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# ABSTRACT

## The Relation between Skills and Job Security: Identifying the Contractual Return to Skills*

The last decades have shown that the traditional steady job with a permanent contract is on the decline. While permanent contracts and the insider position that they bring are highly valued by workers, research on the returns to human capital have predominantly focused on wages as subject of that return. This study uses PIAAC data from 29 countries to estimate how skills relate to the odds of obtaining a permanent contract, versus alternative contractual arrangements for employees. Our pooled analysis shows that skills substantially relate to having a permanent contract across the full sample. Numeracy skills contribute more than literacy skills; a difference that is largely driven by sorting to occupations and industries. We further identify substantial heterogeneities across countries, in which either no skills, only numeracy skills or only literacy skills significantly predict permanent employment at the country level, but never both. Moreover, this "contractual return to skills" differs substantially from the traditional wage return to skills across countries. We find suggestive evidence that these differences relate to demand factors and labour market institutions.

**JEL Classification:** I21, J24

**Keywords:** skills, human capital, labour markets, temporary employment

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# 1 Introduction

Recent years have shown that the share of workers on a permanent contract is steadily declining (OECD, 2019). In addition to increases in alternative work arrangements such as gig work, fixed-term employment has also increased compared to work on permanent contracts. For current European Union countries, the share of temporary employment steadily increased from 9% in 1985 to 16% in 2017, with particular strong increases in France, Italy, the Netherlands, Portugal and Spain (OECD, 2019). Additionally, there is evidence for some countries that the stepping stone function of temporary work towards permanent jobs has eroded over time (Barbieri et al., 2019). Thus, average job security appears to be declining. Research shows that such job security is highly valued by workers, and that they are willing to sacrifice a substantial share of their wage for more security, more so than for any other non-wage attribute (Datta, 2019). Traditionally, labour market research has focused on wages as determinant of the desirability of a job from the employee perspective, and as reflection of productivity from the employer perspective. A multitude of studies quantify the importance of human capital for labour market success by estimating returns to education and cognitive skills that are exclusively focused on wages as output measures (Psacharopoulos and Patrinos, 2004; Hanushek et al., 2015; Falck et al., 2021). The fact that workers also value other job attributes implies that better non-wage attributes may also reflect higher productivity, and subsequently that skills may be rewarded through alternative outcomes than only higher wages.

This study provides an analysis of the relation between cognitive skills and job security. In particular, we relate the odds of obtaining a permanent contract (versus other contract forms for employees) to literacy and numeracy skills, using data from the Programme for the International Assessment of Adult Competencies (PIAAC) for 29 OECD countries. We find that both numeracy and literacy skills contribute substantially to higher odds of being on a permanent contract. A one standard deviation increase in skill scores increases the odds of being on a permanent contract by 9% and 5% for numeracy and literacy, respectively, across the sample (17% and 8% respectively

when we do not condition on human capital measures). The difference in the contribution of the skills is largely driven by sorting to industries and occupations. Additionally, we find substantial heterogeneity across countries, wherein either numeracy or literacy skills contribute, but never both. At the country level, the relation between skills and the odds of permanent contract status are as strong as 33% for numeracy (United Kingdom) and 26% for literacy (Ireland). We find that country-level differences in absolute and relative returns to skills are largely driven by demand-side factors. Additionally, we find that country-level estimates for the return to skills on job security differ from country-level estimates for the return to skills on wages. This may indicate that higher job security can act as a substitute for higher wages. We find that the differences in these two types of skill returns are partially explained by wage rigidities and the size of social safety nets.

The rise in non-standard employment (NSE) or alternative work arrangements has been the subject of many recent studies. One branch of research focuses in particular on the rise of gig work, contract work and on-call work; e.g. Katz and Krueger (2019) find that such work arrangements have increased by around 50% between 2005 and 2015 in the United States. This increase has typically been related to technological change and the associated increased risks of unemployment for particular types of work (Katz and Krueger, 2017). Other research, closer to the current study, has focused on the split between temporary work and permanent work. Traditionally, positive efficiency aspects of temporary work arrangements have been highlighted; e.g. they allow for a faster adjustment to supply and demand shocks, and they allow employer and employee to increase their information set, and to engage in more permanent arrangements in case of a successful match (Faccini, 2014). More recent research however calls into question this screening function of temporary contracts in the current labour market, and highlights that transitions from temporary to permanent contracts are becoming more rare (Barbieri and Scherer, 2009; Barbieri et al., 2019; Biegert, 2019). This has been argued to create a two-tier labour market of insiders, on a permanent contract, and outsiders, who go from temporary work to temporary work. Such lock-out effects of temporary employment not only relate negatively to earnings (also conditional on personal characteristics and occupational dummies; see Katz and Krueger (2017)), but also to human capital investments,

job satisfaction, and educational outcomes of children (Fouarge et al., 2012; Chadi and Hetschko, 2016; Ruiz-Valenzuela, 2020).

The insider position of permanent contracts and its associated benefits highlight that other job attributes than wages matter for employees. Hypothetical choice experiments show this directly, by revealing that workers are willing to sacrifice part of their wage for secondary benefits such as flexible schedules and working from home (Mas and Pallais, 2017) and training or health insurance (Eriksson and Kristensen, 2014).[1] A recent study by Datta (2019) shows, using a similar choice experiment, that contract longevity is valued most across a range of job characteristics. In particular, the willingness to pay for a contract of one year or a permanent contract, compared to a baseline of a one month contract, equals 38% and 55% respectively in the United Kingdom, and 32% and 44% respectively in the United States. These results show that wages do not fully capture the utility that workers derive from a certain job, and that job security is valued especially among non-wage attributes.

This more "hedonic" approach to job utility has long been recognized in labour economic research, building on the early theoretical work of Rosen (1974, 1986). It has been particularly dominant in the search literature, which shows that non-wage attributes matter greatly when matching workers to jobs; see, e.g., Hall and Mueller (2018) and Taber and Vejlin (2020). Nonetheless, studies that estimate the returns to human capital or investments in human capital focus predominantly on wages. A large set of studies has established that schooling results in a substantial wage return, also causally (Card, 1999; Harmon et al., 2003). More recently, studies have focused on the returns to skills. Hanushek et al. (2015) show substantial returns to especially numeracy skills, while Falck et al. (2021) identify a strong return from ICT skills. While thus varying their measure of human capital on the right-hand side, all such studies still use wages as outcome measure on the left-hand side. A recent exception by Stijepic (2020) looks at the skill returns to employment. The current study is, to the best of our knowledge, the first to consider the returns to skills in terms of contract

[1] Commuting time is another non-wage attribute that has been studied extensively, also in the context of willingness to pay; see, e.g., Le Barbanchon et al. (2021) and Meekes and Hassink (2022). This is somewhat separately from the current context, as it is part of the individual's circumstances and not of the contract offer itself.

status.

Our study also adds to the literature on the determinants of different forms of non-standard employment. A large share of studies focuses on macro-level determinants, such as technological change and institutions (Parker and Robson, 2004; Hipp et al., 2015; Been and Van Vliet, 2017; Katz and Krueger, 2019; Van Doorn and Van Vliet, 2022). Research on the micro-level has revealed that several background characteristics (gender, age, educational level) are predictive for non-standard employment (Emmenegger et al., 2012; Schwander and Häusermann, 2013; Biegert, 2014). As such, this literature has mainly focused on identifying risk factors that indirectly relate to NSE, but still lacks evidence on factors that directly relate to worker productivity, such as skills. Moreover, we elaborately exploit the nature of this relationship, and the potential channels through which it operates. While it is not our goal to identify a causal link between skills and job security as exogenous variation in skills is extremely rare, we extensively assess the sensitivity of the results to omitted variable bias. We further analyze the potential role of measurement error and reverse causality.

The premise of this study is that workers strongly value job security, which implies that higher skills may not only be rewarded in the labour market by higher wages but also by higher odds of permanent employment. The implications for such a potential "contractual" return to skills are twofold. For one, any positive return would imply that the broad returns to skills in terms of overall job utility are underestimated, and those of effective investments into skills as well, when only looking at wages. Secondly, the return to skills may be different when looking at wages than when looking at job security. As such, skills that may have been deemed relatively unimportant by earlier findings on wage returns, as made by e.g. Hanushek et al. (2015), may still be important for job utility through their effect on job security, and thus worth investing in.

To elaborate on the second implication, the relation between wage returns to skills and contractual returns to skills is not trivial. On the one hand, one may expect that high productivity individuals are both rewarded with high wages and high job security, and that differences in wage returns

across types of skills, across time or across countries will align with differences in the contractual return along these same dimensions (e.g. contractual returns to skill are high in countries with high wage returns to skills). On the other hand, there are several potential reasons why contractual returns will not provide a mirror image of wage returns. For one, wages can be rigid, especially in countries with strong collective bargaining agreements. In such a setting, a permanent (temporary) contract may be a substitute for a higher (lower) wage when the latter is more difficult to adjust. Second, whether skills are rewarded through higher wages, higher job security or both depends on workers' preferences for these attributes, which depend on the institutional setting. In particular, workers may value job security more when income losses through job loss are higher (i.e. social safety nets are weaker). This would imply that high productivity workers would prefer to be rewarded by higher job security, leading to a higher contractual return to skills. Finally, while it has been established that there is a wage return to skill, it is not trivial that skills directly contribute to permanent contract status. Given that temporary employment is especially concentrated within certain sectors and among young workers, the contribution of skills to contract status may not be apparent anymore once we condition on factors such as age, education, industry and occupation. The analyses in this study aim to shed light on these potential drivers of (differences in) contractual returns to skill. We do so by both a pooled (micro) analysis that explores the mediators of the relation between skills and job security, and by a macro-analysis that explores determinants of potential differences in contractual skill returns across countries, and of potential differences with the wage return to skills.

This study proceeds as follows. Section 2 describes the data and presents descriptive statistics. The methodological approach is discussed in Section 3, while Section 4 presents results. Section 5 provides robustness analysis. Section 6 concludes.

# 2 Data and descriptive statistics

## 2.1 PIAAC

We use data from the adult skills survey PIAAC (OECD, 2016). PIAAC comprises a survey of adult skills across 37 countries across the world. It administers tests across several domains and collects detailed questionnaire data on skill use, job characteristics and individual characteristics. For most countries, data collection took place in 2011-2012, while other countries were administered in 2014-15 or in 2017. The 37 countries that participate in PIAAC comprise 31 OECD members and 6 non-members. In order to increase comparability in institutional setting and economic development, we drop the 6 non-members from our analysis (Ecuador, Indonesia, Kazakhstan, Peru, Russian Federation, Singapore). Because of data limitations, we further exclude Australia and Canada from the sample.[2] This leaves a sample of 29 countries: Austria, Belgium (Flanders), Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Israel, Japan, Korea, Lithuania, Mexico, Netherlands, Norway, Poland, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom (England and Northern Ireland), and United States.

The outcome variable in this study is a dichotomous indicator of having a permanent contract. The alternative (employer-employee) contract arrangements, which form the counterfactual, combine fixed-term positions (56%), temporary employment agency contracts (7%), apprenticeships (3%), employment without a contract (28%) and other arrangements (7%).[3] We group these alternative arrangements together in the main approach, as they all provide less job security compared to a permanent contract. Additional analysis also provides results for each condition separately.

The two main independent variables are numeracy skills and literacy skills. We use Item Response Theory (IRT) to construct latent skill scores from the individual items for each subject. While it is common to directly use the plausible values (PV) that PIAAC reports, we refrain from doing so.

[2] Australia offers limited data availability on relevant variables, while Canada does not register contract status.

[3] The "other" contract form only exceeds 5% in Greece (8%) and New Zealand (11%). Average salaries are above any of the other temporary work forms, but still substantially below permanent work.

The main reason is that, in order to reduce measurement error, PV's also incorporate other variables that are administered in PIAAC. This is done by combining the IRT scaling of the cognitive items with a latent regression model that uses the full background questionnaire. This means that indicators such as educational degree, job characteristics (including the contract type) and reading practices also enter the determination of these skill scores. This would create two main problems in the context of our study. For one, it creates an artificially high correlation between the numeracy and literacy scores as they partly rely on the same inputs. This is problematic as these two variables jointly enter our model as main explanatory variables. Secondly, it muddles an assessment of the sensitivity of the regression coefficients to additional controls, as these controls are also incorporated in the construction of the plausible values. We therefore believe that while PIAAC's approach to constructing plausible values is sensible in the context of constructing average scores with minimal measurement error, they are not the best approach for regression analysis especially when more than one skill score enters the model. The correlation between our IRT skill measures of numeracy and literacy equals 0.53.[4].

Additionally, we include a set of control variables and potential mediators in specifications of our empirical model. Background controls include age, gender, migration status (separating natives, first generation immigrants and second migration immigrants), years of labour market experience, and education level (measured in years of schooling). As measures of industry and occupation, we rely on ISIC (rev 4) and ISCO (2008) classifications respectively (either one-digit or two-digit level, depending on the specification).

We exclude several subgroups from the sample. We focus on the working age population, and therefore exclude those below 18 and above 60, as well as those still in full-time education. We further exclude the self-employed. While studies focusing on alternative work arrangements often focus on self-employment and the distinction between full-time and part-time work, we specifically focus on contractual relations between employer and employee.[5] In our setting, we consider

[4]Country-specific correlations can be found in Appendix Table A2, which shows that these differ little

[5]We note that part-time workers are included in our sample, and can be classified as either permanent or temporary workers depending on their stated contract form.

a permanent contract as the highest form of job security and thus providing higher job utility, ceteris paribus, than less secure contract forms. Self-employment and part-time work, on the other hand, can often be preferred choices over full-time employer-employee relations. Naturally, non-employed are also excluded from the estimation. Standardization of test scores is done after these exclusions. The lower age limit of 18 is relatively low compared to other labour market studies. A substantial share of the young are still excluded because we drop those still in education. Among the working young, temporary employment is highly prevalent and dropping such a large share of our group of interest would limit the external validity of our results. We provide supplementary analyses with different age ranges.

## 2.2 Descriptive statistics

Figure 1 shows the share of temporary employment across all countries in our sample. There is substantial variation in these shares across OECD countries. The (largely non-European) countries on the far right side have especially substantial shares of work under "no contract" arrangements (see Appendix Figure A1 for a full split of contract types by country). In the United States, permanent contracts equate to less than 50% of all contractual arrangements, while they form a majority in all other countries. The high number for the United States is a consequence of their widespread "employment-at-will" approach to labour law, in which employment can be terminated unilaterally by any party. The statistics indicate that this is classified under "no contract" employment in the dataset. Other countries with high shares of "no contract" workers may operate similarly or otherwise offer working arrangements that do not require a formal written contract.[6]

Figure 2 shows raw descriptive results on the relation between skill decile and temporary employment, separately for numeracy and literacy (corrected for country fixed effects). The figure provides probabilities of temporary employment relative to the lowest decile, pooled across countries. Three main conclusions can be drawn from Figure 2: 1) there is a clear negative relation

[6]PIAAC statistics show that "no contract" workers are far more often paid by hour, day or week and far less often by month, which suggests that there is a strong overlap with on-call work. No contract workers are strongly overrepresented in construction, sales, food services and cleaning.

between skills and temporary contract status, wherein the probability decreases by around 9 (13) percentage points when moving from the lowest to the highest literacy (numeracy) decile. This implies a relative drop of 30% for literacy skills and 40% for numeracy skills when moving from the bottom to the top of the skill distribution; 2) the relation is somewhat stronger at the extremes of the distribution compared to the middle; and 3) the relation is slightly stronger for numeracy skills compared to literacy skills. This is mainly driven by a disproportionally high probability to be in temporary work for the very lowest numeracy decile, as the respective lines are rather parallel from the second decile onward. Naturally, these are only correlations and we need regression analysis to determine how these relations are when we enter both skills simultaneously, and when we control for other covariates.

Appendix Table3 A1-A3 provides summary statistics for all key variables in our estimation sample, for the pooled sample and by country. These are weighted by PIAAC's sampling weights. Numeracy and literacy levels have mean 0 and standard deviation of 1 by construction. The data collection of PIAAC and the application of sampling weights should ensure that PIAAC respondents are representative for the average working-age employee in the selected set of countries.

