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SKILLS ACQUIRED FROM FIELDS OF STUDY: EVIDENCE FROM THE PIAAC SURVEYS*

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Abstract

We study the skill sets of the working population, paying particular attention to whether the skills of recent labor market entrants correlate to their earlier field of study in the education system. We do so using the PIAAC Survey of Adult Skills that measures individual numeracy and literacy skills in a representative sample: we focus our core analysis on the Danish PIAAC sample. We document three facts. First, among labor market entrants, skills vary significantly by field of study. Second, field of study accounts for 30% of the explained variation in both numeracy and literacy skills, conditional on level of education and background characteristics. Third, there are substantial differences in labor market returns by field of study, so omitting field of study biases standard Mincerian estimates of returns to education. Our findings show the importance of field of study as a determinant of skill acquisition and labor market outcomes, highlighting the role of educational pathways in shaping both the supply and returns to skills in the economy. *JEL: I21, J24.*

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1 Introduction

The skills individuals have at labor market entry are critical for their career success and lifetime welfare. These skills are multidimensional and developed in part through choices made within the education system. In this paper we examine the role of an important but understudied dimension of educational pathways on skills acquired: field of study. We provide novel evidence on how field of study contributes to skills formation at labor market entry, and how this in turns explains variation in earnings over and above levels of education. As a consequence, we document the extent to which Mincerian estimates of the labor market returns to education can be biased if field of study is unaccounted for.

We tackle the issue using the PIAAC Survey of Adult Skills administered by the Organization for Economic Cooperation. The PIAAC data provide a representative sample of a cross-section of working-age adults from middle- and high-income countries. A unique feature of the PIAAC data is they provide detailed and multiple measures of individual skills, at all stages of working lives. These are measured using standardized tests rather than being self-reported and are designed to be comparable across countries. We focus on two skills: (i) numeracy – defined as the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life; (ii) literacy – defined as understanding, evaluating, using and engaging with written texts to participate in society, to achieve one’s goals, and to develop one’s knowledge and potential.

Our main analysis is conducted using the PIAAC data from Denmark: this covers 7287 individuals surveyed in 2011/2. The data records the age of labor market entry of individuals, and so enables us to measure the association of fields of study on individual skills at different career stages. Our analysis is focused on labor market entrants, defined as individuals currently in the labor market and who left formal education five years or less since the PIAAC survey was administered to them. This group is particularly informative because skills evolve over working lives, through on-the-job learning or skill depreciation, and so labor market entrants provide the clearest view of skill levels accumulated immediately following the completion of formal education.

The PIAAC data has two additional key features that underpin our analysis. First, it records six possible levels of completed education (using ISCED codes): from compulsory lower secondary education or less, through to master/research degrees. Second, the data assigns individuals to one of nine fields of study: *Social sciences, business and law*; *Science, mathematics and computing*; *Humanities, languages and arts*; *Services*; *Engineering, manufacturing and construction*; *Health and welfare*; *Agriculture and veterinary*; *Teacher training and education science*; and *General programmes*. Counter to much of the existing literature [Hastings *et al.* 2013, Kirkeboen *et al.* 2016, Britton *et al.* 2022], this data allows us to recover fields of study for both graduate and non-graduate educational pathways.

Our main results are as follows. First, among labor market entrants, skills vary systematically

by both education level and field of study. Standardizing both skills measures to have mean zero and standard deviation one among labor market entrants, we find that as expected, graduates have significantly higher numeracy and literacy scores than non-graduates. Graduates score $.591\sigma$ higher on the numeracy measure and $.566\sigma$ higher on the literacy measure, with both differences being statistically significant ($p = .000$). However, skills among labor market entrants also vary considerably by field of study: (i) the highest measured skill levels are among those with fields of study in *Humanities, languages and arts, Science, mathematics and computing, and Social sciences, business and law*; (ii) the lowest skill levels are recorded among those with fields of study of *Services* and *Agriculture and veterinary* or with no field of study. Relative to the average labor market entrant, those with a *Humanities, languages and arts* field of study score $.319\sigma$ on numeracy skills and $.499\sigma$ on literacy skills; those with a *Agriculture and veterinary* field of study score $.280\sigma$ lower on numeracy skills and $.737\sigma$ lower on literacy skills. In short, among labor market entrants, the magnitude of measured skills differences by field of study are comparable to the size of skills gaps from a simple comparison between graduates to non-graduates.

Second, we use a regression framework to understand how fields of study are associated with skills levels at different career stages, and how much of the explained variation in skills is due to field of study. Given the PIAAC data surveys individuals across working lives, we examine the evolution of skills between those still in education, labor market entrants, and more experienced workers, depending on field of study, and conditional on education level and background characteristics. We find that field of study continues to have a significant association with both numeracy and literacy skills among labor market entrants, all else equal. Examining specific comparisons to the omitted field of study – those with backgrounds in *Social sciences, business and law*, we find that individuals who studied *Engineering, manufacturing and construction, Agriculture and veterinary, and Teacher training and education science* have significantly lower literacy skills. The magnitudes of these skills differences are $.347\sigma$, $.705\sigma$ and $.324\sigma$ respectively, representing economically significant skills differences among labor market entrants by field of study.

To understand the variation in measured skills explained by field of study, we perform a Shapley-Owen decomposition of the R -squared from our regression specification. We use this to quantify the contributions of field of study, level of education and background characteristics. We find that field of study accounts for just under 30% of the explained variation in each skill. The remaining variation is explained by education level and background characteristics, both of which account for similar shares of the explained variation in skills (between 35% and 40% each).

To assess the broader relevance of our findings, we replicate the same analysis across the full set of 28 countries in the PIAAC sample. Field of study explains between 20% and 40% of the variation in numeracy and literacy skills across most countries. Denmark comes in at the lower end of this, but its neighbors such as Sweden, Norway and Finland all have very similar results in the decomposition. At the extremes, countries like Italy and Israel have the most variation in skills explained by field of study (above 40%) while two countries from the former Soviet Bloc –

Kazakhstan and the Russian Federation – have the least variation explained by field of study (less than 20%).

At a final stage of analysis, we consider the labor market returns to field of study. We thus build on a small literature using the PIAAC data to examine how skills translate into labor market outcomes across countries [Hanushek *et al.* 2015, Yao 2019, Graves and Kuehn 2021, Kawaguchi and Toriyabe 2022]. In an otherwise standard earnings regression, we document that field of study matters for labor market returns. Relative to the benchmark group – those with *Social sciences, business and law* backgrounds – all other fields have significantly lower earnings, even after controlling for education and skills. These differences range from 14% lower earnings for those with *Science, mathematics and computing* backgrounds, to 52% lower for those with *Humanities, Languages and Arts* backgrounds. Our findings align with previous work showing large differences in returns by field of study, with the ranges across fields being comparable to differences in moving from the lowest level of completed education to completing some forms of tertiary education [Kirkeboen *et al.* 2016]. A corollary of this last result is that we show the Mincerian estimates of the labor market returns to education can be under or overstated if field of study is not accounted for.

Our analysis contributes to a nascent literature that maps educational pathways to the development of skill sets. While much of the existing work on skills has focused on the *demand* for skills, relatively less attention has been paid to the *supply* side: how different educational pathways shape the skills individuals acquire.¹

A central challenge for such work is the non-random selection of individuals into educational pathways [Altonji *et al.* 2012]. Recent studies have attempted to address this by using curricular content to infer the skills imparted by different programmes. Eggenberger *et al.* [2018] and Girsberger *et al.* [2022] analyze vocational education and training (VET) curricula in Switzerland to map the occupational skill content of educational tracks, while Cnossen *et al.* [2021] link Dutch vocational programmes to O*NET skill categories. We contribute to this literature by leveraging standardized, cross-country skill assessments from the PIAAC data to directly measure the skill profiles associated with different educational pathways and fields of study, rather than inferring these skills from curricula or occupational classifications. Counter to much of the earlier literature, we are able to consider skills imparted and labor market returns to fields of study for both graduate and non-graduate educational pathways.²

¹A large literature in labor economics studies how the skill requirements of jobs have evolved over time, particularly in response to technological change. Seminal work by Autor *et al.* [2003] and Goos and Manning [2007] shows how the spread of computerization led to task-based polarization, increasing the demand for non-routine cognitive skills while displacing routine tasks. More recent research has leveraged job vacancy data to track changes in employer skill demands, documenting the growing importance of social and non-cognitive skills [Deming and Kahn 2018, Hansen *et al.* 2021]. While this literature focuses on the skills required by jobs, our contribution shifts attention to the skills acquired by individuals as they exit the education system.

