early childhood and summer vacations. For adults, tertiary education appears to have a similar compensatory effect as schooling in childhood, but high school completion and adult education and training seem to *exacerbate* skills gaps by SES background. Finally, declining skills gaps when workers exit the labour force implies that for adults, workplaces are more unequal environments than homes.

¹ Reported gaps are in terms of points on the international PIAAC scale (here and throughout the paper), so that they may be linked with PIAAC proficiency levels. A cross-national comparison of SES background skills gaps based on nationally-standardized skills is available in Annex A Figure A1. The ranking of countries is nearly identical to that in Figure 1.

² The stylized graphs in Figure 2 illustrate all changes in skills gaps by SES background as symmetrical. However, it should be noted that skills gaps may widen due to increasing skills of individuals from high SES backgrounds, declining skills of individuals from low-SES backgrounds or both. Similarly, skills gaps may narrow due to declining skills of individuals from high SES backgrounds, increasing skills of individuals from low-SES backgrounds or both. All of these possibilities are examined in the present study.

³ Models were also run including Italy and Poland, and results were nearly identical.

⁴ Belgium-Flemish, Canada, Czech Republic, Denmark, England, Finland, Germany, Ireland, Netherlands, Northern Ireland (United Kingdom), Norway, Sweden and United States.

⁵ This issue has already been noted for respondents' own educational attainment in the same five countries IALS by Gesthuizen et al. (2011).

⁶ Although it is not the primary focus of this study, the figures reveal cross-national differences in the size of literacy skills gaps by SES background. For example, in young adulthood (early-mid-20s), skills gaps range from greater than 20 points in Belgium-Flanders, Germany and the United States to closer to 10 points in the Czech Republic, the Netherlands and Sweden. To some extent, these cross-national differences resemble well-known results about SES gradients in reading literacy at age 15, as reported in PISA. In PISA 2000, whose participants were roughly the same birth cohort as the youngest cohort in this study (born 1977-1986), steep SES gradients were observed in Germany, Belgium and the United States; and a flatter gradient in Sweden (OECD/UIS 2003). This consistency supports the idea that much of the literacy skills gap by SES background is already present in adolescence. However, there are also a number of discrepancies between PISA 2000 results and those reported for young adults in the current study: skills gaps in young adulthood are somewhat larger than expected for Canada and Finland, and much smaller than expected for England and the Czech Republic. These discrepancies illustrate that experiences after the end of compulsory schooling (such as post-secondary education and early labour market experiences) likely also contribute to literacy skills gaps by SES background in young adulthood. This is consistent with findings by Borgonovi et al. (2017) for similar birth cohorts.

⁷ Annex A Figures A2-A14 display the results of Model 1D graphically. For each country, the figure plots gap trajectories by age for all available cohorts, replicating Figures 7-19 (solid dots and fit lines) and then plots gap trajectories adjusted for all 12 time-varying covariates in Model 1D (hollow dots and dashed fit lines). It can be seen from the figures that a large share of the variance in gaps between different age groups within country-cohorts is explained by the covariates included in Model 1D. The SES background gaps average about 0, as expected, since they are computed from residuals based on the predictions of Model 1D. More importantly, age trajectories within country-cohorts are flattened and smoothed compared to the raw gap trajectories, reflecting the fact that they are conditional on changes in the relative education level, occupation type, etc. of high- and low-SES background individuals by age.

⁸ Additional analyses (not shown) reveal that these coefficients are still negative without other attrition controls in the model.

⁹ See Annex A Table A1 for full results.

¹⁰ See Annex A Figure A15 for more information.

¹¹ See Annex A Table A2 for full results.