# 3 Methodology

We specify a logit model in which we predict the probability of a permanent contract with the level of numeracy and literacy skills:

$$P(PC_{ic} = 1) = \Lambda(\alpha_0 + \alpha_1 Num_{ic} + \alpha_2 Lit_{ic} + X_{ic}\alpha_3 + \tau_c + \varepsilon_{ic}), \tag{1}$$

In equation (1), $\Lambda$ is the cumulative distribution function of the logistic distribution. $PC_{ic}$ is a dummy variable that takes value 1 if an individual $i$ in country $c$ is on a permanent contract, and 0 otherwise. We define the outcome variable towards having a permanent contract, rather than a temporary contract, so that positive coefficients can be interpreted as positive returns. $Num_{ic}$ and

$Lit_{ic}$ are standardized test scores for numeracy and literacy respectively. $\alpha_1$ and $\alpha_2$ are our main coefficients of interest, representing the return to skills in terms of higher odds of a permanent contract. We label this as the "contractual return to skill" (as opposed to the "wage return to skill").

$X_{ic}$ is a vector of individual characteristics containing age, age squared, gender, migration status, experience, experience squared and years of education. Finally, we include country fixed effects $\tau_c$. Extensions of this main model further include fixed effects for industry and occupation, based on ISIC and ISCO classifications, respectively. $\varepsilon_{ic}$ represents a classical error term. Standard errors are robust. The main specification is a logit model; we analyse results for alternative specifications (OLS and probit) in the appendix. All estimations apply PIAAC's sampling weights.

We note that some of the controls in vector $X_{ic}$ may be endogenous to skill formation. In particular, the human capital measures (years of education and experience) are likely to be enhanced by higher skill levels. We therefore compare models with and without this set of controls. A comparison of these models is indicative of the extent to which the relation between contract status and skills is mediated by the fact that skills may increase the building up of experience and education years. This also applies to industry and occupation, which is why an extension of the model further includes fixed effects for those indicators, assessing the importance of sorting for the relation between skills and contract status. The different sets of control variables shed light on what drives the raw association between skills and contract status. Nonetheless, we emphasize that also models with extensive control variables should not be interpreted as causal. Unobservable variables may relate to both skills and contract status. Moreover, reverse causality may arise when permanent contract status allows for more investments in skills. While finding exogenous variation in skills is extremely challenging, we specifically assess sensitivity of our results to endogeneity bias in Section 5.2.

In addition to the pooled approach of Model (1), we also estimate the relation between permanent contract status and skills per country. Previous research has revealed that wage returns to skills

show substantial variation across countries (Hanushek et al., 2015). We analyze whether contractual returns to skills show similar heterogeneity and, if so, if this is in line with the heterogeneity in the wage returns. The methodological approach and results of this supplementary macro-level analysis are both discussed in Section 4.3.

# 4 Results

The analysis has the following aims: 1) establish the relation between skills and permanent contract status, and how it is mediated by other variables (section 4.1); 2) explore country heterogeneities in the contractual return to skill and how these relate to the wage return to skill (section 4.2); 3) explore potential explanations for heterogeneities across countries and by type of return (section 4.3).

## 4.1 Main results

Table 1 portrays the main results for the relation between skills and having an permanent contract. We add different sets of controls in different steps to assess how these covariates potentially mediate this relationship. Columns (1) and (2) enter each skill separately. The coefficient for numeracy is slightly larger than for literacy. It implies that a one standard deviation increase is associated with a 27% increase in the odds of having a permanent contract (18% for literacy). When both skills enter jointly (column (3)), we obtain positive and statistically significant coefficients for both skill scores, with the numeracy coefficient being three times larger than the literacy coefficient. Hence, a substantial part of the raw coefficient for literacy in column (2) operates through its association with numeracy skills. The literacy coefficient increases and the numeracy coefficient decreases somewhat when we control for demographic characteristics in column (4). Mainly, the fact that literacy scores and temporary employment both decline with age slightly obscured the relation in previous columns. The coefficient for numeracy scores mainly drops because women tend to have lower numeracy scores and lower incidences of permanent employment.

We continue by adding the (potentially endogenous) controls for experience and years of education in column (5). They rather substantially decrease coefficients for both skill measures, but more so for numeracy skills. This suggests that the stronger coefficients in column (4) are partly due to literacy and (especially) numeracy skills contributing to education levels and labour market experience. Nonetheless, a substantial share of this relation remains when we condition on these human capital controls.

We further control for industry and occupation fixed effects in column (6). The change in coefficients indicates to what extent the earlier estimates are driven by sorting to occupation. We observe that the coefficient reduces for especially numeracy skills, and only slightly for literacy skills. Where the relation for numeracy skills dominates that of literacy skills in columns (1) through (5), coefficients are of roughly similar size in column (6). In other words, numeracy skills partly contribute to permanent contract status because they help getting into industries and occupations in which such contracts are more common.[7] This indirect channel largely explains the dominance of numeracy over literacy in specifications that do not condition on these fixed effects. Still, both skills are positive predictors of permanent contract status also in column (6). Hence, also within industries and occupations, having higher skills contributes to higher chances of obtaining a permanent contract (also net of experience and education effects). We have additionally estimated specifications that more extensively control for the sorting mechanism (not shown here), by more precisely defining industries and occupations (2 digit-level rather than 1 digit-level), and adding firm controls for employment size, growth in employment and whether the firm is part of a bigger organization. This more extensive model does little to change the estimates compared to column (6). There is a slight reduction in the literacy coefficient (0.035 to 0.028) which is mainly due to the firm controls, while the 2-digit ISCO/ISIC fixed effects change little. Hence, a small part of the relation between literacy skills and permanent employment is due to those with higher literacy

[7] Industries with particularly high (low) shares of permanent contracts are financial and insurance services; and ICT (agriculture; and accommodation and food services). Occupations with particularly high (low) shares of permanent contracts are legislators, senior officials and managers; and technicians and associate professionals (skilled agricultural and fishery workers; and elementary occupations.

skill sorting into firms with higher (conditional) prevalence of permanent employment.

Thus, numeracy and literacy skills are statistically significant predictors of contract status, also when conditioned on other factors. But what about the size of the effects? If we look at the most complete specification that does not condition on sorting (column (5)), we obtain coefficients in the logit model of 0.083 and 0.049 for numeracy and literacy skills, respectively. This implies that, for a one standard deviation increase in skills, the odds for obtaining a permanent contract increase by 9% for numeracy and 5% for literacy skills. When we do not condition on education and experience and thus also allow for mechanisms that operate through human capital levels (column (4)), these figures are equal to 17% and 8% respectively.[8]

Table 1 reports average effects, across countries and population groups. The main focus of our study is on country heterogeneity but we briefly review heterogeneity by individual characteristics as well. Most prominently, Appendix Table A2 reports results from the models from columns (4), (5) and (6) separately for younger and older workers. We split the sample at age 35, because that leads to an equal distribution of temporary workers in each sample. Skills are in general more predictive of permanent job status for older workers. Literacy scores are only weak predictors of permanent job status for young workers. These results may relate to the screening hypothesis, indicating that some labour market experience needs to be built up before employers can deduce worker productivity and reward more higher-skilled workers accordingly.[9] This is supported by the fact that the difference is driven by the very young; coefficients are virtually equal when comparing those aged 25-40 with those aged 40-55. A problem with interpreting table A2 is that we cannot distinguish age from cohort effects, as PIAAC relies on a cross-section. Hence, it is unclear whether the low coefficient for literacy for young workers means that the (contractual) return on these skills occurs at a later time in life, or that the valuation of these skills has changed over time. As younger ages are a relatively 'sensitive period' for obtaining a permanent contract this could

[8]Results for an OLS and a probit model can be found in Appendix Tables A13 and A14. The pattern of results is highly similar.

[9]Wage returns to skills (not shown) are also lower for younger versus older workers, although the difference is comparatively smaller than for the contractual return.

indicate that numeracy skills are valued more in today's labour market, compared to when older workers were in this sensitive period.

Appendix Table A3 shows heterogeneities across background variables other than age. There appears little heterogeneity by migration status or education level. We do find substantially lower returns for women, for both skills. This contrasts with the findings from Hanushek et al. (2015) and Stijepic (2020) who find little heterogeneity by gender for wage and employment returns to skills.[10] A substantial part of this heterogeneity is explained by a lower contractual return to skill for part-time workers (see final column of Table A3), which are more often women.

## 4.2 Returns to skills by country

Results presented before rely on a pooled analysis on the full sample. Hanushek et al. (2015) have shown that there is substantial heterogeneity in the wage return to skill across countries. We analyze whether similar heterogeneity applies to the contractual return to skill. Figure 3 plots the country-specific estimates of our preferred specification, which includes demographic controls and human capital controls, but does not correct for sorting (column (5) in Table 1).[11] We observe substantial heterogeneity across OECD countries. The stronger estimates for numeracy in the overall sample occur both because there are more countries in which numeracy dominates than countries in which literacy dominates, and because the coefficients among the former group are stronger than among the latter group. Remarkably, there is no single country in which both skills are statistically (or economically) significant predictors of permanent employment status. Within a country, either only literacy scores are statistically significantly predictive (Ireland, Sweden, Turkey, United States, Japan and Poland), only numeracy scores are predictive (United Kingdom, Iceland, Hungary, Spain, Belgium, Slovakia, Estonia, Denmark), or neither is (Austria, Chile, Czech Republic, Germany, Greece, Finland, France, Italy, Korea, Lithuania, Mexico, Netherlands, New Zealand,

[10] Falck et al. (2021), on the other hand, identify stronger returns to ICT skills for men but this skill is not considered here.

[11] The appendix provides results with ISIC/ISCO fixed effects. It also shows estimates for when we use the comparative advantage in math as main explanatory variable, showing more directly which skill matters more.

Norway, Slovenia).[12] While country samples are not very large and estimates therefore can be imprecise, there is no single country for which the second largest estimate is even close to typical statistical significance thresholds.

A substantial set of countries shows statistically insignificant coefficients for both skill measures. It should not be concluded that skills do not matter for job security for these countries. When we employ an overall skill measure (combing all numeracy and literacy items in one score), we obtain statistically significant estimates for some of these countries (Finland, France, Norway) while others are not far removed from typical statistical significance thresholds (Germany, Greece, Korea, the Netherlands). At the same time, there are countries such as Belgium and Denmark for which this overall measure is low and statistically insignificant while numeracy skills alone are significant predictors of a permanent contract in both countries. For Austria, Chile, Czech Republic, Italy, Lithuania, Mexico, New Zealand, and Slovenia, estimates are statistically insignificant for the overall measure and each separate skill measure. Hence, there is little evidence that skills contribute to permanent contract status in these countries (other than via educational attainment).

As argued before, contractual returns to skills are likely to be associated with wage returns to skills but there are reasons to expect that they may differ as well across countries. Figure 4 shows country-specific estimates for the wage returns to skills, on the same sample as for Figure 3. Despite a substantial heterogeneity, there are multiple countries for which the wage return is substantially positive for both skills. Hence, returns to skills for wages allow for both skills to be predictive while returns to skills for job security allow for only one predictive skill at most. Additionally, the country coefficients for job security show only a small correlation with those for wages: 0.34 for numeracy and 0.11 for literacy. The overall skill measure relates comparatively stronger, with a correlation of 0.43 (see also Appendix Tables A4 to A6). Hence, while positively correlated, the mapping of wage returns to skills and contractual returns to skills is not one to one, and differs even more when we consider which type of skill matters.

[12] Literacy coefficients are statistically significantly *negative* for Spain at the 10% level (p=0.097).

We have established before that there is some heterogeneity in contractual returns to skills, splitting those under 35 from those above 35. Interestingly, the correlations between wage and contractual returns are also sensitive to the age group. Among those under 35, the correlation is substantial (0.57) while it is essentially non-existent among those over 35 (-0.10); results are presented in Appendix Table A4. Hence, it appears that, early in the labour market career, countries that strongly reward skills with higher wages are also those that strongly reward skills with higher job security, but this becomes disconnected as workers mature in the labour market.

## 4.3 Explaining differences by country and type of return

Figures 3 and 4 show heterogeneities that raise three different questions: 1) why are there such strong disparities in the relative importance of numeracy over literacy skills across countries; 2) why are there returns to (any) skill in some countries, but virtually no returns in others; and 3) why do contractual returns to skills across countries differ from wage returns to skills across countries.

### 4.3.1 Analytical approach

We conduct a macro-level analysis that aims to shed light on these questions, by regressing the obtained country-specific coefficients on sets of macro-level variables. Question 1 is on the relative importance of numeracy versus literacy. We therefore use the 'comparative advantage' estimates from Appendix Figure A5 as an outcome measure. These are based on a model that substitutes numeracy and literacy skills with the difference between the two. Note that the correlation with simply taking the difference between the numeracy and literacy estimates from Figure 3 is very high (.99). For question 2, the outcome variable takes the country coefficients for the relation between having a permanent contract and the general skill level that combines both skills (portrayed in Appendix Figure A4). For question 3, the outcome variable takes the difference between the coefficients for the contractual return to skill and the wage return to skills (both for general skill levels; coefficients are standardized before taking the difference).

The macro-level analysis focuses on two types of indicators: supply-demand factors and institu-

tional variables. For question 1, the relative desirability of the different skills towards job security can be expected to relate to differences in relative supply and demand. We look at average skill levels in numeracy and literacy at the country level as a measure of supply, and look at the sector composition of countries as a measure of demand. To assess the latter in a systematic way, we assign to every individual the average score for their industry across the sample, and average those values by country. In other words, this indicator captures what would be the predicted numeracy and literacy scores in a country when looking only at industry composition.

To assess questions 2 and 3, we first use skill supply and skill demand side indicators in a similar approach as for question 1, but now at the general skill level. This analyses whether returns are different for countries that are skill-poor vs. skill-rich (supply), and/or have industries that are relatively more vs. less skill-demanding (demand). We further explore institutional indicators. We thereby largely follow earlier literature that explores country heterogeneity in the (wage) returns to skills, see, e.g., Van Der Velden and Bijlsma (2016); Hanushek et al. (2017); Stijepic (2020); Weisstanner and Armingeon (2020). We particularly focus on indicators that may affect the relative bargaining positions of employers and employees and those that capture labour market rigidities. We group these into three sets of indicators.

Variable set (1) looks at labour market tightness. It can be expected that a better bargaining position of employees (i.e. a tight labour market) positively relates to the rate of permanent contracts. How it relates to the skill return towards permanent contracts may be a different matter. Contractual skill returns may be larger in tight labour markets because they increase the share of workers with realistic prospects of permanent employment, or they may be larger in slack labour markets because a high supply of workers makes obtaining a permanent contract more selective and thus more dependent on skill levels. As indicators of labour market tightness, we use the unemployment rate (reflecting those that want to work but cannot) and the share of involuntary parttime workers (reflecting those that want to work more but cannot).

Variable set (2) measures labour market rigidities. As explained before, rigidities in the setting of

either wages or contract form may lead to substitution in how skills are rewarded. We therefore examine collective bargaining coverage rates (implying higher wage rigidities but possibly higher rigidities in contract setting as well), the share of public employment (associated with lower dispersion in wages; see, e.g. Borjas (2002)), and employment protection legislation (EPL). For EPL, we look at regular and temporary contracts separately. The projected relation between contractual skill returns and temporary EPL is not trivial, as this indicator covers both hiring and firing regulations. Most of the variation occurs in the hiring rules. Stricter hiring rules may be beneficial for temporary workers because they are less likely to be locked into temporary contracts, but can also reduce the odds of obtaining any work. Whether this makes temporary work more attractive or not is therefore ambiguous. Regular EPL predominantly covers dismissal. We expect it to positively relate to contractual returns, since workers are expected to put more value into having a permanent contract when that contract is more certain. Additionally, employers are expected to be more selective when permanent contracts are more secure, and thus more likely to grant such security to high-skilled workers.

Finally, studies have examined social policies in relation to skill returns. In particular, Weisstanner and Armingeon (2020) examine public versus private education spending and tax-transfer policies, arguing that these can shape incentives as well as attitudes towards education/skills premiums. Education spending could increase the supply of skilled workers and thereby also reduce the contractual return to skill. Tax rates and social spending directly reduce dispersion in wages and thereby reduce wage returns to skills. This can potentially lead to substitution towards contractual returns to skills. Additionally, social safety nets reduce income losses of job loss which may reduce the value that workers put in job security.[13] This may imply a lower contractual return to skills. Variable set (3) thus contains the following social policy measures: public spending on education, private spending on education, non-elderly social spending and average tax rates.[14]

[13]This particular social policy variable relates closely to variable set (1) as well, because it is also a determinant of the relative bargaining position of workers.