²Biasi and Ma [2022] also analyze course syllabi, though with a different focus. They develop a text-based measure of the education-innovation gap, defined as the distance between the content of a university course and the

A separate strand of literature emphasizes the importance of field of study for labor market outcomes [Patnaik *et al.* 2021]. Kirkeboen *et al.* [2016] use a rich university admissions dataset from Norway and exploit discontinuities in admissions cutoffs to identify causal returns to field of study, finding that earnings gaps across fields can exceed those across education levels – a result we also document in our data. A related study by Hastings *et al.* [2013] leverages Chile’s score-based admissions rules to implement a regression discontinuity design, showing high returns to selective degrees. Britton *et al.* [2022] provide complementary evidence from the UK, demonstrating that degree subject is a major driver of graduate earnings inequality. While this literature has yielded robust estimates of field-specific returns, less is known about the mechanisms underlying these differences. Our contribution is to highlight one such channel: that fields of study differ systematically in the skills they produce at labor market entry, and these differences in skill by field of study thus help explain variation in earnings outcomes.

The paper is organized as follows. Section 2 describes the PIAAC data. Section 3 presents our main results. Section 4 concludes.

2 Data

2.1 The Survey of Adult Skills

We utilize the PIAAC Survey of Adult Skills administered by the Organization for Economic Cooperation. The PIAAC data provide representative samples of cross-sections of working-age adults (aged 16 to 65) from 37 middle- and high-income countries. The PIAAC data we utilize comes from the first wave of data collection that took place from 2011 to 2018. We restrict attention to countries which have the information required to address our core research question, such as the exact age at which individuals completed their formal education: our working sample then covers 28 countries (222,021 individuals).³

frontier of academic and technological knowledge. To capture frontier knowledge, they draw on the text of recent academic publications in high-impact journals and, for STEM fields, the content of patents.

³The first cycle of data collection occurred over three rounds: (i) 2011/12: Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, South Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States; (ii) 2014/5: Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey; (iii) 2017: Ecuador, Hungary, Kazakhstan, Mexico, Peru, United States. From these 37 countries, we exclude seven (Austria, Canada, Germany, Hungary, New Zealand, Singapore and USA) because in those surveys it is not possible to know the exact age of respondent, nor their exact age when they completed their education (both can be constructed only within a five year range). Two further countries are also excluded (Australia and Indonesia) because their PIAAC data is not publicly available.

2.2 Skill Measures

A key feature of the PIAAC data is that they provide multiple measures of individual skills. These are measured using standardized tests rather than being self-reported and are designed to be comparable across countries. We focus on two skills: (i) numeracy – defined as the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life; (ii) literacy – defined as understanding, evaluating, using and engaging with written texts to participate in society, to achieve one’s goals, and to develop one’s knowledge and potential.⁴

The numeracy and literacy test scores are scaled from 0 to 500 in each country (which we then normalize as described below). However, to get a sense of the extent of skills measured, we note that on the numeracy test, the lowest range (scores below 176) capture the ability to conduct simple processes such as counting, sorting, performing basic arithmetic operations, or understanding simple percentages. The modal range (scores from 226 to 275) capture the ability to identify and act on mathematical information embedded in common contexts. The highest range (scores from 376 to 500) covers the top 1% of the sample, capturing those who can understand complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex text. On the literacy test, the lowest range (scores below 176) capture the ability to understand meaning at the sentence level, identify plausibility of sentences, and the ability to access words in sentences to answer simple and explicit questions. In the modal range (scores from 226 to 275) individuals are assessed to also be able to access and understand information in longer texts with some distracting information, they can understand by paraphrasing, and can make inferences from what they read. The highest range (scores from 376 to 500) covers the top 1% and captures those who can in a short amount of time read long and complex texts to complete tasks involving understanding, evaluation, contrasting and reflection about the texts.

For each individual, the data provide 10 estimates (or what are referred to as ‘plausible values’) of skill levels for numeracy and literacy. Following best practice with PIAAC data, we standardize each of the 10 plausible values so that our reference group (labor market entrants) have a mean of zero and standard deviation of one in each skill.⁵

⁴PIAAC also measure skills related to problem solving in technology-rich environments – defined as the intersection of cognitive capacities required to solve problems and the use of information and communication technologies. We do not use this measure in our analysis because in a substantial share of the Danish sample (17%) problem solving skills could not be measured, predominantly among older individuals.

⁵This approach to standardizing the skill measures closely follows that of Hanushek *et al.* [2015], who use PIAAC data to estimate wage returns to skills across countries. To estimate any sample statistic (such as a mean or regression coefficient), we follow recommended best practice with PIAAC measures, using information from all 10 plausible values in conjunction with sampling and final weights. We implement this approach using the `repest` STATA package created by PIAAC.

2.3 Classifying Individuals

Our aim is to measure the association of fields of study on individual skills at different career stages, with a particular focus on labor market entrants. The data covers those still in education and those in the labor market. For those that have entered the labor market, we distinguish between two career stages: labor market entrants and more experienced workers. We define labor market entrants as individuals currently in the labor market (either employed or unemployed), not in any formal education and who have left formal education five years or less since the PIAAC survey was administered to them. We do so irrespective of whether they fully completed their last level of education. We define more experienced workers in exactly the same way except they left formal education more than five years before the PIAAC survey was administered to them.

Two issues need to be borne in mind with this classification. First, individuals who worked for a few years, returned to education and left education less than five years before the PIAAC survey are classified as labor market entrants, even if they have more than five years of potential experience. Our definition of experienced workers is strict because it considers labor market experience to only be acquired after leaving their highest stage of formal education (although they do not necessarily always complete that level of education). Second, individuals can be employed while being in education – we only classify them as experienced workers after they have spent at least five years in the labor market and not in education.

2.4 The Danish Sample

We focus our main analysis on Denmark, and later demonstrate our findings remain externally valid in other PIAAC country samples. The Danish PIAAC data covers 7287 individuals surveyed in 2011/2. Table A1 presents descriptive statistics on this sample. Columns 1 to 4 divide individuals into four groups by stage of working lives: those still in formal education, labor market entrants, more experienced workers, and those out of the labor force and not in education (e.g. retirees or those on parental leave). All individuals can be uniquely assigned into one of these groups. Panel A shows the groups are similar in terms of gender composition (although men are more likely to be experienced workers given rising female labor participation rates over time), whether they are born in Denmark, and their regional composition. Almost 60% of those in education are working, and unemployment is higher among labor market entrants than experienced workers.

Panel B shows the highest level of education completed, using the six-category ISCED classification. We group these into graduate and non-graduate education levels. Among those currently in education, 24% are enrolled in graduate-level programmes – a figure that likely understates eventual graduate attainment, as individuals can complete their education after the survey date. Among labour market entrants, 56% are graduates, compared to 45% of more experienced workers. This reflects rising levels of educational attainment over time, consistent with broader trends in tertiary education participation.