References

- Adult Literacy and Lifeskills (ALL)* Database, Statistics Canada, <https://nces.ed.gov/surveys/all/>.
- Arum, R., and J. Roksa, (2011), *Academically adrift: Limited learning on college campuses*, University of Chicago Press.
- Baker, D. P., B. Goesling, and G. K. LeTendre, (2002), *Socioeconomic status, school quality, and national economic development: a cross-national analysis of the "Heyneman-Loxley Effect" on Mathematics and Science achievement*, *Comparative Education Review* Vol. 46 (3), pp. 291-312.
- Borgonovi, F., et. al. (2017) *Youth in Transition: How Do Some of the Cohorts Participating in PISA Fare in PIAAC?*, OECD Education Working Papers, No. 155, OECD Publishing, Paris, <https://doi.org/10.1787/19939019>.
- Bradbury, B., et al. (2015), *Too many children left behind: The US achievement gap in comparative perspective*, Russell Sage Foundation.
- Chmielewski, A. K., and S. F. Reardon, (2016), *Patterns of Cross-National Variation in the Association Between Income and Academic Achievement*, *AERA Open* Vol. 2/3: pp. 1-27.
- Davies, S., and J. Aurini, (2013), *Summer learning inequality in Ontario*, *Canadian Public Policy* Vol. 39/2, pp. 287-307.
- De Grip, A., et al. (2008), *Job-worker mismatch and cognitive decline*. Oxford Economic Papers:gpm023.
- Desjardins, R., and A. J. Warnke, (2012); *Ageing and Skills: A Review and Analysis of Skill Gain and Skill Loss Over the Lifespan and Over Time*, in OECD Education Working Papers, No. 72. OECD Publishing, Paris.
- Dinçer, M. A., (2016), *Education, skill formation and inequality: Evidence from compulsory schooling reforms in Europe*, Unpublished Draft. OECD, Paris.
- Downey, D. B., and D. J. Condrón (2016), *Fifty Years since the Coleman Report: Rethinking the Relationship between Schools and Inequality*, *Sociology of Education* 89(3):207-20.
- Downey, D. B., P. T. von Hippel, and B. Broh, (2004), *Are Schools the Great Equalizer? Cognitive Inequality during the Summer Months and the School Year*, *American Sociological Review* Vol. 69, pp. 613-35.
- Edin, P.-A., and M. Gustavsson, (2008), *Time out of work and skill depreciation*, *Industrial & labor relations review* Vol. 61/2, pp. 163-80.
- Gesthuizen, M., H. Solga, and R. Küster, (2011), *Context matters: Economic marginalization of low-educated workers in cross-national perspective*. *European Sociological Review* Vol. 27/2, pp. 264-80.
- Glymour, M M., C. Tzourio, and C. Dufouil, (2012), *Is cognitive aging predicted by one's own or one's parents' educational level? Results from the Three-City Study*, *American journal of epidemiology* Vol. 175/8, pp. 750-759.

- Green, D. A., and W. C. Riddell, (2013). *Ageing and literacy skills: Evidence from Canada, Norway and the United States*, Labour Economics Vol.22, pp. 16-29.
- Heyneman, S. P., and W.A. Loxley, (1983), *The Effect of Primary-School Quality on Academic Achievement across Twenty-nine High- and Low-Income Countries*, American Journal of Sociology Vol. 88/6, pp. 1162-1194.
- International Adult Literacy Survey (IALS) Database, Statistics Canada, <https://nces.ed.gov/surveys/ials/data.asp>
- Jackson, M., (2013), *Determined to Succeed?: Performance Versus Choice in Educational Attainment*, Stanford University Press.
- Marquié, J.-C., et al. (2010), *Higher mental stimulation at work is associated with improved cognitive functioning in both young and older workers*, Ergonomics Vol. 53/11, pp. 1287-1301.
- Mazzonna, F., and F. Peracchi, (2016), *Unhealthy Retirement?*, Journal of Human Resources.
- Merry, J. J. (2013), *Tracing the US Deficit in PISA Reading Skills to Early Childhood Evidence from the United States and Canada*, Sociology of Education: 0038040712472913.
- Mullis, I. V. S., M. O. Martin, P. Foy, and A. Arora (2012), *TIMSS 2011 International Results in Mathematics*, Boston: TIMSS & PIRLS International Study Center, Lynch School of Education, Boston College and IEA.
- OECD (2013a) *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*, OECD Publishing, Paris, <https://doi.org/10.1787/9789264204256-en>
- OECD (2013b) *PISA 2012 Results: Excellence Through Equity: Giving Every Student the Chance to Succeed (Volume II)*, OECD Publishing, Paris, <https://doi.org/10.1787/19963777>.
- Paccagnella, M., (2016a), *Age, Ageing and Skills: Results from the Survey of Adult Skills*, OECD Education Working Papers, No. 132, OECD Publishing, Paris.
- Paccagnella, M., (2016b), *Literacy and Numeracy Proficiency in IALS, ALL and PIAAC*, OECD Education Working Papers No. 142, OECD Publishing, Paris.
- Programme for the International Assessment of Adult Competencies (PIAAC) Database, www.oecd.org/site/piaac/publicdataandanalysis.htm.
- Rohwedder, S., and R. J Willis, (2010), *Mental retirement*, *The Journal of Economic Perspectives* Vol. 24/1, pp. 119-38.
- Schaie, K W.,(1994), *The course of adult intellectual development*, American Psychologist Vol. 49/4, pp. 304.