[14]Non-elderly social spending covers unemployment, health, family, housing, incapacity, and active labour market programmes.

All analyses control for GDP per capita (PPP).[15] It should be noted that these results rely on a cross-section of 29 observations. This limits statistical power, and also strongly precludes any causal interpretation of these regression results. Because of the limited degrees of freedom, we regress the country coefficients separately on each set of variables. Nonetheless, these results are indicative as to what sort of macro-level measures predict differences in the (contractual) returns to skills. We note that we refrain from using a multilevel analysis, or from using interaction terms with macro variables within our main specification (as is done by Hanushek et al. (2017)). The main reason is because they are not well-suited for tackling question 3, which takes the difference between two coefficients. In this way, we use one consistent approach for all three questions. Results for questions 1) and 2) are very similar when using interaction terms (available on request).

### 4.3.2 Results

Table 2 shows results for the supply and demand factors. The results in the three columns pertain to each of the three questions raised above. We find that having comparatively higher average numeracy skills in a country (the supply measure) is positively related to higher relative contractual returns to numeracy, albeit statistically insignificantly. This suggests that higher returns are not driven by a lack of supply. Additionally, we find a positive relation with the predicted score based on sector structure: countries with comparatively higher contractual returns to numeracy in Figure 3 tend to be more abundant in sectors in which the comparative advantage in numeracy is higher. This supports the notion that higher returns are driven by high demand, rather than lack of supply.

For question 2, we find that countries with higher contractual skill returns do not have higher average skill levels in general, but do have more skill-intensive sectors (second column). The

[15] Hanushek et al. (2017) report a strong relation between growth and wage returns to skills. We do not find growth to be predictive in any of our macro models, also not for wage returns. This is driven by the fact that there are several differences between our approach and that of Hanushek et al. (2017): we use a different age sample, different skill scores and different control variables. Mainly the latter, and in particular the inclusion of educational attainment, explains the largest part of this discrepancy. Because growth does not predict our outcomes and our degrees of freedom are limited, we choose to exclude it as a control variable in the main analysis. The same applies to the inclusion of the average share of temporary workers. Results including these two variables provide similar point estimates and are available on request.

latter estimate is large and statistically highly significant. This is in line with the demand-driven results for question 1). The third column shows whether the predicted scores can also explain the difference in contractual versus wage returns. While the point estimate is still positive, it is statistically insignificant. This indicates that wage returns to skills are also higher for countries with more skill-intensive sectors (although to a slightly weaker extent than contractual returns when comparing point estimates).

Table A9 list results for the three sets of institutional indicators, which are used in relation to questions 2 ('Overall skill return') and 3 ('Relative skill return'). For the indicators of labour market tightness, we only identify small and statistically insignificant coefficients for both outcomes. Hence, contractual returns to skills appear not to be related to labour scarcity. For variable set (2), we identify a positive link between the contractual return to skills and public employment. Results for this indicator are even stronger towards question 3. This is suggestive evidence of substitution towards contractual returns when wages are less dispersed. Borjas (2002) discusses that the lower wage dispersion in the public sector compared to the private sector means that the public employers are finding it increasingly difficult to attract and retain high-skilled workers. Possibly, the results reflect that the public sector has responded by offering their high-skilled employees more job security. We do not find statistically significant results for the EPL measures. Coefficients for collective bargaining coverage are also statistically insignificant, while point estimates go against the hypothesis that collective bargaining can increase contractual returns to skills through substitution effects away from wages.[16]

For variable set 3), we find that the contractual return to skills is relatively higher when social spending is lower. The coefficient is just shy of statistical significance towards question 2, but statistically significant and large in magnitude towards question 3. This could reflect that workers

[16]This may imply that collective bargaining also increases job security and therefore leads temporary workers to put less value on permanent contracts.

put higher value on permanent contracts when social safety nets are smaller.[17] Further, we find a marginally significant positive relation with public investment in education. This largely reflects that public education spending lowers the wage return to skills (as also found by Weisstanner and Armingeon (2020)), while it does not appear to be related to the contractual return to skills. Higher tax rates also relate to a higher relative contractual return to skill, which is in line with substitution effects when wage returns are more compressed. The coefficient is sizable but just shy of conventional statistical significance thresholds.[18]

In summary, higher contractual returns to skills relate to higher demand for skills (rather than lower supply), as predicted by sector structures of labour markets. Countries with higher returns have more skill-intensive sectors in general, and have especially high returns to those skills that are especially abundant in its largest sectors. Moreover, returns are higher (in general and/or compared to wage returns) when public employment is higher and social safety nets are weaker.

# 5 Robustness

In this section, we analyze the robustness of the results to measurement error in the skills measures, and explore the extent to which the established associations can be seen as causal. We further assess sensitivity to sample composition, and to the contract types that are considered within temporary employment.

[17] We note that non-elderly spending is a broad category and therefore may be a rough indicator of the size of the social safety net for laid-off workers. As an alternative, we use the OECD's 'labour market insecurity' indicator, which looks at the expected earnings loss from unemployment. This variable is a strong positive predictor of the relative contractual return to skills, confirming the link with weaker social safety nets.

[18] Section 5.2 reported that the discrepancy between contractual return and wage return is especially strong for older workers. Conducting the analysis of Table A9 on the sample of those above 35 confirms the main findings (see Appendix Table A7 for full results). The identified effects from Table A9 for public employment and social spending become more pronounced. The results for older workers also suggest that contractual returns are higher when regular EPL is stronger, and when CBA coverage is lower.

## 5.1 Measurement error

Any skill measure is subject to measurement error. Classical measurement error implies attenuation bias in our measures of the effect of skills on job security. A common approach to correct for such measurement error is to use different skill measures as instruments for one another, see, e.g., Hausman (2001). This effectively exploits the overlap in these skill measures, thereby eliminating measurement error that is specific to one particular skill measure. For this purpose, we use the item-level data from the tests and generate numeracy and literacy scores for a randomly selected half of each of the two tests. This creates two separate numeracy scores and two separate literacy scores. One issue is that there are four different ways in which these four skill measures can be combined into two instrumented variables and two instruments. Table 4 reports all four alternatives and the average. Coefficients are around two times larger than in the OLS specification. Moreover, they increase somewhat stronger for numeracy compared to literacy skills, indicating that measurement error in the former is stronger. This emphasizes the stronger average effect of numeracy skills over literacy skills. On the other hand, the coefficients are still roughly equal when industry and occupational fixed effects are included, strengthening the conclusion that this difference is largely mediated by sorting. Table 4 also shows results for an alternative measurement error correction approach in which we look at overall skills, as a combination of both numeracy and literacy skills. We once more split the items randomly in two, leading to two different overall skill measures. Again, skills measures increase by around a factor two.[19]

PIAAC's plausible values are designed to reduce measurement error. As explained before, we believe that these plausible values are ill-suited for this particular analysis, but we report results based on plausible values in the appendix for completion (Appendix Table A11). Effect sizes are larger when using plausible values, which can both occur because of the lower sensitivity to measurement error or because of a bias from including background variables in their construction. Relative sizes between numeracy and literacy are very comparable. The estimates by country

[19]Because IV is by nature less efficient, it leads to rather imprecise results when applied to the country-specific estimates. Still, the relative increases in the country-specific point estimates is largely similar. Thus, measurement error does not appear to have strong implications for the relative country-specific results and the macro-level analysis.

are rather different, however. This can be seen in Appendix A3. The estimates for literacy and numeracy are almost complete opposites; the correlation equals -0.88. It appears likely that this is due to the aforementioned limitations of the plausible values in a regression framework that simultaneously includes both skills scores.[20]

## 5.2 Exploring causality

While the estimates of the relation between skills and job security condition on several background characteristics and potential mechanisms, they still reflect (conditional) associations rather than causal effects. Moreover, they may be vulnerable to reverse causality, as higher job security may foster investments in skills. Results therefore are informative for the predictive value of these skills, but not directly of the precise return from investing in these skills in terms of higher job security. This is an issue that affects all of the returns to skill literature, as plausibly exogenous variation in skills is very rare. Other studies on the returns to skills, including those using PIAAC data, have used several approaches to deal with this issue (Hanushek et al., 2015; Stijepic, 2020). These include employing own education or parental education as instruments for skills. PIAAC also contains retrospective information on the number of books at home at age 16, which could similarly serve as an instrument. We report different IV models in the appendix for completion that confirm that positive contractual returns to skills exist, but emphasize that these instruments are highly likely to violate the exclusion restriction. In fact, even exogenous variation in educational attainment that occurs for example through changes in compulsory schooling laws are unlikely to resolve these issues, since education affects much more than cognitive skills (e.g. non-cognitive skills, networks, status).[21] In essence, these different IV models are likely to be positively biased, but for different reasons than the expected positive bias in the OLS estimates. From an optimistic

[20] Results are highly similar to those in the main analysis when we use percentile scores rather than the continuous IRT scores (available on request).

[21] Given that we have only around 3,000 observations per country which are spread out across many cohorts, there is not enough power to exploit compulsory schooling changes across our sample. Appendix Table A12 shows an alternative instrument that uses the average years of schooling per country and cohort as an instrument. This essentially exploits any deviations from trends (captured by the age controls) in educational attainment across cohorts, assuming that these occur from cohort-specific policies in education.

perspective, it is at least reassuring that the estimates from Appendix Table A12 are not zero or negative, but they are not a reliable lower bound.

A second-best approach is to assess sensitivity of the estimates to control variables. This is not a straightforward exercise as one has to distinguish between omitted variable bias and variables that may represent a mechanism for the relation between skills and job security. For example, skills may enhance job security through enhancing educational attainment. Table 1 has shown that results are stable when including background variables such as age, gender and migration status, but sensitive to the inclusion of educational attainment. Hence, when using selection on observables to assess sensitivity to selection on unobservables by estimating Oster's delta (Oster, 2019), values are low once we include educational attainment.[22] Both the coefficient for the return to skills and Oster's delta are extremely stable however when we add more variables to the model, such as trust, non-cognitive skills, preferences and health (see Table 5).[23] The plausibility of these results reflecting causal estimates thus relies on whether one believe that educational attainment is a mechanism for the relation between skills and job security, or represents a source of bias.

Finally, we should consider the potential for reverse causality. Previous studies have shown that temporary workers invest less in training; see, e.g., Fouarge et al. (2012). We confirm in our sample that temporary workers are substantially less likely to have followed a training in the past year, also when including all defined control variables. Additionally, temporary workers learn less on the job (PIAAC extensively measures learning at work and constructs a learning index from these items). When including measures of training, training intensity and the learning at work index, the coefficient for the contractual return to skills (overall skill measure) falls from 0.115 to 0.096.[24] We conclude that it appears likely that reverse causality is part of our estimated effects, but unlikely that it strongly dominates those effects.

[22]This is not solved by dropping educational attainment from this exercise, as these additional controls typically correlate strongly with educational attainment and thus take over this potential selection bias.

[23]Results are also virtually identical when we add ICT skills to the model (available upon request).

[24]Note that this can potentially be an overcorrection, since higher training and learning may also be a result of having higher skills ex ante, and as such a part of a true treatment effect of having more skills.

## 5.3 Sample selection

Figure 1 has shown that there is large variation in the share of temporary employment. This may imply that results for the full sample are dominated by one or a few countries. In Table 6, we analyze whether results are robust to excluding countries with very high prevalence of temporary employment. The first column provides baseline results. The second column excludes the United States, which is a clear outlier in the prevalence of temporary employment. This leads to similar results. Excluding other high prevalence countries also leads to rather minor changes in the coefficients, with the estimate for literacy reducing slightly. This suggests that literacy skills relate somewhat more to permanent contract status in countries where permanent jobs are more rare, and comparatively less in (largely European) countries with a more modest prevalence of temporary employment. Excluding those with the "no contract" status leads to only minor reductions in the estimates. The sixth column of Table 6 excludes the lowest skill decile. This addresses, for one, how dominant those with very low skill levels are in the identified effects and, two, to what extent estimates may be driven by those who apply little to no effort on the (low-stakes) test of PIAAC. Results excluding those workers are very similar to the main estimates. Finally, we exclude those with very short tenure (under two full years). A share of those in temporary contracts may represent recent job switchers in their probation period that soon will transition to a permanent contract. Their contract status does not necessarily reflect a lower desirability to employers, and their inclusion in the group of temporary workers may attenuate the return to skill. We find that excluding low tenure workers leads to largely similar coefficients, with a slightly higher coefficient for literacy skills. This suggests that the aforementioned group of recently hired temporary workers does not have a large bearing on the results. It also indicates that part of the dominance of numeracy skills is because those skills are related to fewer recent job switches.

Finally, we show results for alternative age ranges. The main sample includes those aged 18-60, which represents a relatively young lower threshold compared to other studies on labour markets. Appendix Table A11 shows results for more narrow age ranges. In general, sensitivity is modest. A

higher lower bound increases the coefficient for numeracy somewhat. When increasing the lower bound to age 30, estimates for literacy increase as well compared to the base age range. This conforms the results from Appendix Table A1 that compares those under age 35 with those over age 35, which showed stronger returns (especially for literacy) for older workers.

### 5.4 Distinguishing types of temporary employment

The previous subsection has shown that results are not very sensitive for excluding the "no contract' situation. For completion, we provide results for all the different forms of contract status that are considered under temporary employment, in Appendix Table A10. Note that these estimations still include the full sample, and pit the defined contract status against all alternative statuses. The table shows that the results for getting "no contract" work are indeed not far from the coefficients for the main specification, although slightly stronger for literacy. For the two less prevalent forms of temporary work (TWA work/apprenticeships and "other contract forms"), literacy skill coefficients are stronger than numeracy skill coefficients. This is especially the case for the "other" contract form. Numeracy skills are strongly dominant when reducing the odds of fixed-term work. The results show no clear pattern by the degree of precariousness of temporary work.

## 6 Conclusion

This study has analyzed the relation between skills and job security, distinguishing permanent contracts from less secure employer-employee relations. We find that both numeracy and literacy skills contribute to the odds of obtaining a permanent contract, also when conditioned on background characteristics. Estimates for numeracy are stronger than estimates for literacy, a difference that is predominantly mediated by human capital levels and sorting to industries and occupations. An important conclusion from the analyses is that there is large heterogeneity in these returns by country. Either only numeracy skills contribute to permanent contract status, only literacy skills, or neither, but never both. The country-specific returns with respect to permanent contract status also

differ substantially from the country-specific returns with respect to wages. In particular, country-specific estimates for wages do show that both skills can matter, and their relative contributions correlate strongly. An analysis on macro variables finds that heterogeneities in returns relate to demand factors, rather than supply factors. Countries with higher contractual returns to skills tend to have larger skill-intensive sectors. Sector structures also explain part of the relative importance of numeracy vs. literacy in explaining contract status. Moreover, we find evidence that institutions matter; contractual returns to skill are higher when public employment is higher, and social safety nets are weaker. This applies both in absolute terms and relative to wage returns. While this evidence is only indicative, the former finding supports the idea that contractual returns can act as a substitute for wage returns when the latter are more rigid. The finding with respect to social safety nets is consistent with workers putting higher value on job security and thus being more willing to sacrifice higher wages for this purpose when the consequence of losing one's job is stronger.

The difference between wage returns and contractual returns has implications for how we may perceive the return on these skills, and which type of skills appears to be more valued in a particular labour market. For example, wage results for Sweden would suggest that literacy and numeracy are equally predictive, while effects for permanent contract status are heavily skewed towards literacy. The opposite applies to countries such as the United Kingdom, Iceland and Hungary. Similarly, wage results for Turkey would suggest that neither skill has a meaningful return in the labour market, while results for permanent contract status indicate that literacy skills have a substantial return. This indicates that a broader perspective on the concept of "skill returns" may change the conclusions that are typically drawn from these analyses.