Panel C details fields of study. The PIAAC data distinguishes between nine fields, and these are known for 99% of individuals who have achieved any education at upper-secondary level or above. For those who only complete the first level of education recorded – compulsory lower secondary education or less – only 21% of individuals have a recorded field of study because of the lack of specialization at such an early stage of the education system. We thus assign all individuals who fall into the lowest level of education as not having any field of study. As a result, Panel C reports field of study only for those with at least post-compulsory schooling, and percentages are calculated within this group (so they all sum to 100%).

The modal field of study for labor market entrants is *Social sciences, business and law*, that 19% of them have graduated in, followed by *Health and welfare* (15%), *Engineering, manufacturing and construction* (14%) and *Teacher training and education science* (12%). Among experienced workers, the composition of field of study differs – with *Engineering, manufacturing and construction* being the modal pathway (23%) followed by *Social sciences, business and law* (16%) and *Teacher training and education science and services* (both at 12%).

Given that education level will also matter for the accumulation of skills (beyond field of study), the remaining Columns of Table A1 re-consider these descriptives splitting between graduates and non-graduates for those already in the labor market: labor market entrants and experienced workers. We see that graduates are more likely to be women, and have lower unemployment rates. Fields of study also differ between graduates and non-graduates: graduates are largely similar to labor market entrants except there is a far higher share of them that have studied *Teacher training and education science* (21% of graduates vs. 12% of labor market entrants), and far fewer of them have studied *General Programmes* (1% vs. 9%). Among non-graduates the most common fields of study are *Engineering, manufacturing and construction* (29%), *Services* (20%) and *General programmes* (13%). These differential patterns of entry into field of study over cohorts will be relevant for the later analysis examining labor market returns to fields of study.

3 Results

3.1 Skill Sets Across the Population

We start by examining how the skill sets of individuals vary across working lives: for those in education, labor market entrants, and experienced workers. We split each group by education level, distinguishing between graduates and non-graduates. As described earlier, both skills measures are standardized to have mean zero and standard deviation one among labor market entrants.

The results are in Table 1. Panel A focuses on those still in education. As expected, we see that those in graduate courses have significantly higher numeracy and literacy skills than those in non-graduate courses: their numeracy skills are $.584\sigma$ higher and their literacy skills are $.488\sigma$ higher. Once we condition on individual characteristics (gender, whether born in country, region, age and

age squared), the magnitudes of these differences remain first order and statistically different: the numeracy skills of those on graduate courses are $.422\sigma$ higher and their literacy skills are $.500\sigma$ higher. The next row focuses on the dispersion of skills – as measured by the standard deviation of each skill measure. Among those still in education, the dispersion in numeracy skills is not different between those on graduate and non-graduate courses ($p = .200$) and nor is the dispersion different for literacy ($p = .212$).

Panel B focuses on labor market entrants – those not currently in formal education and who left formal education within the last five years. The results mirror those of individuals still in education. First, graduates have significantly higher skill levels than non-graduates on both skill measures, conditional on observables ($p = .000$). Second, the dispersion of skills remains similar across groups: the standard deviations in numeracy and literacy do not differ between graduates and non-graduates ($p = .945$ and $.149$ for numeracy and literacy respectively). These patterns suggest that skill differences between graduates and non-graduates are stable across recent cohorts, implying that sorting into education levels has not substantially changed between those currently in education and recent labor market entrants.

Panel C focuses on experienced workers, and so helps assess the evolution of skills later in working lives – numeracy and literacy skills might depreciate or accumulate on-the-job. As in earlier stages, graduates continue to have higher skill levels than non-graduates, but the magnitude of the differences becomes larger than earlier career stages: conditional on observables, their numeracy skills are $.791\sigma$ higher and their literacy skills are $.785\sigma$ higher. In contrast to earlier career stages we also see that the dispersion in skills is different between graduates and non-graduates ($p = .000$ for both numeracy and literacy). The evidence suggests that with greater labor market experience, both the level and dispersion in numeracy and literacy skills increases in the working-age population, and this applies both to graduates and non-graduates. This pattern is consistent with on-the-job skill accumulation outweighing skill depreciation, but may also reflect cohort-based changes in the composition of graduates and non-graduates over time, as access to higher education has expanded and selection into educational pathways has evolved. Differences in career paths – such as the extent to which workers are matched to jobs that use their skills – may also contribute to the widening dispersion of skills later in working life.⁶

3.2 Skills and Fields of Study

We now turn to examine how fields of study help explain these differences in skills sets in the working-age population. To begin with, we examine raw differences in skills by education level and field of study. Panel A of Figure 1 shows a clear positive relationship between the six education levels and the average level of each skill. This reinforces the importance of conditioning

⁶Bandiera *et al.* [2024] use the PIAAC data on skills and job requirements from 28 countries to document that workers' skills better match their jobs' skill requirements in higher-income countries.

on education levels when considering the association between field of study and acquired skills. Panels B to D show how the average level of skills vary by field of study for those still in education, labor market entrants and experienced workers respectively, where the final row in each Panel also shows skills for those with no recorded field because they achieve an education level of compulsory lower secondary or less. Table A2 shows the same results (where by construction, the mean literacy and numeracy skills for labor market entrants are normalized to zero).

Among those still in education, there is wide variation in skills by field: numeracy skills are highest among those studying *Science, mathematics and computing* and *Agriculture and veterinary* courses; literacy skills are highest among those studying *Science, mathematics and computing*. Comparing Panels B and C we see a sharper gradient of skills differences emerges across some fields of study for recent labor market entrants compared to those still in education – hinting at the possibility that fields of study contribute to skills accumulation and do not just reflect differential sorting. Among labor market entrants: (i) the highest measured skill levels are among those studying fields of *Humanities, languages and arts*, *Science, mathematics and computing*, and *Social sciences, business and law*; (ii) the lowest skill levels are recorded among those with fields of study of *Services* and *Agriculture and veterinary* or with no field of study. We see that relative to the average labor market entrant, those with a *Humanities, languages and arts* field of study score $.319\sigma$ on numeracy skills and $.499\sigma$ on literacy skills; those with a *Agriculture and veterinary* field of study score $.280\sigma$ lower on numeracy skills and $.737\sigma$ lower on literacy skills.

Finally, Panel D shows that the variation in skills across field of study is larger among experienced workers than among recent labor market entrants and those still in education. This is reflected in a larger number of fields showing statistically significant skill differences relative to the baseline category. Among experienced workers the highest skills are measured among those with *Science, mathematics and computing backgrounds* (overtaking those with *Humanities, languages and arts* backgrounds).

Among labor market entrants and experienced workers, for each field of study the correlation across the numeracy and literacy skills measures is very high, mostly ranging between .8 and .9. These correlations are lower among individuals still in education, suggesting that numeracy and literacy skills tend to become more closely correlated as individuals complete their education.

Of course these raw differences could arise from various sources: different fields of study have different average levels of education which are strongly correlated with skill levels (as evidenced in Panel A of Figure 1), or the pre-existing skills of individuals entering each field of study may differ. To account for potential confounders and narrow in more closely on the association between fields of study and skills among the working-age population, we estimate the following regression specification, for each skill S_{ig}^k of individual i in career stage g :

$$S_{ig}^k = \beta_1 Field_i + \sum_g \beta_{2g} Group_{ig} + \sum_g \beta_{3g} [Field_i \times Group_{ig}] + \lambda \mathbf{X}_i + \epsilon_i, \quad (1)$$

where $k \in \{\text{literacy, numeracy}\}$, $Field_i$ is one of the nine fields of study recorded in the PIAAC data, $Group_{ig}$ refers to whether the individual is in career stage group g , namely still in education, a labor market entrant or experienced worker. The interaction terms between field of study and career stage enable us to test whether the association between field and skills varies across each group. The individual controls in $\mathbf{X}_i$ are the highest education level achieved (including those who complete compulsory lower secondary or less and so have no field of study), gender, whether the individual is born in Denmark, their region, age and age squared. The omitted categories are labor market entrants, and the omitted field of study is *Social sciences, business and law*. We use a seemingly unrelated regression to simultaneously estimate the literacy and numeracy equations, as it is likely the error terms across skills are correlated (as Figure 1 suggests). Table 2 shows the results where for expositional ease we only show the β_1 coefficients of interest, on field of study for labor market entrants (relative to those with a *Social sciences, business and law* field of study).