Annexe A.

Figure A A.1. Nationally standardized gaps in literacy skills by SES background

Note: Countries sorted from the largest to the smallest literacy gap.

Source: Author's own calculations from PIAAC dataset www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.2. Raw and adjusted gaps in literacy skills by SES background, by age, Belgium-Flanders

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.3. Raw and adjusted SES in literacy skills by SES background, by age, Canada

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.4. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Czech Republic

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.5. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Denmark

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.6. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, England (UK)

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.7. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Finland

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.8. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Germany

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.9. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Ireland

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.10. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Netherlands

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.11. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Northern Ireland (UK)

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.12. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Norway

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.13. Raw and adjusted SES origin gaps in literacy skills by SES background, by age, Sweden

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Figure A A.14. Raw and adjusted SES origin gaps by social origin in literacy skills by SES background, by age, United States

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm

Figure A A.15. Difference in proportion of high-SES and low-SES background who completed high school or more, by country, birth cohort and age

Source: Author's own calculations from IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

Table A A.1. Coefficients on high-SES background from regressions predicting age when individual completed education, by country and education level

Country	Less than High School		HS or Some Voc. Training		Tertiary or more	
	b	(se)	b	(se)	b	(se)
Belgium-Flanders	0.17	(0.59)	0.10	(0.22)	0.24	(0.25)
Canada	-0.30	(0.31)	0.01	(0.42)	-0.14	(0.34)
Czech Republic	-0.59	(0.57)	-0.56	(0.30)	+	-0.50 (0.65)
Germany	0.83	(1.56)	0.53	(0.36)		-0.47 (0.43)
Denmark	-1.08	(1.02)	1.56	(0.56)	**	-0.73 (0.34) *
England (UK)	-0.22	(1.76)	1.07	(1.28)		-1.56 (0.54) **
Finland	0.26	(0.25)	-0.54	(1.14)		-1.42 (0.44) **
Ireland	-0.58	(0.20)	**	1.38 (1.00)		-1.09 (0.65) +
Northern Ireland (UK)	-3.74	(0.93)	***	0.47 (1.31)		-0.86 (0.66)
Netherlands	1.65	(0.93)	+	0.80 (0.54)		-1.26 (0.39) **
Norway	1.03	(0.76)		-1.27 (0.72)	+	-1.53 (0.44) ***
Sweden	-0.37	(1.44)		-0.58 (0.48)		-0.94 (0.52) +
United States	-0.33	(0.51)		-1.50 (0.48)	**	-1.95 (0.51) ***

Note: Models control for age and exact degree attained. Data limited to individuals age 35 and older (i.e., the three oldest birth cohorts). Individuals who immigrated after age 10 are omitted for consistency with main analyses.

Source: Author's own calculations using IALS (<https://nces.ed.gov/surveys/ials/data.asp>), ALL (<https://nces.ed.gov/surveys/all/>) and PIAAC datasets, www.oecd.org/site/piaac/publicdataandanalysis.htm.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A A.2. Coefficients on high-SES background from logistic regressions predicting that job involves long periods of physical work at least weekly

Country	b	(se)	odds ratio
Belgium-Flanders	-0.99	(0.09)	*** 0.37
Canada	-0.52	(0.06)	*** 0.60
Czech Republic	-1.24	(0.21)	*** 0.29
Germany	-0.65	(0.08)	*** 0.52
Denmark	-0.59	(0.09)	*** 0.55
England (UK)	-0.76	(0.12)	*** 0.47
Finland	-0.89	(0.12)	*** 0.41
Ireland	-0.78	(0.09)	*** 0.46
Northern Ireland (UK)	-0.63	(0.13)	*** 0.53
Netherlands	-0.71	(0.09)	*** 0.49
Norway	-0.68	(0.08)	*** 0.51
Sweden	-0.52	(0.10)	*** 0.60
United States	-0.64	(0.09)	*** 0.53

Note: Models control for age. Individuals who immigrated after age 10 are omitted for consistency with main analyses.

Source: Author's own calculations using PIAAC dataset, www.oecd.org/site/piaac/publicdataandanalysis.htm.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.