We have particularly focused on the "contractual return" to skills because recent studies suggest that job security is the most valuable among non-wage job attributes (Datta, 2019), and because it is central to current concerns about a growing group of labour market outsiders which have lower job security that may also translate into fewer human capital investments, negative intergenerational effects, and potentially various other negative spillovers. Our results indicate that being

an "outsider" in the labour market is partially skill driven. This may be considered all the more problematic given that opportunities to invest in skills are typically smaller in temporary jobs. In fact, a part of the established relations in our analysis may be due to such a reverse causality. The findings may thus also reflect one of the mechanisms that keep outsiders locked out. When considering the need for investments to overcome these limitations of temporary workers to invest in human capital, spillovers into higher odds of permanent employment should be considered as part of the cost-benefit framework. At the same time, having a permanent contract is barely or not at all skill-driven in a substantial set of OECD countries (which appear to have large skill-poor sectors). Hence, being an insider or outsider has virtually no relation to one's set of productive skills there. In particular for this set of countries, future research has potential to reveal more about what drives the distinction between permanent and temporary work status.

This paper provides a starting point for exploring the relation between skills and job security and provides ample other opportunities for future research. While we provide indicative evidence for factors that can explain part of the country heterogeneity, the PIAAC data have limitations in this regard as they consist of one cross-section. This also applies to exploring the differences between the estimates for wages and those for job security. Longitudinal data would be more suited to explore the role of institutions in these differences. Future research may profit from using the second cycle of PIAAC, which is administered in 2022-2023. Especially for exploring the role of indicators related to labour market tightness, such longitudinal data are better suited. Additionally, we emphasize that while we condition on multiple control variables and explore several potential mechanisms, the results we present are not causal in nature. As such, the estimates should not be seen as reflecting the direct effect of improving numeracy and literacy skills through extra investments. As exogenous variation in skills is rare, identifying such a causal impact is highly challenging. Experimental interventions that invest in skills can provide valuable insights into the question of causality, although even in those cases the fact that investments may increase multiple (cognitive and non-cognitive) skills simultaneously will make causal inference difficult. Finally, this study provides new avenues for considering contract status as an important determinant of job

utility and thus as a relevant outcome to consider when analyzing welfare implications of policies and investments. This can apply to other studies in which one analyzes the returns to skills or human capital investments, but potentially also other settings in which labour market returns are considered.

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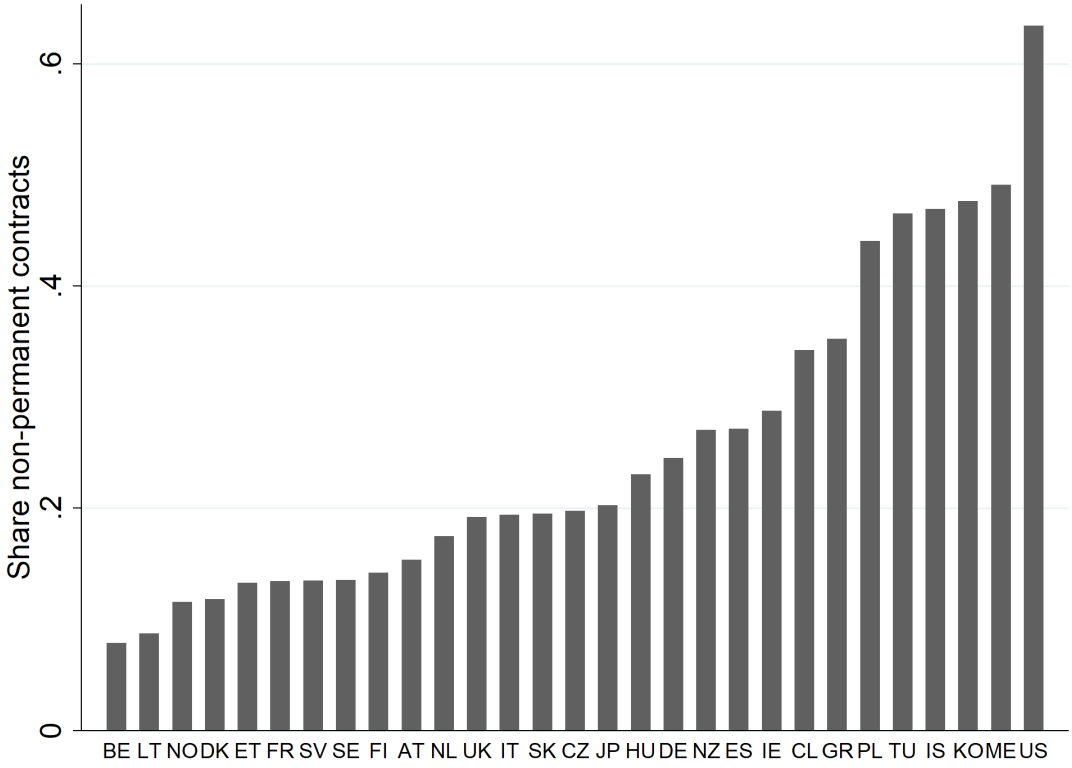
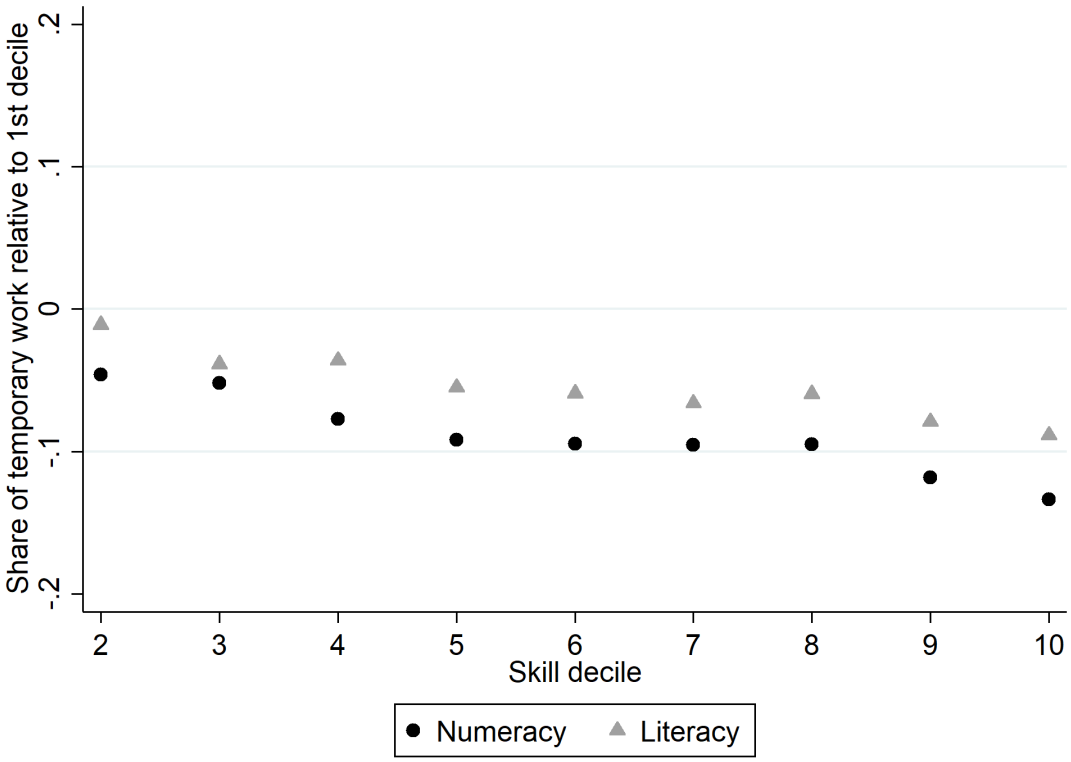
Figure 1: Share of temporary employment across countries



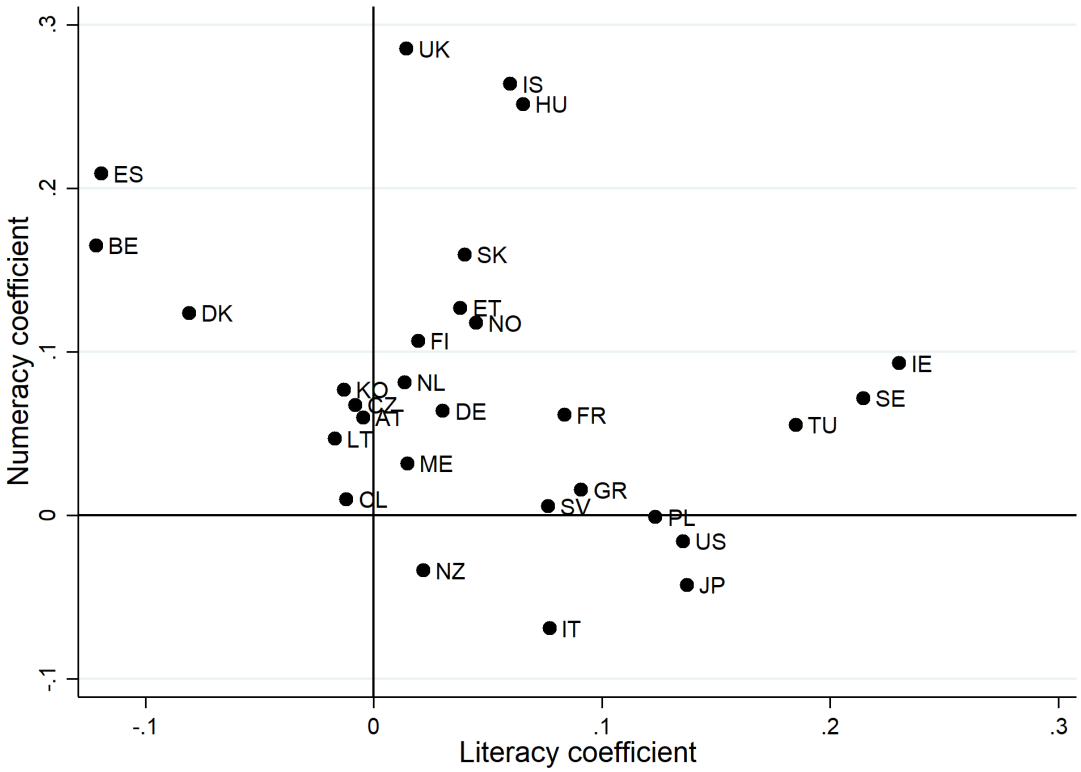

**Notes:** The figure shows the combined shares of fixed-term contracts, apprenticeships, temporary work agency contracts, no contract work and other contract forms, across countries. Source: own calculations based on PIAAC.

Figure 2: Share of temporary employment across skill deciles



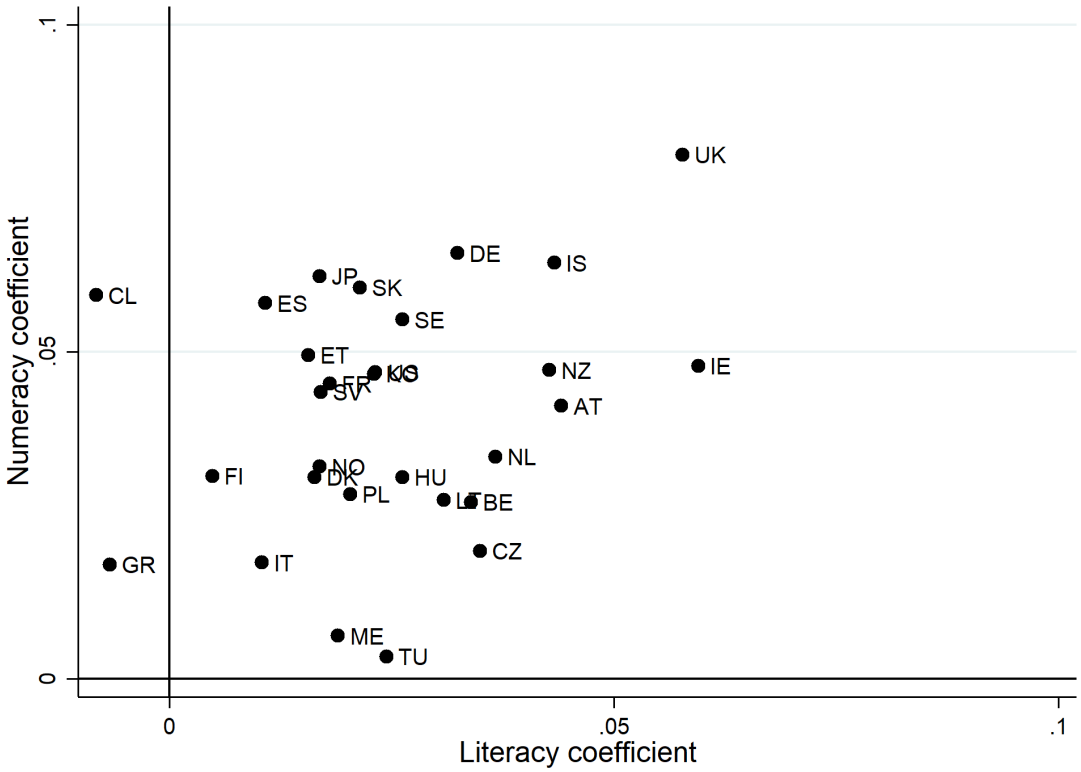

**Notes:** The figure shows the probability of being on a permanent contract, relative to those in the lowest skill decile. Results are corrected for country-level differences. Estimates do not condition on the other skill under examination. Source: own calculations based on PIAAC.

Figure 3: Contractual return to skills: estimates by country




**Notes:** The figure shows estimates per country for a regression of having a permanent contract on numeracy (y-axis) and literacy (x-axis) skills, controlling for demographic characteristics, experience and years of education (logit).

Figure 4: Wage return to skills: estimates by country




**Notes:** The figure shows estimates per country for a regression of wages on numeracy (y-axis) and literacy (x-axis) skills, controlling for demographic characteristics, experience and years of education (OLS).

Table 1: The relation between skills and job security

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Numeracy | 0.212*** | - | 0.180*** | 0.158*** | 0.083*** | 0.048*** |
| | (0.011) | | (0.012) | (0.013) | (0.013) | (0.014) |
| Literacy | - | 0.154*** | 0.060*** | 0.081*** | 0.049*** | 0.035*** |
| | | (0.011) | (0.012) | (0.013) | (0.013) | (0.013) |
| Age | | | | 0.143*** | 0.046*** | 0.045*** |
| | | | | (0.004) | (0.006) | (0.006) |
| Age sq | | | | -0.002*** | -0.001*** | -0.001*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Female | | | | -0.191*** | -0.107*** | -0.081*** |
| | | | | (0.022) | (0.023) | (0.026) |
| 1st gen migrant | | | | -0.233*** | -0.116*** | -0.074* |
| | | | | (0.040) | (0.041) | (0.041) |
| 2nd gen migrant | | | | -0.042 | -0.025 | -0.058 |
| | | | | (0.041) | (0.042) | (0.043) |
| Experience | | | | | 0.116*** | 0.112*** |
| | | | | | (0.005) | (0.005) |
| Exper. sq. | | | | | -0.001*** | -0.002*** |
| | | | | | (0.000) | (0.000) |
| Yrs of schooling | | | | | 0.085*** | 0.055*** |
| | | | | | (0.004) | (0.005) |
| ISIC-1/ISCO-1 | | | | | | X |
| N | 82,239 | 82,239 | 82,239 | 82,239 | 82,239 | 82,239 |
| Pseudo-$R^2$ | 0.093 | 0.090 | 0.094 | 0.129 | 0.152 | 0.175 |

**N**ote: Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). A logit specification is applied. All specifications include country fixed effects. Column (6) adds fixed effects for ISIC and ISCO at the one-digit level.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2: Explaining country differences: skill scores

| | Comparative advantage return | Overall skill return | Relative skill return |
|---|---|---|---|
| Average score | 0.226 | -0.365 | -0.192 |
| (supply) | (0.193) | (0.274) | (0.339) |
| Predicted score | 0.541** | 0.837*** | 0.313 |
| (demand) | (0.263) | (0.249) | (0.308) |