Columns 1a and 1b highlight the existence of significant unconditional differences in skill levels by field of study, for both numeracy and literacy. Columns 2a and 2b show that once we condition on levels of education and individual controls in $\mathbf{X}_i$, differences in measured skills remain by field of study. At the foot of each Column we report an F-statistic on the null joint hypothesis that all field of study coefficients are zero, separately for those in education, labor market entrants and experienced workers. In all cases, we reject the null hypothesis that these coefficients are all equal to zero. This indicates that field of study plays a significant role in determining both numeracy and literacy skills among labor market entrants and more experienced workers, even conditional on education level and other individual characteristics.

Examining specific comparisons to the omitted field of study for labor market entrants (*Social sciences, business and law*), individuals who studied *Engineering, manufacturing and construction*, *Agriculture and veterinary*, and *Teacher training and education science* have significantly lower literacy skills: the magnitudes of these skills differences are $.347\sigma$, $.705\sigma$ and $.324\sigma$ respectively, representing significant differences in labor market entrants by field of study. In short, among labor market entrants, the conditional skill gaps across fields of study are of a similar magnitude to those observed between graduates and non-graduates, highlighting the importance of field of study in explaining variation in skill levels.

Figure 2 goes further to perform Wald tests of equality in all pairwise comparisons of fields of study, for those in education, labor market entrants and experienced workers (unlike in Table 2, which compares each field to a single omitted category). These tests are based on the estimates from Columns 2a and 2b in Table 2 so conditional on levels of education and individual characteristics. In the first Column Panel in Figure 2, among those still in education, there are significant differences across fields. More specifically, for numeracy skills we find 8 out of 36 pairwise comparisons to be statistically significant, and for literacy skills 6 out of 36 pairwise comparisons are statistically significant.

In the middle Column Panel of Figure 2, among labor market entrants, there are also significant

differences in skills across fields of study. More specifically, for numeracy skills we find 3 out of 36 pairwise comparisons to be statistically significant, and for literacy skills 12 out of 36 pairwise comparisons are statistically significant. *Engineering, manufacturing and construction; Agriculture and veterinary, Teacher training and education science* show markedly different contributions to literacy skills compared to other fields.

Finally, for experienced workers, there are very few significant differences across fields – so that the role of field of study weakens over careers as individuals gain labor market experience. Consistent with the earlier descriptive patterns, skill levels tend to rise with labor market experience, implying that over time, field-specific differences at entry become less predictive of observed skill differences. This suggests that variation in skills is increasingly shaped by labor market experience.

To assess the relative importance of field of study in shaping skill variation, we perform a Shapley-Owen decomposition on the R -squared values from our main regression specifications (Columns 2a and 2b of Table 2), which are .278 for numeracy and .286 for literacy. This allows us to quantify the share of explained variation attributable to three components: field of study, education level, and background characteristics. We see that field of study accounts for 29% of the explained variation in numeracy skills, and 28% of the variation in literacy skills. Education level and background characteristics both explain similar shares of the overall variation in skills (between 35% and 40% each). These results highlight the sizable role that field of study plays in explaining differences in skill levels – nearly on par with the influence of education level itself.

Robustness As a robustness check we re-estimate equation (1) but only for labor market entrants, rather than pooling across all career groups g in a single regression and assuming constancy of some effects across groups. Table A3 shows the results where we see: (i) we still reject the null that field of study coefficients are all zero for both numeracy and literacy skills; (ii) we see relative to the omitted group of those with pathways through *Social sciences, business and law*, individuals who studied *Engineering, manufacturing and construction, Agriculture and veterinary*, and *Teacher training and education science* have significantly lower literacy skills; (iii) in the Shapley-Owen decomposition, the R -squared to be explained remains around .3, and field of study accounts for 17% of the explained variation in numeracy skills among labor market entrants, and 21% of the explained variation in literacy skills among labor market entrants. Figure A1 shows Wald tests of equality between all possible pairwise comparisons of fields of study for labor market entrants, finding a very similar pattern of results as our main specification. For numeracy skills 4 out of 36 pairwise comparisons are statistically significant, and for literacy skills 13 out of 36 pairwise comparisons are significant.

3.3 Skill and Fields of Study Across Countries

To establish the broader relevance and external validity of our findings, we repeat our main analysis for the other 27 countries in the PIAAC sample. We summarize results for each country using the same approach from estimating equation (1) and deriving the Shapley-Owen decomposition of the explained variation in numeracy and literacy skills among labor market entrants. The results are in Figure A2. Field of study accounts for between 20% and 40% of the explained variation in numeracy and literacy skills of labor market entrants across most countries. Denmark comes in at the lower end of this, but its neighbors such as Sweden, Norway and Finland all have very similar results. This pattern mirrors Hanushek *et al.* [2015], who find that Scandinavian countries exhibit relatively low wage returns to skills, which they link to institutional features such as collective bargaining and high public sector employment. This suggests that both skill acquisition and labor market payoffs may be attenuated by broader institutional settings in Scandinavia.

At the extremes, countries like Italy and Israel have the most variation in skills accounted for by field of study (above 40% for each skill), where family backgrounds play the smallest role in explaining variation in skills. Two countries from the former Soviet Bloc – Kazakhstan and the Russian Federation – have the least variation explained by field of study (less than 20% for each skills). In those countries, background characteristics are predominant, accounting for 60% or more of the variation in numeracy and literacy skills of labor market entrants.⁷

3.4 Returns to Fields of Study

Given that skills differ by field of study for those in the labor market, it is natural to ask what are the labor market returns to field of study. We do so by estimating a wage regression in the Danish PIAAC sample, to assess the relative contributions of education level, field of study and measured skills to earnings. This allows us to evaluate whether and how standard Mincerian estimates of the returns to education might be biased when field of study is omitted. We restrict the sample to men in the group of labor market entrants and experienced workers. We regress the log of their monthly earnings (for those reporting positive earnings at the time of the PIAAC survey) on four sets of controls: levels of education, fields of study, skills, and the individual characteristics in Table A1: whether they are born in Denmark, their region of residence, age and age squared. We also condition on years of labor market experience and its square. The results are in Table 3.⁸

In Column 1 we only control for education levels. Relative to the omitted category of those that

⁷The actual R -squared for each country typically lies between .2 and .4 for both skill measures.

⁸A growing literature also leverages PIAAC data to examine how skills translate into labor market outcomes across countries. Hanushek *et al.* [2015] show that a one standard deviation increase in numeracy skills is associated with an 18% increase in wages among prime-age workers, with substantial cross-country variation. Graves and Kuehn [2021] find that individuals who select into fields of study aligned with expanding sectors earn 2-3% higher hourly wages later in life, even conditional on measured skills. Kawaguchi and Toriyabe [2022] extend this work by constructing indices of both skills and skill use, showing that gaps in skill use (beyond skill levels) help explain persistent wage differences across gender and immigration status.

complete upper secondary, we see that earnings rise with education levels as expected. Column 2 additionally controls for fields of study, and clearly documents that field of study matters for labor market returns. Relative to the omitted field of study of *Social sciences, business and law*, all other fields have significantly lower returns: this ranges from returns being 13% lower for those with *Science, mathematics and computing* backgrounds to being 50% lower for those with *Humanities, languages and arts* backgrounds. Our findings align with previous work showing large differences in returns across fields of study, with the ranges across fields of study being comparable to differences in moving from the lowest level of completed education to completing some forms of tertiary education [Kirkeboen *et al.* 2016].

Once we condition on field of study, the Mincerian estimates of returns to education are for those with the omitted field of study: *Social sciences, business and law*. We see these returns are slightly adjusted when field of study is also accounted for: returns to education can be over or under stated if field of study is not controlled for. The extent of this bias in any given context will depend on the composition of fields of study among the working-age population.

Column 3 additionally controls for measured numeracy and literacy skills – these have no significant impact on earnings over and above that captured by education level and field of study, but reduce the returns to each level of education as expected, given the strong correlation between the two (Figure 1).

Fields of study can encompass a wide range of education levels, which raises the question of whether labor market returns to field of study differ by education level. Estimating fully interacted models between fields and specific education levels is not feasible, as the sample sizes within field-education cells become too small to deliver precise estimates. As a more tractable alternative, Table A4 allows returns to field of study to vary between graduates and non-graduates. We find no statistically significant interactions. That is, while the absolute returns to particular fields are large, the returns do not seem to differ systematically between graduates and non-graduates. This suggests that it is the field of study itself – rather than the level at which it is pursued – that is the key driver of differences in labor market returns.⁹

4 Conclusion

We study the skill sets of the working-age population, focusing on whether the skill set of recent labor market entrants correlates to their field of study in the education system. Using the Danish

⁹In Table A4, Column 1 just controls for graduate status and background characteristics. When we additionally control for field of study, Column 2 shows that all fields of study yield significantly lower returns than *Social Sciences, Business and Law* – the omitted category – with gaps of 15% to nearly 50% depending on the field. When field of study is controlled for, the returns to graduate education fall, underscoring the importance of accounting for field when interpreting graduate earnings premiums. Column 3 additionally controls for skills measures – returns to field of study remain highly significant, and the Mincerian returns to graduate status falls further. Column 4 tests for heterogeneous returns by graduate status in Column 4, finding no statistically significant interactions.

PIAAC sample, we document three facts. First, skills among labor market entrants strongly correlate to their field of study. Second, field of study accounts for just under 30% of the explained variation in both skills, conditional on education and background characteristics. Third, there are large earnings returns to fields of study over and above returns to levels of education. Not accounting for field of study can therefore bias Mincerian estimates of the labor market returns to education. Our analysis is distinct from and complements the far wider literature on the demand for skills in the labor market, and changing returns to skills prices. It pushes forward an open agenda on the role of the education system in the process of skills acquisition for individuals, and the drivers of the supply of skills in the economy.

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Table 1: Skill Sets Across the Population

Means, standard deviations in parentheses

p-values in brackets

	Numeracy	Literacy	Numeracy	Literacy	Numeracy	Literacy
	Graduate		Non Graduate		Graduate - Non Graduate	
A. Still in Education						
Mean	.255	.280	-.329	-.208	.584	.488
	(1.07)	(1.04)	(1.01)	(.983)		
Unconditional test of equality					[.000]	[.000]
Conditional mean differences					.422	.500
Conditional test of equality					[.000]	[.000]
Standard Deviation					.057	.061
Unconditional test of equality					[.200]	[.212]
B. Labor Market Entrants						
Mean	.266	.255	-.325	-.311	.591	.566
	(.957)	(.929)	(.954)	(.995)		
Unconditional test of equality					[.000]	[.000]
Conditional mean differences					.589	.585
Conditional test of equality					[.000]	[.000]
Standard Deviation					-.003	.066
Unconditional test of equality					[.945]	[.149]
C. Experienced Workers						
Mean	.312	.157	-.453	-.635	.765	.792
	(.932)	(.889)	(1.02)	(1.03)		
Unconditional test of equality					[.000]	[.000]
Conditional mean differences					.791	.785
Conditional test of equality					[.000]	[.000]
Standard Deviation					.088	.141
Unconditional test of equality					[.000]	[.000]

Notes: The sample is based on the Danish PIAAC survey. Panels A, B and C respectively refer to the sample of individuals that are in education, labor market entrants, and experienced workers. The mean unconditional tests of equality are t-tests testing the equality of two means. The standard deviation tests are F-tests testing the equality of two variances. For the mean conditional tests of equality, the two skills (numeracy and literacy) are regressed on control variables (gender, born in country, region, age and age squared) and an indicator for whether the individual is a graduate or non-graduate. The skills are regressed together using seemingly unrelated regression. All weights and all plausible values are used in the estimations.

Table 2: Skills and Fields of Study

Dependent Variable: Skills in numeracy, literacy

Seemingly unrelated regression, robust standard errors

	Numeracy (1a)	Literacy (1b)	Numeracy (2a)	Literacy (2b)
Labor Market Entrants				
Social sciences, business and law	omitted	omitted	omitted	omitted
Science, mathematics and computing	-.009 (.177)	-.079 (.16)	.017 (.167)	-.047 (.147)
General programs	-.482*** (.165)	-.39*** (.151)	-.023 (.162)	.008 (.152)
Humanities, languages and arts	-.013 (.154)	-.017 (.148)	-.062 (.136)	-.062 (.141)
Services	-.323** (.16)	-.307* (.16)	.056 (.143)	.064 (.153)
Engineering, manufacturing and construction	-.316** (.143)	-.561*** (.131)	-.147 (.131)	-.347*** (.126)
Health and welfare	-.363*** (.132)	-.268** (.120)	-.156 (.118)	-.106 (.109)
Agriculture and veterinary	-.612** (.292)	-1.07*** (.271)	-.297 (.291)	-.705*** (.263)
Teacher training and education science	-.449*** (.128)	-.390*** (.130)	-.369*** (.126)	-.324** (.138)
Level of education	No	No	Yes	Yes
Background controls	No	No	Yes	Yes
Group x area of study interactions	Yes	Yes	Yes	Yes
F-test field of study Still in education [p-value]	[.000]	[.000]	[.000]	[.000]
F-test field of study Labor Market Entrants [p-value]	[.000]	[.000]	[.000]	[.000]
F-test field of study Experienced Workers [p-value]	[.114]	[.046]	[.069]	[.012]
R-squared	.151	.153	.278	.286
R-squared Shapley-Owen decomposition				
<i>Field of study</i>	-	-	.081	.080
<i>Level of education</i>	-	-	.097	.103
<i>Background controls</i>	-	-	.109	.095
Correlation of residuals				
<i>Still in education</i>	.855		.834	
<i>Labor market entrants</i>	.853		.850	
<i>Experienced workers</i>	.864		.833	
Observations	6045		6045	

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The sample is based on the Danish PIAAC survey. Each pair of a-b regressions are simultaneously estimated using seemingly unrelated regressions. The controls in Specifications 2a and 2b are the highest education level completed, gender, whether born in country, region, age and age squared. The null hypothesis on the F-test is all coefficients of fields of study of those still in education, labor market entrants or experienced workers are equal to zero. The Shapley-Owen decomposition of the R-squared is conducted with three different sets of variables: fields of study, level of education and background controls (gender, age, age squared, foreign born and region). All weights and all plausible values are used in the estimations.