**N**ote: Results from regressions of country-specific contractual skill returns on average and predicted scores by country. 'Average score' refers to country average scores; 'Predicted score' refers to scores predicted by the sector structure (ISIC) of the country. Average and predicted scores refer to numeracy scores in the first column. In the first column, the outcome variable is the contractual skill return to the comparative advantage in numeracy versus literacy skills (Figure A5), and average and predicted scores refer to comparative advantage scores. In the second column, the outcome variable is the country-specific contractual return to the overall skills (Figure A4), and average and predicted scores refer to overall skill scores. In the third column, the outcome variable is the difference between the contractual return to overall skills and the wage return to overall skills, and average and predicted scores refer to overall skill scores. All outcome variables and independent variables are standardized with mean 0 and standard deviation 1. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 3: Explaining country differences: institutions

| | Overall skill return | Relative skill return |
|---|---|---|
| Unemployment rate | 0.125 | 0.212 |
| | (0.263) | (0.265) |
| Involuntary part-time employment | -0.167 | -0.096 |
| | (0.276) | (0.278) |
| GDP per capita | 0.038 | -0.203 |
| | (0.229) | (0.231) |
| Collective bargaining coverage | -0.418 | -0.284 |
| | (0.258) | (0.238 |
| Public employment rate | 0.396* | 0.409** |
| | (0.212) | (0.196) |
| EPL temporary workers | -0.280 | 0.272 |
| | (0.247) | (0.227) |
| EPL regular workers | 0.087 | -0.063 |
| | (0.235) | (0.216) |
| GDP per capita | -0.074 | -0.138 |
| | (0.262) | (0.242) |
| Public education spending | 0.469 | 0.604* |
| | (0.370) | (0.326) |
| Private education spending | 0.202 | -0.161 |
| | (0.310) | (0.273) |
| Social spending (non-elderly) | -0.196 | -0.745** |
| | (0.351) | (0.309) |
| Average tax rate | 0.343 | 0.443 |
| | (0.358) | (0.266) |
| GDP per capita | 0.332 | -0.269 |
| | (0.229) | (0.266) |

**N**ote: Outcome variables are either the country-specific return to the overall skills ('Overall skill return') or the difference between contractual and wage returns to overall skills ('Relative skill return'). Social expenditure excludes old age and survivor benefits. See the appendix for more details on the independent variables. All outcome variables and independent variables are standardized with mean 0 and standard deviation 1. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4: The relation between skills and job security: measurement error correction

| | OLS | IV 1 | IV 2 | IV 3 | IV 4 | Avg coef |
|---|---|---|---|---|---|---|
| Base model | | | | | | |
| Numeracy | 0.011*** | 0.024*** | 0.023*** | 0.028*** | 0.020*** | 0.023 |
| | (0.002) | (0.006) | (0.006) | (0.006) | (0.006) | |
| Literacy | 0.007*** | 0.013** | 0.009 | 0.008 | 0.014** | 0.011 |
| | (0.002) | (0.005) | (0.006) | (0.005) | (0.006) | |
| Overall | 0.018*** | 0.030*** | 0.028*** | - | - | 0.029 |
| | (0.002) | (0.003) | (0.003) | | | |
| ISIC/ISCO FE | | | | | | |
| Numeracy | 0.005** | 0.010* | 0.009* | 0.014** | 0.006 | 0.010 |
| | (0.002) | (0.006) | (0.006) | (0.006) | (0.006) | |
| Literacy | 0.005*** | 0.010* | 0.007 | 0.005 | 0.012** | 0.009 |
| | (0.002) | (0.005) | (0.005) | (0.005) | (0.005) | |
| Overall | 0.010*** | 0.014*** | 0.028*** | - | - | 0.021 |
| | (0.002) | (0.003) | (0.003) | | | |

**N**ote: Outcome variable is equal to 1 for those on a permanent contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). The first column applies an OLS specification. The following columns apply IV specifications using each half of the items of numeracy and literacy skills as instrumented variables and instruments (four combinations). The final column gives the average of the four IV coefficients. The lower panel adds ISIC and ISCO fixed effects. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 5: Sensitivity to additional controls

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Skills | 0.030*** | 0.017*** | 0.017*** | 0.017*** | 0.016*** | 0.016*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Yrs of schooling | | 0.014*** | 0.013*** | 0.014*** | 0.013*** | 0.013*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Parental education | | | 0.007*** | 0.008*** | 0.007*** | 0.007*** |
| | | | (0.003) | (0.003) | (0.003) | (0.003) |
| Nr books | | | -0.001 | 0.001 | -0.000 | -0.000 |
| | | | (0.001) | (0.001) | (0.002) | (0.002) |
| Persistence | | | | 0.004* | 0.004** | 0.004** |
| | | | | (0.002) | (0.002) | (0.002) |
| Openness | | | | -0.008*** | -0.007*** | -0.008*** |
| | | | | (0.002) | (0.002) | (0.002) |
| Political effec. | | | | 0.003** | 0.003* | 0.002 |
| | | | | (0.001) | (0.002) | (0.002) |
| Volunteering | | | | | -0.008*** | -0.009*** |
| | | | | | (0.002) | (0.002) |
| Trust I | | | | | -0.000 | -0.001 |
| | | | | | (0.002) | (0.002) |
| Trust II | | | | | 0.006*** | 0.005** |
| | | | | | (0.002) | (0.002) |
| Health | | | | | | -0.014*** |
| | | | | | | (0.002) |
| Demogr. controls | X | X | X | X | X | X |
| Oster's $\delta$ | 2.39 | 0.148 | 0.132 | 0.128 | 0.125 | 0.123 |
| N | 72,232 | 72,232 | 72,232 | 72,232 | 72,232 | 72,232 |
| $R^2$ | 0.138 | 0.153 | 0.153 | 0.154 | 0.154 | 0.155 |

Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). An OLS specification is applied. All regressions include controls for age, age squared, gender and migration status, and country fixed effects. See the appendix for a description of the additional variables. Standard errors are robust. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: The relation between skills and job security: excluding parts of sample

| | All | Under 60% | Under 40% | Under 30% | Drop no contract | Drop 1st decile | Drop <2 tenure |
|---|---|---|---|---|---|---|---|
| Base model | | | | | | | |
| Numeracy | 0.083*** | 0.083*** | 0.075*** | 0.083*** | 0.075*** | 0.080*** | 0.070*** |
| | (0.013) | (0.013) | (0.015) | (0.016) | (0.015) | (0.017) | (0.017) |
| Literacy | 0.049*** | 0.045*** | 0.047*** | 0.033* | 0.039*** | 0.058*** | 0.074*** |
| | (0.013) | (0.013) | (0.015) | (0.017) | (0.015) | (0.015) | (0.016) |
| Pseudo-$R^2$ | 0.152 | 0.137 | 0.113 | 0.108 | 0.098 | 0.150 | 0.187 |
| ISIC/ISCO FE | | | | | | | |
| Numeracy | 0.046*** | 0.046*** | 0.038** | 0.048*** | 0.043*** | 0.045*** | 0.035** |
| | (0.014) | (0.014) | (0.015) | (0.017) | (0.015) | (0.017) | (0.017) |
| Literacy | 0.032** | 0.029** | 0.032** | 0.018 | 0.027* | 0.039*** | 0.064*** |
| | (0.013) | (0.014) | (0.015) | (0.017) | (0.015) | (0.015) | (0.017) |
| Pseudo-$R^2$ | 0.182 | 0.169 | 0.145 | 0.140 | 0.133 | 0.180 | 0.219 |
| N | 82,239 | 80,386 | 70,997 | 61,392 | 76,170 | 73,988 | 65,880 |
| Nr of temp | 19,560 | 18,385 | 13,932 | 10,465 | 13,526 | 16,862 | 11,821 |

**N**ote: 'All' provides baseline results (including the full set of controls). Columns 2, 3 and 4 exclude countries with shares of temporary employment exceeding 60%, 40% and 30% respectively. Column 5 excludes those with "no contract" status from the sample. Column 6 excludes those in the lowest skill decile. The lower panel adds ISIC and ISCO fixed effects. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

# Appendix

# Data documentation

Below are listed the definitions for the variables used in the macro-level analysis of Section 5.3. Measures are taken from the same year in which PIAAC was administered to that particular country.

- **Unemployment rate**: people of working age who are without work, are available for work, and have taken specific steps to find work.This indicator is measured in numbers of unemployed people as a percentage of the labour force. Data are based on labour force surveys (LFS). Source: OECD.
- **Involuntary part-time employment**: workers working less than 30-usual hours per week because they could not find a full-time job, as a share of all part-time workers. Source: OECD.
- **Collective bargaining coverage**: number of employees covered by a collective agreement in force as a proportion of the number of eligible employees equipped. Source: OECD.
- **EPL regular**: strictness of dismissal regulation for workers on regular contracts (individual and collective dismissals). Source: OECD.
- **EPL temp**: strictness of regulation of temporary contracts (both on hiring and on firing regulations). Source: OECD.
- **Public expenditure on education**: total public spending on education, including direct expenditure on educational institutions as well as educational-related public subsidies given to households and administered by educational institutions. Expressed as a percentage of GDP. Source: OECD.
- **Private expenditure on education**: Private spending on education refers to expenditure

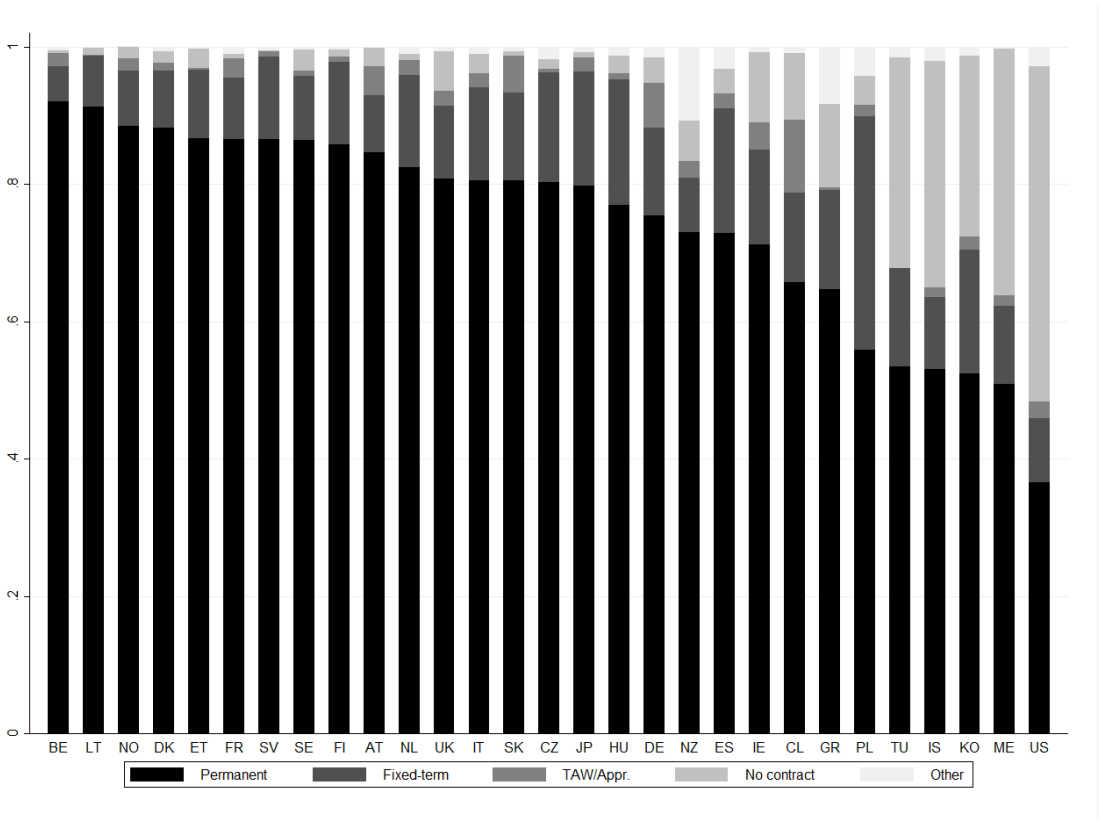
funded by private sources (households and other private entities). Expressed as a percentage of GDP. Source: OECD.

- **Social expenditure**: social spending as a percentage of GDP (cash and in-kind), excluding old age and survivor spending. It covers unemployment, health, family, housing, incapacity, and active labour market programmes spending. Source: OECD.
- **Tax rate**: Average income tax rate as a % of gross wage earnings, for single person without children at average earnings. Source: OECD Taxing Wages.
- **GDP**: Gross domestic product per capital in purchasing power parity. Source: OECD.
- **GDP growth**: average annual growth in real GDP per capita between 1990 and 2011. Source: Penn World Tables.
- **Average temp**: country share of workers without a permanent contract (comprises fixed-term work, no contract work, temp agency work and other forms of work without indefinite contract terms). Source: own calculations based on PIAAC.

Below are listed the definitions for the additional variables used in the sensitivity analysis of Table 5.

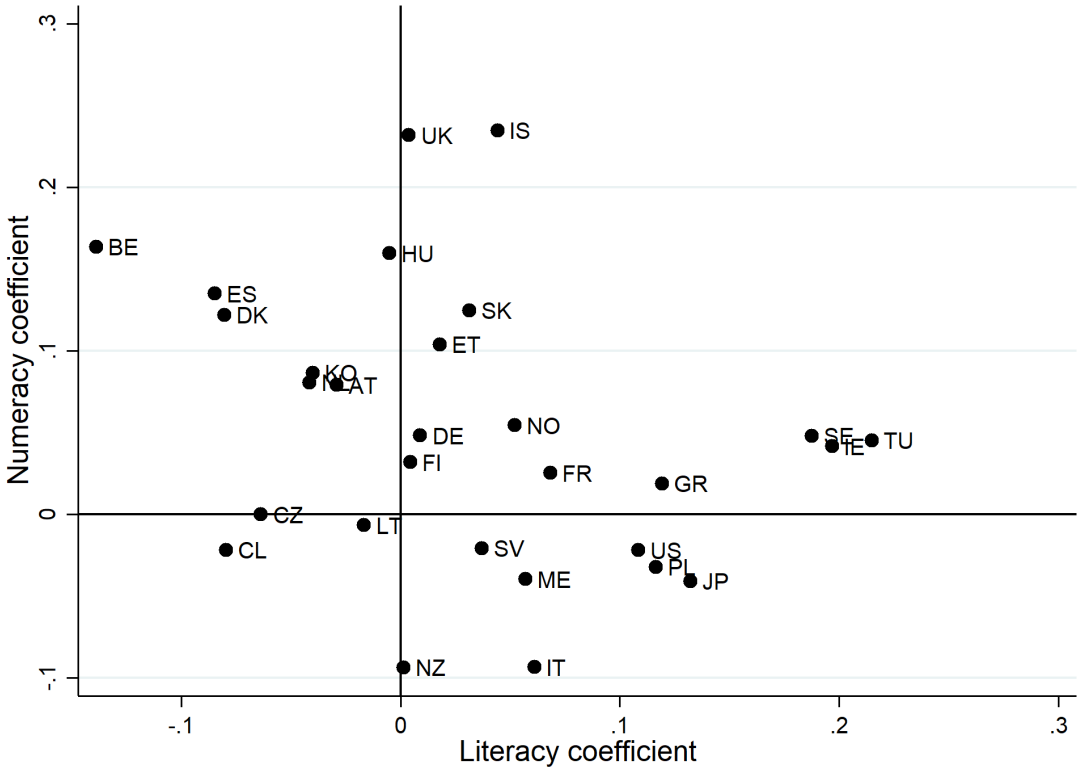
- **Nr books**: asks respondents on a scale of 1 (10 or less) to 6 (more than 500): 'About how many books were there in your home when you were 16 years old? Do not include magazines, newspapers or schoolbooks. To give an estimation, one meter of shelving is about 40 books.'
- **Persistence**: asks respondents on a scale of 1-5 whether they agree with the statement 'I like to get to the bottom of difficult things'.
- **Openness to experience**: asks respondents on a scale of 1-5 whether they agree with the statement 'I like learning new things'.
- **Political efficacy**: asks respondents on a scale of 1-5 whether they agree with the statement 'People like me don't have any say about what the government does'.
- **Volunteering:**: asks people whether they do voluntary work for a non-profit organization: ranging from 1 (never) to 5 (every day).
- **Trust I**: asks respondents on a scale of 1-5 whether they agree with the statement 'There are only a few people you can trust completely'.
- **Trust II**: asks respondents on a scale of 1-5 whether they agree with the statement 'If you are not careful, other people will take advantage of you'.
- **Health**: asks respondents to rate their health on a scale from 1 (excellent) to 5 (poor).