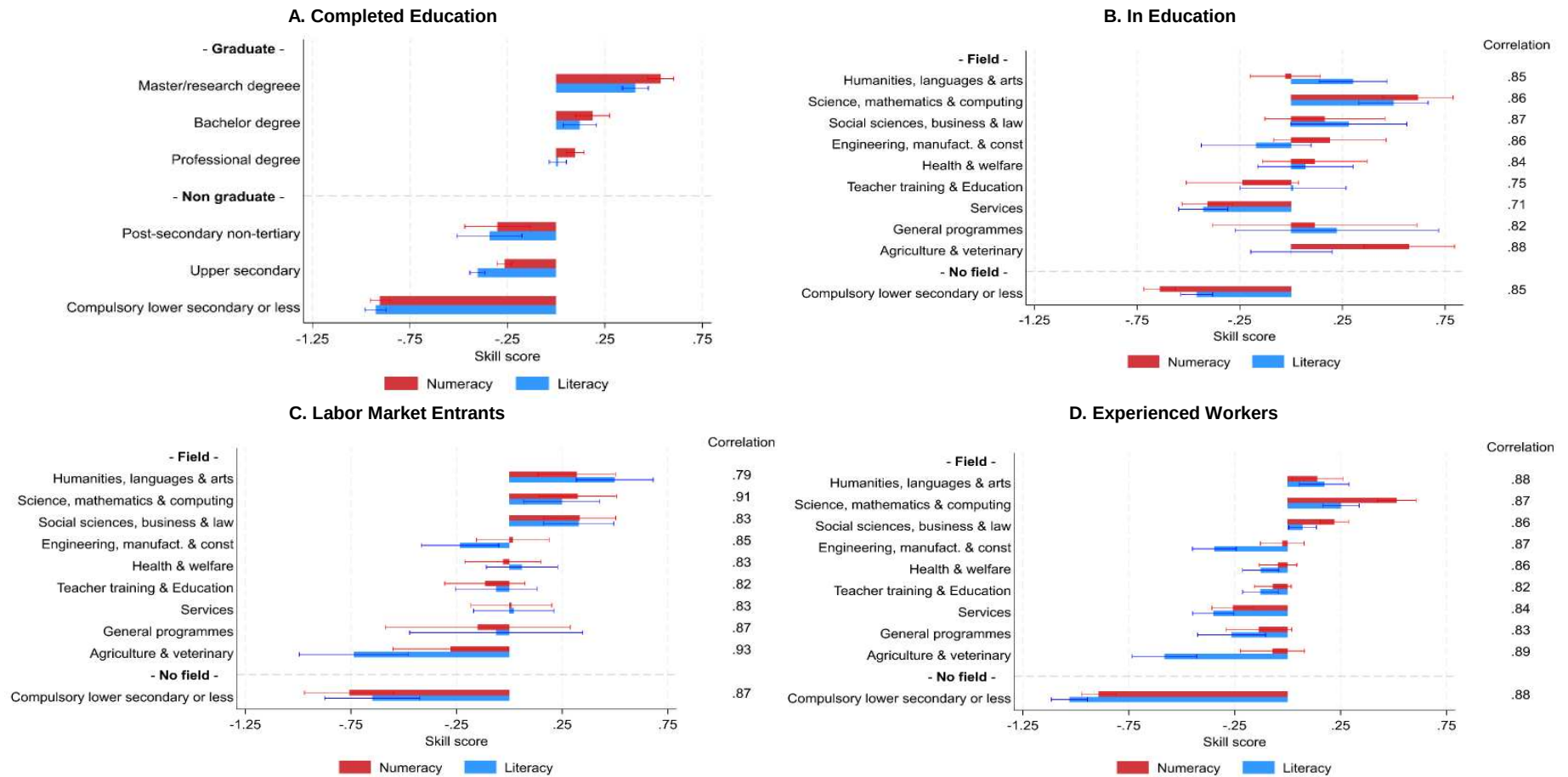
Table 3: Returns to Fields of Study

Dependent Variable: log monthly earnings
OLS regressions, robust standard errors

	(1)	(2)	(3)
Upper secondary (ISCED 3A-B, C long)	omitted	omitted	omitted
Post-secondary, non-tertiary (ISCED 4A-B-C)	.123*	.087	.079
	(.071)	(.066)	(.069)
Tertiary – professional degree (ISCED 5B)	.148***	.156***	.123**
	(.044)	(.058)	(.059)
Tertiary – bachelor degree (ISCED 5A)	.282***	.293***	.251***
	(.066)	(.059)	(.061)
Tertiary – master/research degree (ISCED 5A/6)	.456***	.435***	.383***
	(.046)	(.052)	(.055)
Social sciences, business and law		omitted	omitted
Science, mathematics and computing		-.127***	-.138***
		(.040)	(.042)
General programs		-.189**	-.192**
		(.080)	(.081)
Humanities, languages and arts		-.521***	-.515***
		(.116)	(.112)
Services		-.137**	-.133**
		(.063)	(.064)
Engineering, manufacturing and construction		-.172***	-.165***
		(.054)	(.054)
Health and welfare		-.275***	-.279***
		(.081)	(.080)
Agriculture and veterinary		-.235***	-.230***
		(.082)	(.084)
Teacher training and education science		-.365***	-.354***
		(.063)	(.061)
Numeracy skills			.058
			(.048)
Literacy skills			-.001
			(.048)
Background controls	Yes	Yes	Yes
Lowest level of education	No	No	No
R-squared	.096	.116	.121
Observations	1892	1892	1892

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The sample is based on the Danish PIAAC survey for male respondents only. The background controls include gender, whether born in country, region, age and age squared, experience and experience squared. All labor market entrants and experienced workers with positive earnings are included in the regressions. All weights and all plausible values are used in the estimations.

Figure 1: Skills by Completed Education and Fields of Study



Notes: The sample is based on the Danish PIAAC survey. Each bars shows the mean level of each skill - by highest level of completed education (Panel A), for those in education (Panel B), labor market entrants (Panel C), and experienced workers (Panel D). The lines overlaying the bars are the confidence intervals for each estimate of the mean skill. The right hand side of each panel shows the correlation between numeracy and literacy skills. All weights and all plausible values are used in the estimations.

Figure 2: Pairwise Tests of Equality of Skills Across Fields of Study

Wald tests, p-values reported

	Still in education								Labor Market Entrants								Experienced workers							
	Science, math & computing	General programs	Social sciences, business & law	Humanities, lang & arts	Services	Engineering, manufac & construc	Health and welfare	Agriculture & veterinary	Science, math & computing	General programs	Social sciences, business & law	Humanities, lang & arts	Services	Engineering, manufac & construc	Health and welfare	Agriculture & veterinary	Science, math & computing	General programs	Social sciences, business & law	Humanities, lang & arts	Services	Engineering, manufac & construc	Health and welfare	Agriculture & veterinary
A: Numeracy																								
Science, math & computing																								
General programs	.525								.874								.427							
Social sciences, business & law	.012	.106							.917	.887							.161	.819						
Humanities, lang & arts	.065	.225	.793						.730	.867	.648						.237	.703	.715					
Services	.033	.099	.274	.494					.872	.737	.692	.591					.064	.284	.152	.536				
Engineering, manufac & construct	.220	.568	.493	.531	.235				.480	.588	.264	.690	.345				.399	.994	.780	.673	.254			
Health and welfare	.172	.417	.812	.744	.366	.789			.440	.535	.187	.633	.300	.963			.317	.913	.917	.740	.279	.903		
Agriculture & veterinary	.638	.356	.050	.075	.039	.195	.149		.364	.426	.307	.481	.303	.649	.668		.923	.635	.494	.459	.225	.634	.572	
Teacher training & educ science	.049	.168	.577	.848	.604	.409	.622	.058	.091	.123	.003	.132	.042	.274	.260	.823	.520	.828	.521	.538	.167	.820	.713	.736
B: Literacy																								
Science, math & computing																								
General programs	.685								.810								.467							
Social sciences, business & law	.060	.182							.749	.960							.191	.873						
Humanities, lang & arts	.224	.419	.975						.541	.741	.551						.330	.816	.837					
Services	.023	.054	.097	.227					.625	.811	.673	.931					.099	.417	.249	.587				
Engineering, manufac & construct	.217	.412	.977	.969	.248				.145	.101	.006	.043	.057				.752	.637	.305	.485	.159			
Health and welfare	.122	.227	.554	.685	.420	.725			.762	.574	.331	.328	.412	.193			.320	.894	.979	.887	.429	.497		
Agriculture & veterinary	.663	.453	.099	.184	.030	.185	.107		.035	.020	.007	.009	.016	.230	.041		.799	.411	.279	.332	.155	.624	.336	
Teacher training & educ science	.277	.476	.878	.938	.217	.908	.637	.201	.202	.150	.019	.064	.090	.911	.260	.204	.715	.687	.383	.526	.191	.949	.547	.598

Notes: The sample is based on the Danish PIAAC survey. We report p-values from Wald tests for each pairwise equality of coefficients between fields of study. Panel A does for numeracy skills, Panel B does so for literacy skills. The three panels refer to those still in education, labor market entrants, and experienced workers. The underlying regressions are simultaneously estimated using seemingly unrelated regressions, with the following controls: the highest education level completed, gender, whether born in country, region, age and age squared. All weights and all plausible values are used in the estimations.