Figure A1: All contract types by country



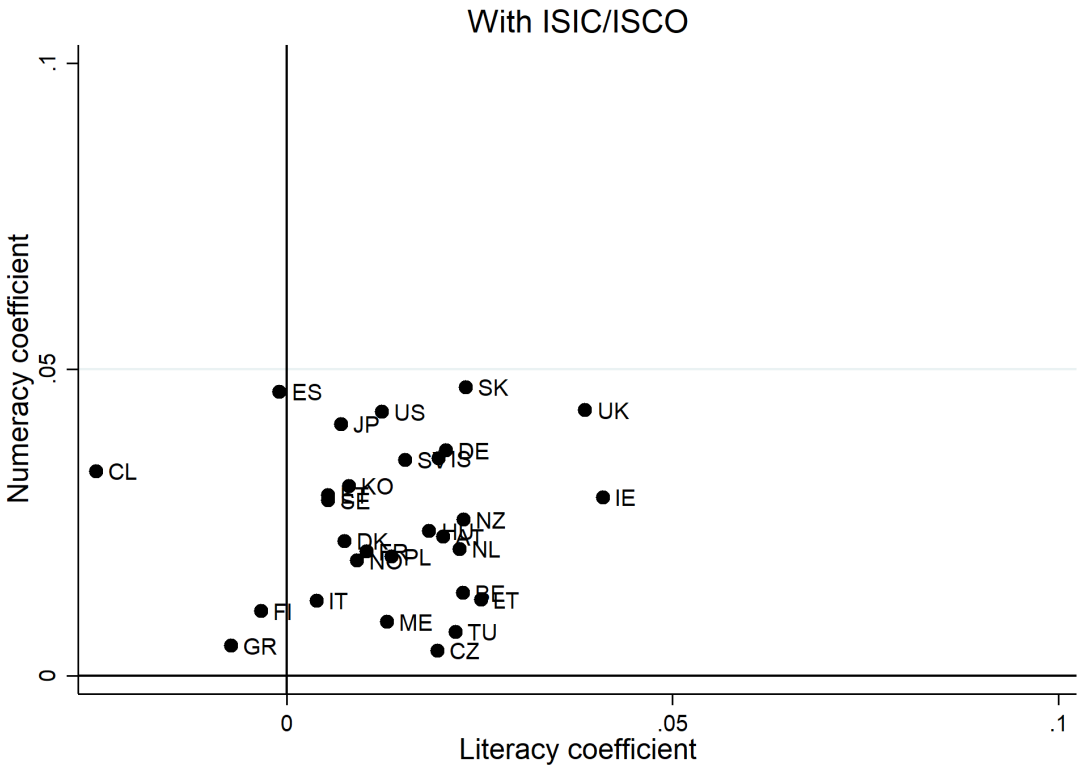

**Notes:** The figure shows the distribution of contract types by country. 'TAW/appr' refers to temp agency work and apprenticeships.

Figure A2: Estimates by country: with ISIC/ISCO fixed effects



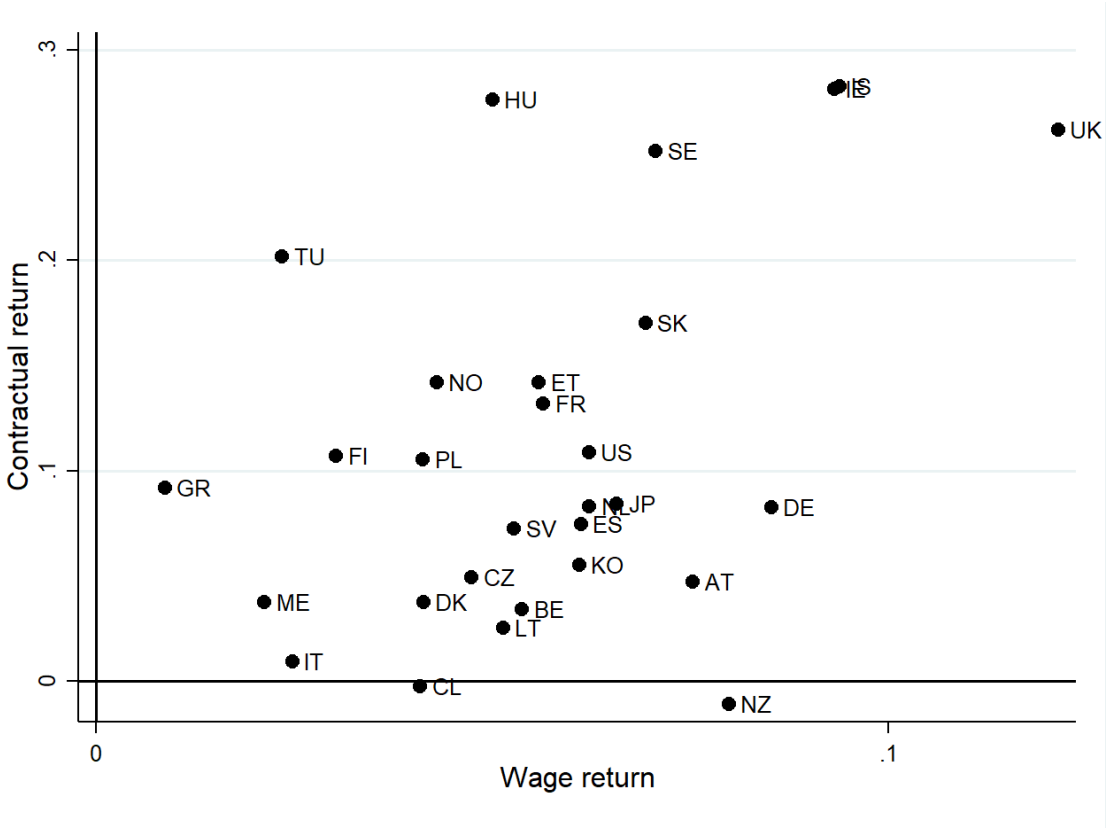

**Notes:** The figure shows contractual returns to numeracy and literacy skills, including ISIC and ISCO fixed effects.

Figure A3: Estimates by country for wages: with ISIC/ISCO fixed effects



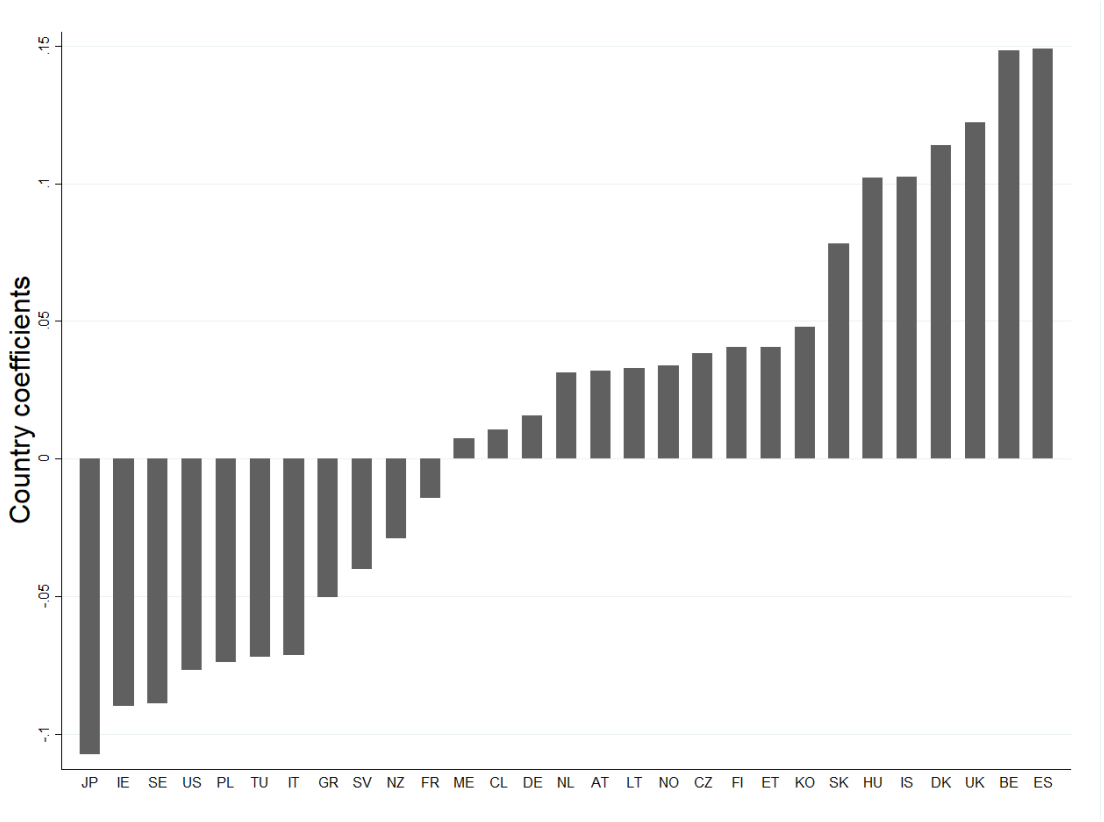

**Notes:** The figure shows wage returns to numeracy and literacy skills, including ISIC and ISCO fixed effects.

Figure A4: Returns to skills: contractual vs. wage return (overall skill)



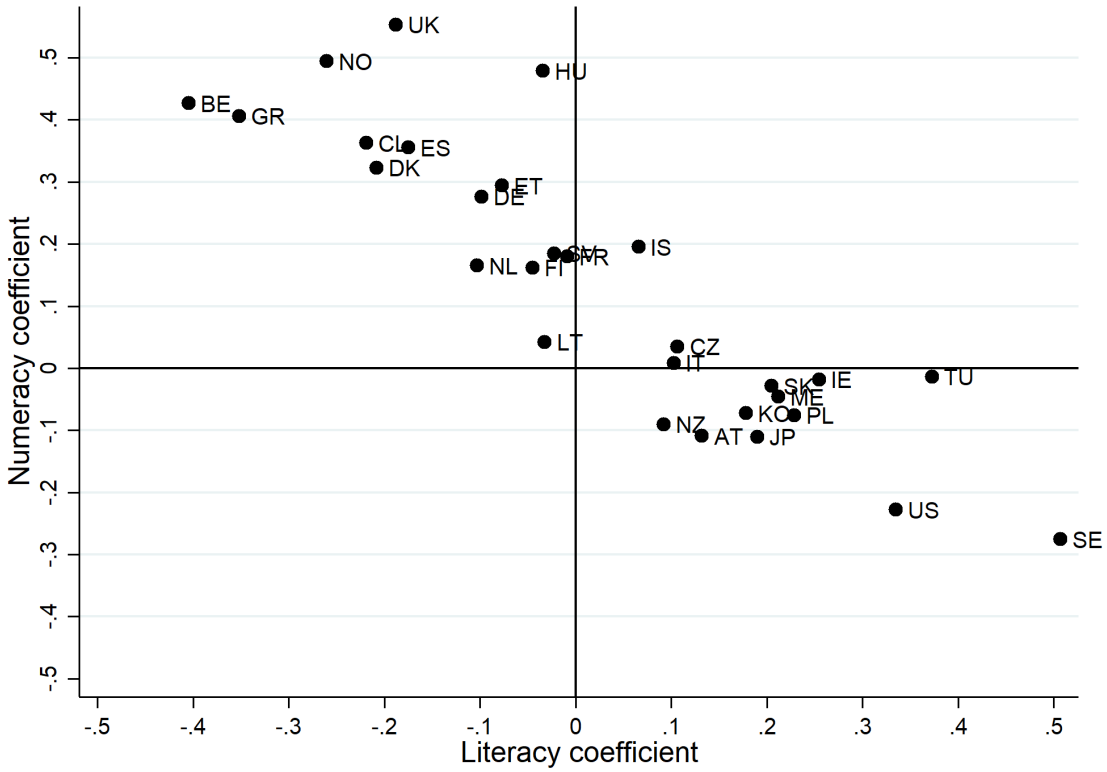

**Notes:** The figure shows contractual returns to overall skills (y-axis) against wage returns to overall skills (x-axis).

Figure A5: Country estimates for comparative advantage in numeracy



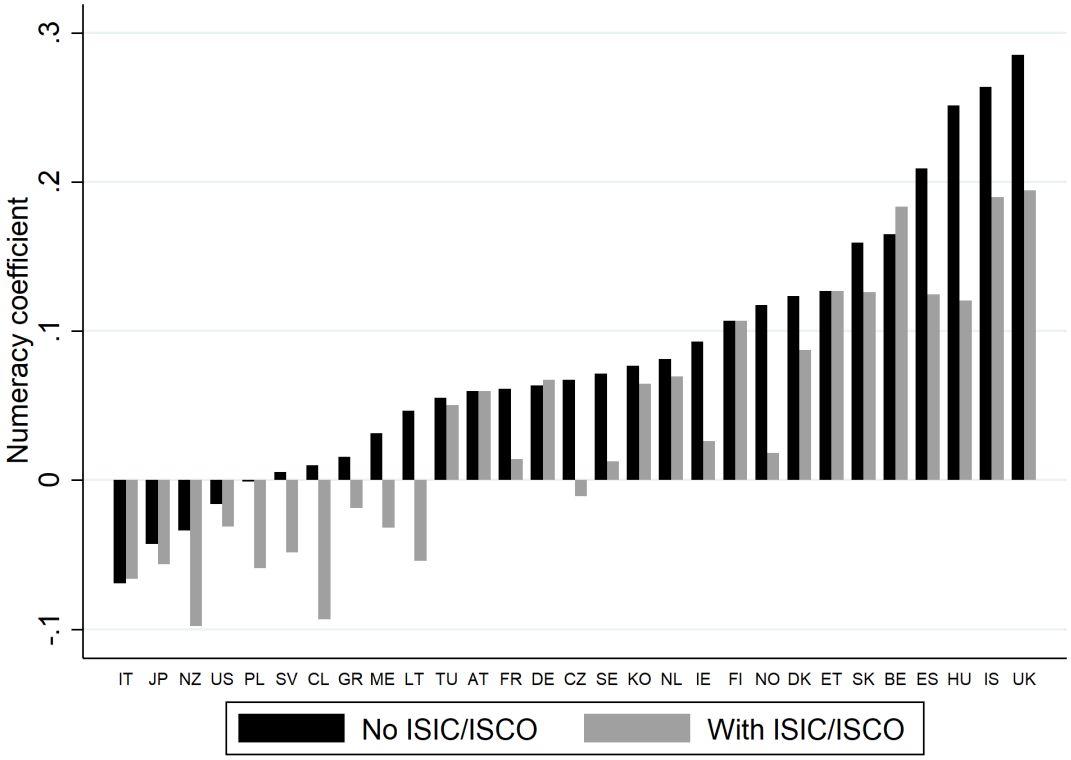

**Notes:** The figure shows contractual returns to the comparative advantage in numeracy over literacy skills. Comparative advantages are calculated at the individual level by subtracting the literacy score from the numeracy score.

Figure A6: Estimates by country: plausible values



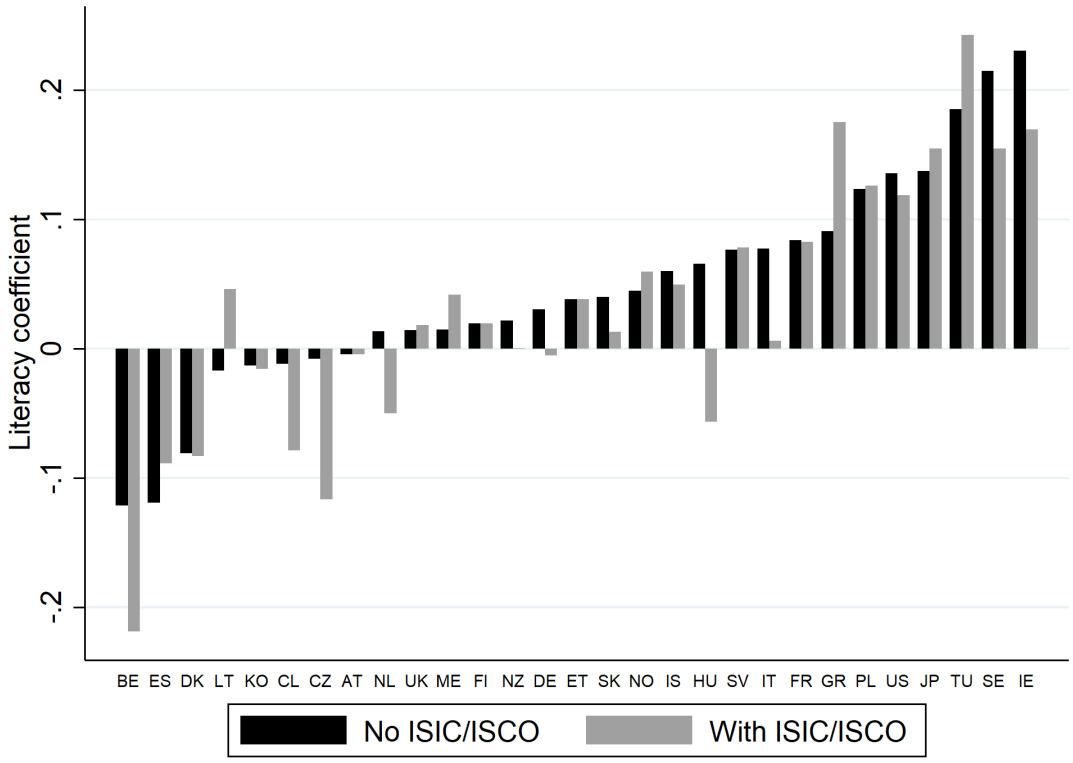

**Notes:** The figure shows estimates for the effect of numeracy skills and literacy skills on the odds of permanent contract status per country (logit), where skills are measured by PIAAC's first plausible value.

Figure A7: Country estimates with and without ISCO/ISIC controls: numeracy



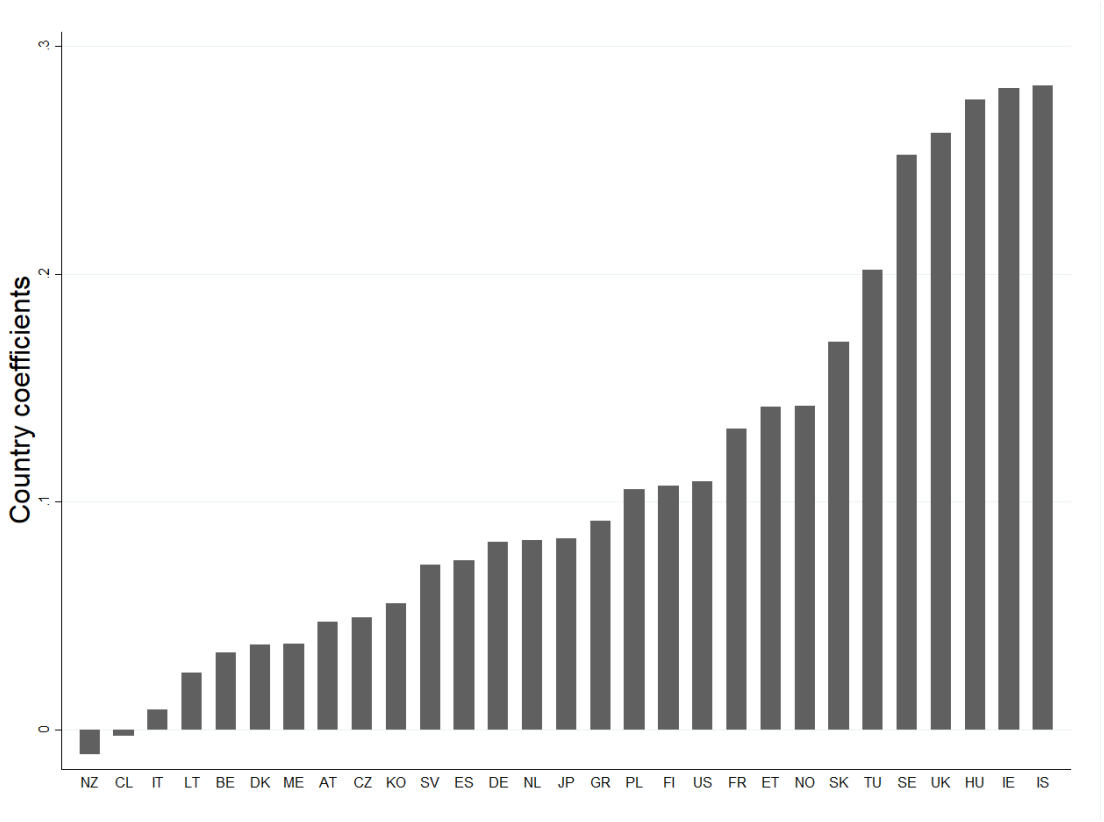

**Notes:** The figure shows a comparison of estimates with and without ISIC and ISCO fixed effects for the contractual return to numeracy skills.

Figure A8: Country estimates with and without ISCO/ISIC controls: literacy



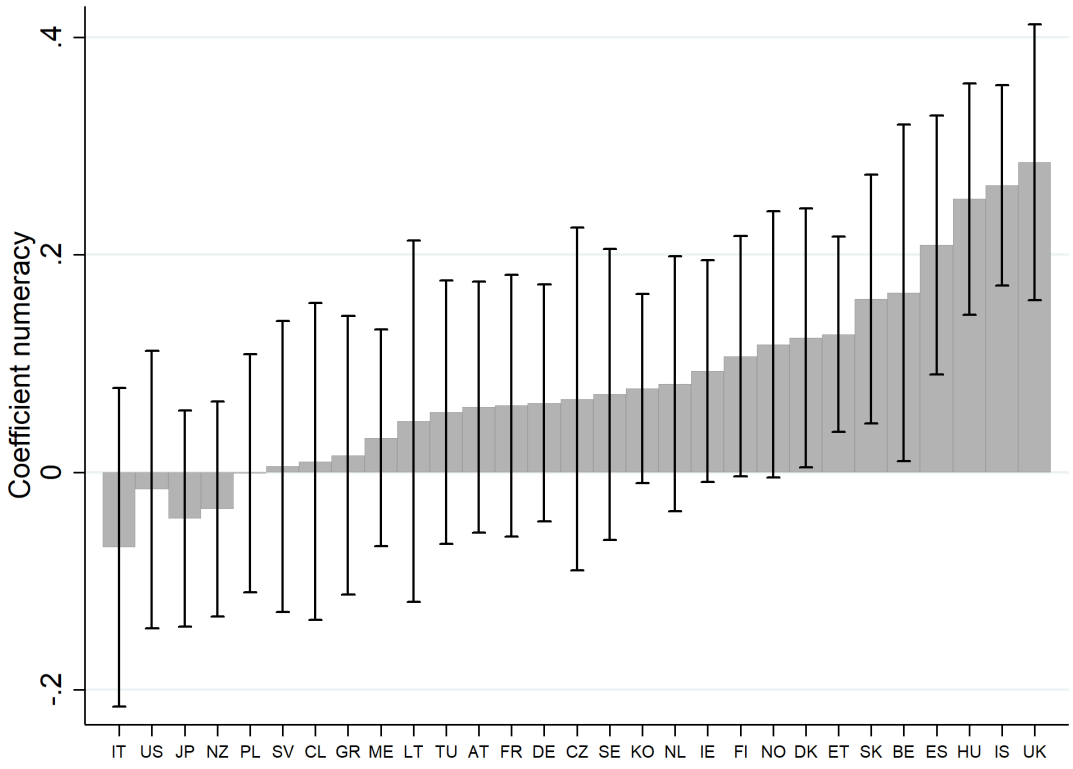

**Notes:** The figure shows a comparison of estimates with and without ISIC and ISCO fixed effects for the contractual return to literacy skills.

Figure A9: Country estimates for overall skill level



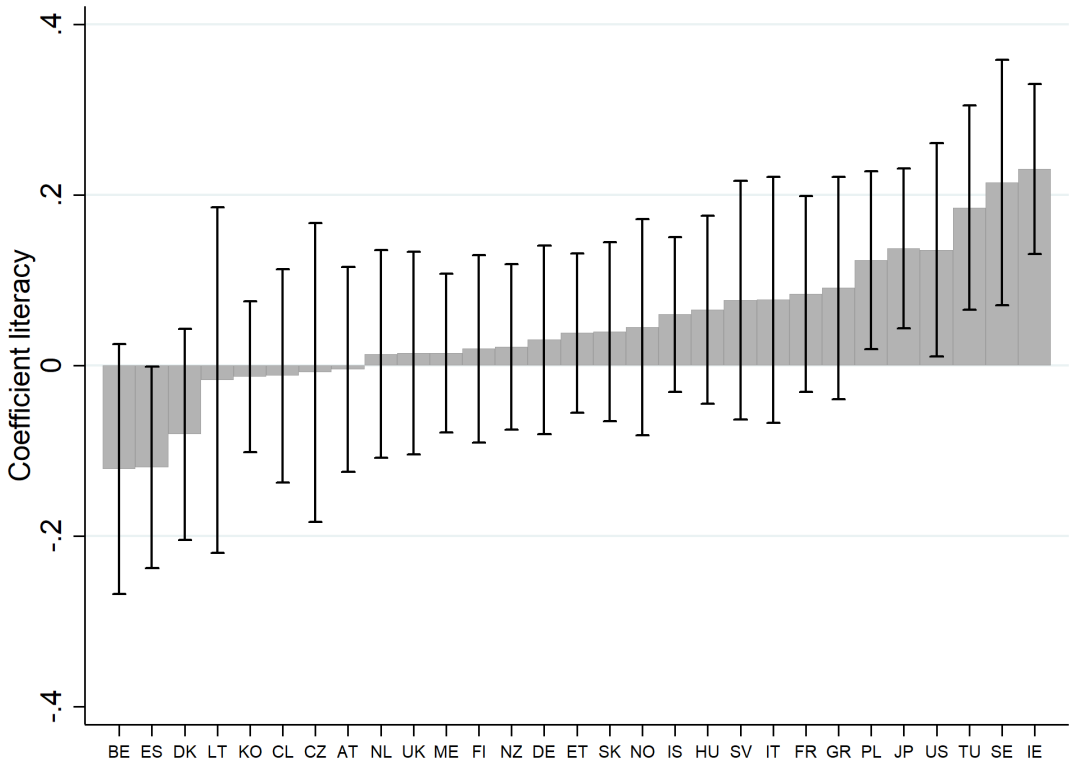

**Notes:** The figure shows the contractual return to overall skill levels. Overall skill levels take the average of literacy and numeracy scores.

Figure A10: Country estimates with confidence interval: numeracy




**Notes:** The figure shows country-specific estimates of the contractual return to numeracy skills, including 95% confidence intervals.

Figure A11: Country estimates with confidence interval: literacy




**Notes:** The figure shows country-specific estimates of the contractual return to literacy skills, including 95% confidence intervals.

Table A1: Summary statistics

| | Mean | Std. dev. |
|---|---|---|
| Permanent contract | 0.769 | 0.422 |
| Numeracy | 0 | 1.000 |
| Literacy | 0 | 1.000 |
| Age | 39.94 | 10.89 |
| Female | 0.473 | 0.499 |
| Native | 0.817 | 0.387 |
| First gen. immigrant | 0.097 | 0.296 |
| Second gen. immigrant | 0.086 | 0.281 |
| Experience | 17.97 | 11.13 |
| Education yrs | 12.99 | 2.99 |
| N | 82,440 | |

**N**ote: Summary statistics for the main estimation sample (age 18-60, excluding self-employed and those still in education). Statistics pertain to the pooled sample including 29 countries. Numeracy and literacy scores are set at mean zero and standard deviation 1 within each country by construction. Source: own calculations based on PIAAC.

Table A2: Summary statistics by country: individual-level variables

| Country | Permanent contract | Numeracy score | Literacy score | Score correlation | Age | Female | Native | Years of experience | Years of schooling | N |
|---|---|---|---|---|---|---|---|---|---|---|
| Austria | 0.85 | 0.34 | 0.15 | 0.54 | 38.20 | 0.50 | 0.78 | 17.82 | 12.45 | 3,137 |
| Belgium | 0.92 | 0.30 | 0.26 | 0.55 | 40.56 | 0.49 | 0.88 | 19.14 | 12.98 | 2,762 |
| Chile | 0.66 | -0.76 | -0.70 | 0.48 | 39.26 | 0.51 | 0.96 | 14.07 | 12.06 | 2,166 |
| Czech Republic | 0.80 | 0.30 | 0.13 | 0.50 | 39.13 | 0.51 | 0.89 | 17.35 | 13.74 | 2,620 |
| Denmark | 0.88 | 0.39 | 0.18 | 0.54 | 44.09 | 0.52 | 0.78 | 23.39 | 13.50 | 3,893 |
| Estonia | 0.87 | 0.21 | 0.14 | 0.50 | 41.23 | 0.56 | 0.67 | 19.45 | 12.63 | 4,063 |
| Finland | 0.86 | 0.49 | 0.51 | 0.48 | 41.86 | 0.51 | 0.95 | 18.92 | 13.35 | 2,928 |
| France | 0.87 | 0.04 | 0.03 | 0.64 | 41.58 | 0.50 | 0.80 | 19.61 | 12.04 | 3.694 |
| Germany | 0.75 | 0.34 | 0.19 | 0.54 | 38.89 | 0.50 | 0.71 | 17.10 | 12.79 | 3,431 |
| Greece | 0.65 | 0.02 | -0.10 | 0.44 | 39.72 | 0.49 | 0.89 | 15.32 | 13.30 | 1,435 |
| Hungary | 0.77 | 0.04 | -0.13 | 0.54 | 41.08 | 0.49 | 0.95 | 18.69 | 11.81 | 3,331 |
| Ireland | 0.71 | 0.11 | 0.21 | 0.50 | 39.29 | 0.55 | 0.78 | 17.81 | 15.90 | 2,710 |
| Israel | 0.53 | -0.07 | -0.13 | 0.55 | 37.13 | 0.48 | 0.43 | 15.94 | 13.19 | 2,631 |
| Italy | 0.81 | -0.04 | -0.17 | 0.56 | 41.43 | 0.47 | 0.89 | 17.56 | 12.43 | 2,073 |
| Japan | 0.80 | 0.57 | 0.57 | 0.44 | 40.97 | 0.48 | 0.99 | 17.94 | 13.63 | 3,055 |
| Korea | 0.52 | 0.05 | 0.11 | 0.55 | 39.71 | 0.46 | 0.97 | 12.91 | 13.63 | 2,966 |
| Lithuania | 0.91 | 0.19 | -0.03 | 0.56 | 42.16 | 0.61 | 0.90 | 19.16 | 14.13 | 2,594 |
| Mexico | 0.51 | -0.72 | -0.62 | 0.35 | 36.63 | 0.40 | 0.99 | 14.05 | 11.07 | 2,255 |
| Netherlands | 0.83 | 0.40 | 0.38 | 0.55 | 42.12 | 0.51 | 0.87 | 20.73 | 13.73 | 2,785 |
| New Zealand | 0.73 | 0.16 | 0.23 | 0.58 | 37.19 | 0.55 | 0.60 | 17.15 | 13.87 | 3,351 |
| Norway | 0.88 | 0.43 | 0.34 | 0.54 | 40.99 | 0.49 | 0.84 | 19.23 | 14.86 | 3,047 |
| Poland | 0.56 | 0.06 | 0.07 | 0.45 | 33.33 | 0.42 | 0.97 | 11.42 | 13.32 | 3,268 |
| Slovak Republic | 0.81 | 0.31 | 0.16 | 0.47 | 40.68 | 0.50 | 0.93 | 18.73 | 13.63 | 2,590 |
| Slovenia | 0.87 | 0.05 | -0.20 | 0.53 | 41.63 | 0.49 | 0.79 | 19.50 | 10.94 | 2,534 |
| Spain | 0.73 | -0.16 | -0.20 | 0.65 | 40.44 | 0.48 | 0.86 | 17.17 | 12.22 | 2,507 |
| Sweden | 0.86 | 0.47 | 0.44 | 0.54 | 41.47 | 0.50 | 0.76 | 19.36 | 13.00 | 2,578 |
| Turkey | 0.53 | -0.24 | -0.41 | 0.40 | 36.07 | 0.26 | 0.97 | 12.08 | 10.12 | 1,505 |
| United Kingdom | 0.81 | 0.16 | 0.21 | 0.57 | 40.29 | 0.59 | 0.80 | 19.85 | 13.51 | 4,477 |
| United States | 0.37 | -0.08 | 0.13 | 0.59 | 38.11 | 0.51 | 0.78 | 18.57 | 14.13 | 1,853 |
| Total | 0.76 | 0.15 | 0.09 | 0.53 | 39.97 | 0.50 | 0.83 | 17.88 | 13.09 | 82,239 |

Note: All values are weighted by PIAAC's sampling weights. 'Score correlation' measures the correlation between literacy and numeracy scores within the country.