Table A1: Descriptives, PIAAC Denmark

Frequencies and percentages

	Labor Market Entrants and Experienced Workers					
	(1) In Education	(2) Labor Market Entrants	(3) Experienced Workers	(4) Out of Labor Force and not in Education	(5) Graduates	(6) Non Graduates
Number of observations	1267	877	3980	1163	2263	2594
A. Background						
Male	46.1	44.7	53.6	41.3	45.9	57.3
Born in country [yes]	75.2	73.3	82.7	76.5	79.8	82.0
Region: DK01 - Hovedstaden	30.2	32.2	27.4	22.6	36.7	20.8
Region: DK02 - Sjælland	12.9	11.3	14.5	15.3	12.2	15.5
Region: DK03 - Southern Denmark	24.5	24.1	22.1	27.3	18.3	26.1
Region: DK04 - Midtjylland	22.7	23.3	24.9	24.4	23.3	25.8
Region: DK05 - Nordjylland	9.79	9.24	11.0	10.4	9.46	11.8
Employed	59.7	88.9	95.6	-	96.3	92.8
Unemployed	5.29	11.1	4.37	-	3.71	7.21
Out of the labor force	35.0	-	-	100	-	-
B. Highest education level achieved						
Non graduates:						
Compulsory lower secondary or less (ISCED 1,2, 3C short or less)	43.5	9.81	16.9	33.5	-	29.2
Upper secondary (ISCED 3A-B, C long)	31.4	32.7	36.8	38.6	-	67.5
Post-secondary, non-tertiary (ISCED 4A-B-C)	.711	1.60	1.81	2.75	-	3.32
Graduates:						
Tertiary – professional degree (ISCED 5B)	8.21	21.6	23.2	16.7	49.2	-
Tertiary – bachelor degree (ISCED 5A)	10.5	11.4	6.69	3.35	16.2	-
Tertiary – master/research degree (ISCED 5A/6)	5.69	22.9	14.6	5.07	34.6	-
C. Field of study (only for post-compulsory education)						
Social sciences, business and law	19.0	18.8	15.5	9.46	20.7	10.6
Health and welfare	8.95	15.4	10.6	11.7	15.4	6.75
Engineering, manufacturing and construction	7.69	14.0	22.6	18.4	14.3	29.1
Teacher training and education science	8.11	12.3	12.2	16.5	20.6	1.96
Humanities, languages and arts	10.1	9.61	5.87	5.70	9.77	2.67
Science, mathematics and computing	18.2	9.48	8.44	5.31	11.6	5.01
General programs	21.5	9.23	8.68	12.6	1.37	17.9
Services	4.76	8.22	12.1	17.7	3.93	20.4
Agriculture and veterinary	1.68	2.91	3.99	2.72	2.39	5.50

Notes: The sample is based on the Danish PIAAC survey. In Column 1, the in education group are defined as individuals who are still in formal education at the time of the PIAAC survey. In Column 2, labor market entrants are defined as individuals in the labor market (employed or unemployed), not in any formal education and who left formal education (completed or not) five years or less before the PIAAC survey. In Column 3, experienced workers are defined as individuals who satisfy the same conditions as labor market entrants, but who left formal education more than five years before the PIAAC survey. As field of study is not known for most individuals with compulsory lower secondary education or less, Panel C shows percentages for those with an identified field of study (and so sum to 100% in each Column).

Table A2: Skills by Labor Market Experience and Field of Study

Means, p-values in brackets

	In Education		Labor Market Entrants		Experienced Workers		Entrants = Experienced		Entrants = In Education	
	Numeracy	Literacy	Numeracy	Literacy	Numeracy	Literacy	Numeracy	Literacy	Numeracy	Literacy
All fields of study	-.204	-.103	.000	.000	-.165	-.338	[.385]	[.076]	[.167]	[.474]
Social sciences, business and law	.165	.281	.333	.328	.221	.071	[.472]	[.091]	[.237]	[.734]
Science, mathematics and computing	.618	.499	.324	.249	.515	.252	[.294]	[.988]	[.059]	[.100]
General programs	.115	.223	-.150	-.062	-.136	-.265	[.935]	[.223]	[.063]	[.039]
Humanities, languages and arts	-.028	.302	.319	.499	.141	.173	[.235]	[.028]	[.007]	[.111]
Services	-.408	-.429	.010	.021	-.258	-.351	[.120]	[.029]	[.001]	[.000]
Engineering, manufacturing and construction	.189	-.170	.017	-.233	-.025	-.346	[.838]	[.585]	[.256]	[.687]
Health and welfare	.115	.069	-.030	.060	-.046	-.128	[.915]	[.179]	[.293]	[.942]
Agriculture and veterinary	.576	.002	-.280	-.737	-.072	-.582	[.333]	[.468]	[.000]	[.000]
Teacher training and education science	-.237	.010	-.116	-.062	-.070	-.129	[.765]	[.658]	[.291]	[.526]
Compulsory lower secondary or less	-.641	-.460	-.758	-.649	-.892	-1.030	[.566]	[.123]	[.538]	[.330]
F-stat	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]				

Notes: The sample is based on the Danish PIAAC survey. The values shown are mean skills in literacy and numeracy for individuals in education, labor market entrants and experienced workers, by field of study. Those whose highest level of completed education is compulsory lower secondary education or less have no assigned field of study. At the foot of the Columns, the values in brackets show p-values of an F-test on the equality of means across Columns. The p-values in the last four Columns are from a mean differences t-test between groups (in education, labor market entrants, experienced workers) for a given field of study. All weights and all plausible values are used in the estimations.

Table A3: Skill Sets and Field of Study, Robustness**Dependent Variable: Skills in numeracy, literacy****Seemingly unrelated regression, robust standard errors**

	Labor Market Entrants	
	Numeracy (1a)	Literacy (1b)
Social sciences, business and law	-	-
Science, mathematics and computing	.023 (.169)	-.029 (.149)
General programs	-.036 (.167)	-.006 (.164)
Humanities, languages and arts	-.026 (.142)	.126 (.148)
Services	.017 (.153)	.018 (.162)
Engineering, manufacturing and construction	-.207 (.140)	-.412*** (.132)
Health and welfare	-.142 (.119)	-.111 (.113)
Agriculture and veterinary	-.347 (.291)	-.775*** (.260)
Teacher training and education science	-.368*** (.126)	-.338*** (.137)
Level of education	Yes	Yes
Background controls	Yes	Yes
F-test field of study [p-value]	[.000]	[.001]
R-squared	.308	.296
R-squared Shapley-Owen decomposition		
<i>Field of study</i>	.053	.062
<i>Level of education</i>	.090	.070
<i>Background controls</i>	.165	.165
Residuals correlation Numeracy & Literacy	.809	
Observations	869	

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The sample is based on the Danish PIAAC survey. Each pair of a-b regressions are simultaneously estimated using seemingly unrelated regressions. The controls are the highest education level completed, gender, whether born in country, region, age and age squared. The null hypothesis on the F-test is all coefficients of fields of study are equal to zero. The Shapley-Owen decomposition of the R-squared is conducted with three different sets of variables: fields of study, level of education and background controls (gender, age, age squared, foreign born and region). All weights and all plausible values are used in the estimations.

Table A4: Heterogeneous Returns to Fields of Study**Dependent Variable: log monthly earnings****OLS regressions, robust standard errors**

	(1)	(2)	(3)	(4)
Graduate	.263*** (.028)	.258*** (.036)	.211*** (.040)	.273*** (.056)
Social sciences, business and law	omitted	omitted	omitted	omitted
Science, mathematics and computing		-.150*** (.038)	-.160*** (.040)	-.195** (.078)
General programs		-.236*** (.080)	-.236*** (.080)	-.195** (.096)
Humanities, languages and arts		-.489*** (.115)	-.486*** (.112)	-.597** (.251)
Services		-.192*** (.066)	-.183*** (.066)	-.140* (.080)
Engineering, manufacturing and construction		-.211*** (.052)	-.198*** (.052)	-.115** (.057)
Health and welfare		-.303*** (.085)	-.306*** (.084)	-.169*** (.057)
Agriculture and veterinary		-.270*** (.079)	-.259*** (.081)	-.266** (.107)
Teacher training and education science		-.470*** (.054)	-.450*** (.053)	-.217 (.175)
Numeracy skills			.061 (.049)	.063 (.049)
Literacy skills			.005 (.050)	0.009 (.050)
Field x Graduate Interactions				
Social sciences, business and law				omitted
Science, mathematics and computing				.052 (.099)
General programs				.158 (.361)
Humanities, languages and arts				.132 (.263)
Services				-.017 (.118)
Engineering, manufacturing and construction				-.172 (.112)
Health and welfare				-.168 (.112)
Agriculture and veterinary				.182 (.137)
Teacher training and education science				-.265 (.186)
Background controls	Yes	Yes	Yes	Yes
R-squared	.082	.106	.112	.117
Observations	1893	1892	1892	1892

Notes: ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The sample is based on the Danish PIAAC survey for male respondents only. The background controls include gender, whether born in country, region, age and age squared, experience and experience squared. Another control is an indicator for having graduate studies. All labor market entrants and experienced workers with positive earnings are included in the regressions. All weights and all plausible values are used in the estimations.

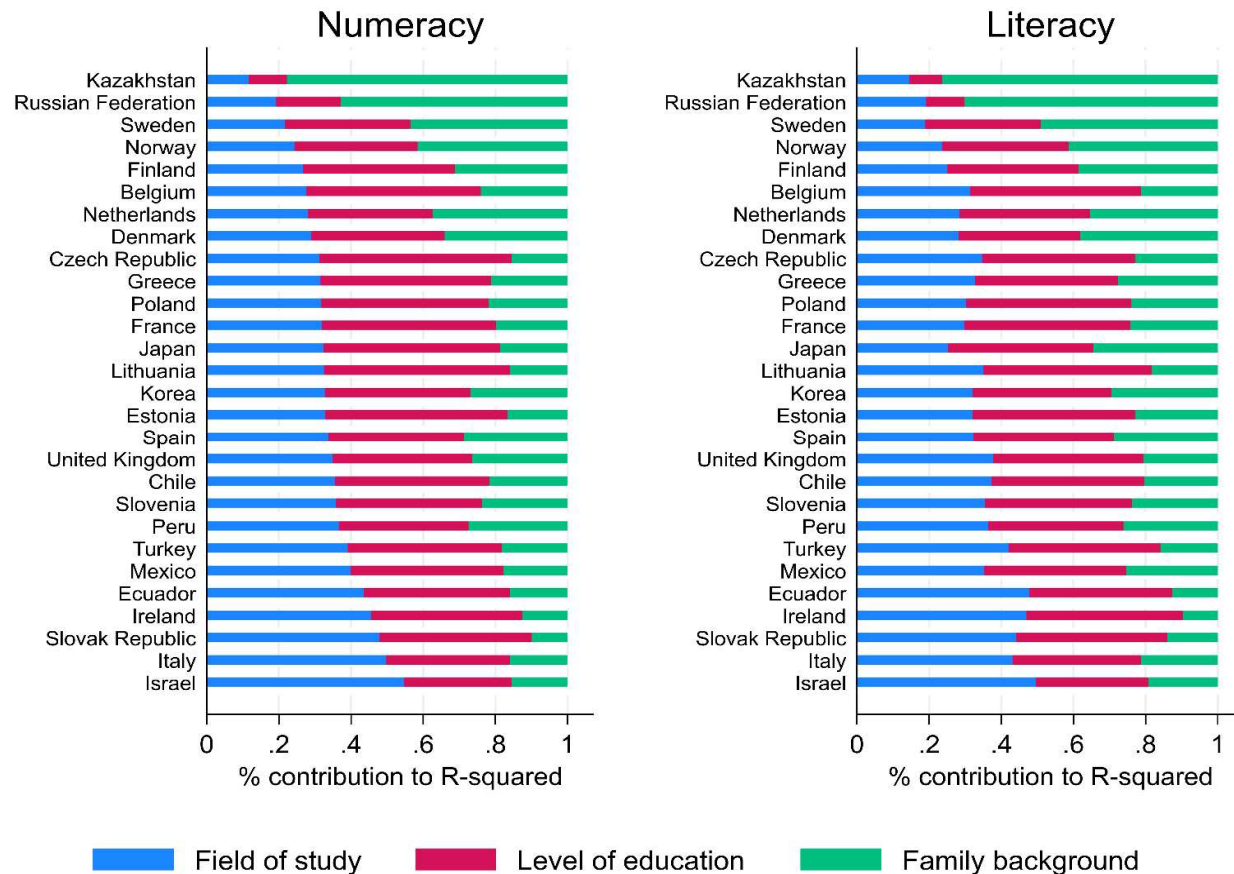
Figure A1: Pairwise Tests of Equality of Skills Across Fields of Study, Robustness

Wald tests p-values

Labor Market Entrants								
	Science, math & computing	General programs	Social sciences, business & law	Humanities, lang & arts	Services	Engineering, manufac & construction	Health and welfare	Agriculture & veterinary
Reg A: Numeracy								
Science, math & computing								
General programs	.825							
Social sciences, business & law	.893	.830						
Humanities, lang & arts	.838	.967	.855					
Services	.981	.835	.914	.854				
Engineering, manufac & construction	.339	.475	.138	.415	.336			
Health and welfare	.473	.631	.235	.563	.457	.744		
Agriculture & veterinary	.291	.373	.233	.341	.296	.679	.533	
Teacher training & educ science	.093	.147	.003	.095	.075	.438	.230	.947
Reg B: Literacy								
Science, math & computing								
General programs	.924							
Social sciences, business & law	.844	.970						
Humanities, lang & arts	.484	.586	.393					
Services	.846	.927	.914	.644				
Engineering, manufac & construction	.071	.076	.002	.015	.063			
Health and welfare	.688	.625	.328	.238	.557	.115		
Agriculture & veterinary	.017	.014	.003	.003	.014	.228	.024	
Teacher training & educ science	.160	.163	.014	.036	.130	.721	.244	.141

Notes: The sample is based on the Danish PIAAC survey. We report p-values from Wald tests for each pairwise equality of coefficients between fields of study. Panel A does for numeracy skills, Panel B does so for literacy skills. The panels refers to labor market entrants only. The underlying regressions are simultaneously estimated using seemingly unrelated regressions, with the following controls: the highest education level completed, gender, whether born in country, region, age and age squared. All weights and all plausible values are used in the estimations.

Figure A2: Skills and Fields of Study Across Countries
Shapley-Owen Decomposition



Notes: The sample is based on the relevant PIAAC survey from each of 27 countries. The left hand Panel shows the Shapley-Owen decomposition of the R-squared in numeracy skills explained by field of study, level of study and family background (gender, whether born in country, region, age and age squared). The right hand Panel does the same for literacy skills. These are based on simultaneously estimating each skills equation using seemingly unrelated regressions. Note that the Israel PIAAC sample has no data on region, and the UK PIAAC sample have five levels of completed education recorded. All other country samples are as in the Danish PIAAC sample. All weights and all plausible values are used in the estimations.