Table A3: Summary statistics by country: Macro variables

| CNT | Pred. numeracy | Pred. literacy | Pred. skill | GDP | Unempl. rate | Invol. PT empl. | CBA coverage | Public employm. | EPL temp | EPL regular | Public educ exp. | Private educ exp. | Social spending | Tax wedge |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | -0.00 | -0.01 | -0.00 | 50,287 | 0.03 | 9.68 | 98.00 | 16.79 | 1.47 | 2.29 | 2.99 | 0.21 | 13.55 | 48.84 |
| BE | 0.02 | 0.02 | 0.02 | 45,037 | 0.02 | 9.28 | 96.00 | 18.68 | 1.91 | 1.69 | 4.18 | 0.33 | 18.46 | 55.99 |
| CL | -0.10 | -0.09 | -0.09 | 22,413 | 0.04 | 49.47 | 18.10 | - | 2.07 | 2.67 | 2.46 | 2.11 | 7.42 | 7.00 |
| CZ | 0.01 | -0.01 | -0.00 | 31,579 | 0.05 | 20.86 | 33.90 | 16.03 | 2.01 | 3.26 | 2.49 | 0.50 | 11.04 | 42.45 |
| DK | 0.02 | 0.03 | 0.03 | 47,496 | 0.05 | 16.85 | 76.60 | 29.71 | 1.49 | 1.53 | 4.51 | 0.23 | 20.51 | 36.16 |
| ET | -0.00 | -0.01 | -0.01 | 27,205 | 0.06 | 18.98 | 23.00 | 23.27 | 2.49 | 1.81 | 3.13 | 0.29 | 9.08 | 40.41 |
| FI | 0.01 | 0.01 | 0.01 | 43,327 | 0.04 | 21.09 | 89.70 | 24.64 | 1.62 | 2.08 | 3.89 | 0.10 | 16.68 | 42.49 |
| FR | 0.00 | 0.01 | 0.01 | 40,332 | 0.07 | 29.13 | 98.00 | 21.96 | 2.69 | 2.50 | 3.44 | 0.63 | 17.21 | 50.10 |
| DE | 0.00 | 0.00 | 0.00 | 46,412 | 0.04 | 14.44 | 58.30 | 10.86 | 1.56 | 2.60 | 2.73 | 0.60 | 14.36 | 49.65 |
| GR | -0.01 | -0.00 | -0.01 | 26,637 | 0.14 | 66.43 | 21.90 | 17.93 | 2.33 | 2.45 | 2.68 | 0.31 | 8.85 | 40.19 |
| HU | -0.00 | -0.01 | -0.00 | 28,724 | 0.03 | 24.00 | 22.80 | 20.55 | 1.60 | 1.59 | 2.61 | 0.57 | 10.70 | 46.15 |
| IE | 0.02 | 0.03 | 0.02 | 51,229 | 0.09 | 37.20 | 32.50 | 16.08 | 0.86 | 1.23 | 4.14 | 0.41 | 17.31 | 33.02 |
| IS | 0.05 | 0.06 | 0.05 | 35,389 | 0.04 | 13.99 | 26.10 | 20.04 | 1.48 | 2.37 | 3.98 | 1.25 | 10.03 | 21.07 |
| IT | -0.05 | -0.05 | -0.05 | 37,637 | 0.09 | 57.07 | 80.00 | 13.88 | 2.25 | 3.02 | 2.77 | 0.44 | 11.41 | 47.72 |
| JP | -0.01 | -0.01 | -0.01 | 39,235 | 0.02 | 25.32 | 17.50 | 6.07 | 1.27 | 1.37 | 2.64 | 1.20 | 10.64 | 31.27 |
| KO | -0.01 | -0.01 | -0.01 | 35,189 | 0.03 | - | 13.20 | 7.65 | 2.21 | 2.42 | 3.05 | 1.59 | 6.01 | 20.53 |
| LT | -0.01 | -0.02 | -0.02 | 27,998 | 0.08 | 29.44 | 7.10 | - | 2.63 | 2.63 | 2.47 | 0.46 | 8.58 | 40.98 |
| ME | -0.09 | -0.09 | -0.09 | 18,946 | 0.03 | - | 13.80 | 12.62 | 2.00 | 2.15 | 2.83 | 0.72 | 4.82 | 18.13 |
| NL | 0.02 | 0.03 | 0.03 | 49,231 | 0.04 | 8.16 | 85.10 | 12.83 | 1.25 | 3.24 | 3.21 | 0.97 | 11.76 | 38.62 |
| NZ | 0.00 | 0.01 | 0.00 | 36,427 | 0.06 | 22.51 | 15.30 | - | 1.02 | 1.64 | 3.91 | 1.37 | 14.67 | 17.25 |
| NO | 0.02 | 0.02 | 0.02 | 59,408 | 0.03 | 13.06 | 73.10 | 30.30 | 2.72 | 2.33 | 4.61 | 0.06 | 13.95 | 37.41 |
| PL | 0.00 | -0.01 | -0.00 | 24,300 | 0.07 | 34.85 | 17.70 | 16.69 | 1.77 | 2.33 | 3.12 | 0.55 | 8.90 | 35.51 |
| SK | -0.00 | -0.02 | -0.01 | 27,633 | 0.07 | 63.52 | 35.00 | 19.15 | 2.02 | 2.38 | 2.31 | 0.57 | 10.08 | 39.80 |
| SV | 0.01 | -0.00 | 0.01 | 30,970 | 0.08 | 8.38 | 69.20 | 17.58 | 2.09 | 2.08 | 3.15 | 0.48 | 11.60 | 42.51 |
| ES | -0.04 | -0.03 | -0.03 | 33,407 | 0.14 | 62.93 | 70.00 | 16.26 | 2.50 | 2.21 | 2.77 | 0.69 | 14.57 | 40.62 |
| SE | 0.03 | 0.03 | 0.03 | 46,569 | 0.05 | 27.66 | 88.10 | 28.63 | 1.55 | 2.45 | 3.65 | 0.17 | 16.83 | 42.86 |
| TU | -0.03 | -0.03 | -0.03 | 24,700 | 0.04 | 8.70 | 6.60 | 11.09 | 3.72 | 2.98 | 2.54 | 1.33 | 4.51 | 38.09 |
| UK | 0.03 | 0.04 | 0.04 | 40,731 | 0.06 | 17.75 | 29.30 | 17.95 | 0.41 | 1.51 | 3.70 | 1.44 | 16.36 | 32.09 |
| US | 0.00 | 0.01 | 0.01 | 58,198 | 0.04 | 6.32 | 11.60 | 15.15 | 0.27 | 0.09 | 3.24 | 1.98 | 11.34 | 31.78 |
| Total | 0.00 | 0.00 | 0.00 | 38,038 | 0.06 | 25.13 | 47.29 | 18.24 | 1.78 | 2.13 | 3.28 | 0.72 | 12.59 | 37.16 |

Table A4: The relation between skills and job security: by age

| | 35 years and under | | | Over 35 | | |
|---|---|---|---|---|---|---|
| | (4) | (5) | (6) | (4) | (5) | (6) |
| Numeracy | 0.103*** | 0.059*** | 0.037* | 0.196*** | 0.105*** | 0.062*** |
| | (0.020) | (0.020) | (0.021) | (0.017) | (0.018) | (0.018) |
| Literacy | 0.037* | 0.024 | 0.015 | 0.115*** | 0.075*** | 0.057*** |
| | (0.020) | (0.020) | (0.021) | (0.017) | (0.018) | (0.018) |
| Age | 0.268*** | 0.124*** | 0.122*** | 0.098*** | 0.023 | 0.040* |
| | (0.017) | (0.019) | (0.019) | (0.020) | (0.022) | (0.022) |
| Age sq | -0.007*** | -0.005*** | -0.004*** | -0.001*** | -0.001** | -0.001*** |
| | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| Female | -0.128*** | -0.117*** | -0.055 | -0.248*** | -0.094*** | -0.090** |
| | (0.033) | (0.033) | (0.039) | (0.029) | (0.031) | (0.036) |
| 1st gen migrant | -0.223*** | -0.065 | -0.056 | -0.283*** | -0.164*** | -0.092* |
| | (0.060) | (0.061) | (0.062) | (0.054) | (0.055) | (0.055) |
| 2nd gen migrant | -0.092 | -0.058 | -0.100 | -0.015 | -0.003 | -0.030 |
| | (0.061) | (0.062) | (0.065) | (0.056) | (0.057) | (0.057) |
| Experience | - | 0.206*** | 0.196*** | - | 0.091*** | 0.083*** |
| | | (0.012) | (0.012) | | (0.007) | (0.007) |
| Exper. sq. | - | -0.006*** | -0.006*** | - | -0.001*** | -0.001*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Yrs of schooling | - | 0.078*** | 0.071*** | - | 0.087*** | 0.038*** |
| | | (0.008) | (0.009) | | (0.006) | (0.007) |
| N | 30019 | 30019 | 30019 | 52220 | 52220 | 52220 |
| Pseudo-$R^2$ | 0.112 | 0.133 | 0.160 | 0.127 | 0.152 | 0.176 |

**N**ote: Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). A logit specification is applied. Column labels (3), (4) and (5) refer to the models defined in Table 2. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A5: The relation between skills and job security: subgroup heterogeneity

| | Women | Migrant | High Educ | Part-time |
|---|---|---|---|---|
| Numeracy baseline | 0.111*** | 0.077*** | 0.094*** | 0.102*** |
| | (0.018) | (0.015) | (0.018) | (0.015) |
| Numeracy interaction | -0.061** | 0.025 | 0.025 | -0.099*** |
| | (0.026) | (0.034) | (0.026) | (0.030) |
| Literacy baseline | 0.084*** | 0.044*** | 0.037** | 0.056*** |
| | (0.018) | (0.015) | (0.018) | (0.015) |
| Literacy interaction | -0.078*** | 0.023 | 0.015 | -0.038 |
| | (0.026) | (0.034) | (0.026) | (0.031) |

**N**ote: The table reports baseline estimates as well as interactions with subgroup indicators, for both numeracy and literacy. Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). A logit specification is applied. All models include demographic controls and human capital controls. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A6: Correlation matrix country coefficients (overall skill)

| | Main | Main w/s | Wage | Main young | Main old | Wage young | Wage old |
|---|---|---|---|---|---|---|---|
| Main | 1 | | | | | | |
| Main with sorting | 0.92*** | 1 | | | | | |
| Wage return | 0.43** | 0.35* | 1 | | | | |
| Main young | 0.52*** | 0.44** | 0.21 | 1 | | | |
| Main old | 0.79*** | 0.72*** | 0.31 | 0.17 | 1 | | |
| Wage return young | 0.45** | 0.37* | 0.68*** | 0.57*** | 0.25 | 1 | |
| Wage return old | 0.11 | 0.09 | 0.68*** | -0.03 | -0.10 | 0.37** | 1 |

**N**ote: The table reports correlations between the country coefficients of the different returns to (overall) skill specifications. Country-level estimates pertain respectively to the main approach (column (5) in table 1), the model that corrects for ISIC/ISCO fixed effects (column (6) in Table 1), wage returns to skills, contractual returns for those under 35 (young) and over 35 (old), and wage returns for those under 35 and over 35.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A7: Correlation matrix country coefficients (numeracy skill)

| | Main | Main w/s | Wage | Main young | Main old | Wage young | Wage old |
|---|---|---|---|---|---|---|---|
| Main | 1 | | | | | | |
| Main with sorting | 0.95*** | 1 | | | | | |
| Wage return | 0.34* | 0.38** | 1 | | | | |
| Main young | 0.74*** | 0.72*** | 0.26 | 1 | | | |
| Main old | 0.67*** | 0.65*** | 0.19 | 0.04 | 1 | | |
| Wage return young | 0.62*** | 0.62*** | 0.76*** | 0.57*** | 0.29 | 1 | |
| Wage return old | 0.02 | 0.07 | 0.86*** | -0.04 | 0.05 | 0.35* | 1 |

**N**ote: The table reports correlations between the country coefficients of the different returns to (numeracy) skill specifications. Country-level estimates pertain respectively to the main approach, the model that corrects for ISIC/ISCO fixed effects, wage returns to skills, contractual returns for those under 35 (young) and over 35 (old), and wage returns for those under 35 and over 35.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A8: Correlation matrix country coefficients (literacy skill)

| | Main | Main w/s | Wage | Main young | Main old | Wage young | Wage old |
|---|---|---|---|---|---|---|---|
| Main | 1 | | | | | | |
| Main with sorting | 0.95*** | 1 | | | | | |
| Wage return | 0.11 | 0.04 | 1 | | | | |
| Main young | 0.64*** | 0.61*** | 0. | 1 | | | |
| Main old | 0.76*** | 0.73*** | -0.04 | 0.03 | 1 | | |
| Wage return young | 0.18 | 0.09 | 0.50*** | 0.27 | 0.01 | 1 | |
| Wage return old | 0.05 | 0.01 | 0.85*** | 0.06 | -0.04 | 0.06 | 1 |

**N**ote: The table reports correlations between the country coefficients of the different returns to (literacy) skill specifications. Country-level estimates pertain respectively to the main approach, the model that corrects for ISIC/ISCO fixed effects, wage returns to skills, contractual returns for those under 35 (young) and over 35 (old), and wage returns for those under 35 and over 35.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A9: Explaining country differences: institutions (>35 sample)

| | Overall skill return | Relative skill return |
|---|---|---|
| Unemployment rate | 0.117 | 0.161 |
| | (0.272) | (0.249) |
| Involuntary part-time employment | -0.113 | -0.005 |
| | (0.285) | (0.261) |
| GDP per capita | 0.086 | -0.234 |
| | (0.237) | (0.217) |
| Collective bargaining coverage | -0.737*** | -0.537*** |
| | (0.219) | (0.172) |
| Public employment rate | 0.520*** | 0.530*** |
| | (0.174) | (0.137) |
| EPL temporary workers | -0.195 | 0.117 |
| | (0.188) | (0.147) |
| EPL regular workers | 0.367* | 0.282* |
| | (0.184) | (0.144) |
| GDP per capita | 0.355 | -0.068 |
| | (0.213) | (0.167) |
| Public education spending | 0.211 | 0.199 |
| | (0.376) | (0.280) |
| Private education spending | -0.100 | -0.430* |
| | (0.310) | (0.235) |
| Social spending (non-elderly) | -0.432 | -0.730** |
| | (0.356) | (0.309) |
| Average tax rate | 0.261 | 0.266 |
| | (0.363) | (0.271) |
| GDP per capita | 0.197 | -0.068 |
| | (0.306) | (0.228) |

**N**ote: Outcome variables are either the country-specific return to the overall skills ('Overall skill return') or the difference between contractual and wage returns to overall skills ('Relative skill return'). Social expenditure excludes old age and survivor benefits. See the appendix for more details on the independent variables. All outcome variables and independent variables are standardized with mean 0 and standard deviation 1. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A10: Explaining country differences: institutions (>35 sample)

| | Overall | Rel CW | | Overall | Rel CW | | Overall | Rel CW |
|---|---|---|---|---|---|---|---|---|
| Unempl. | 0.117 | 0.161 | Coll. barg. | -0.737*** | -0.537*** | Pub. educ. | 0.211 | 0.199 |
| | (0.272) | (0.249) | | (0.219) | (0.172) | | (0.376) | (0.280) |
| Invol. PT | -0.113 | -0.005 | Pub. empl. | 0.520*** | 0.530*** | Priv. educ | -0.100 | -0.430* |
| | (0.285) | (0.261) | | (0.174) | (0.137) | | (0.315) | (0.235) |
| | | | EPL temp. | -0.195 | 0.117 | Soc. exp. | -0.432 | -0.730** |
| | | | | (0.188) | (0.147) | | (0.356) | (0.309) |
| | | | EPL reg. | 0.367* | 0.282* | Tax | 0.261 | 0.266 |
| | | | | (0.184) | (0.144) | | (0.363) | (0.271) |
| GDP/c | 0.086 | -0.234 | | 0.355 | -0.068 | | 0.197 | -0.068 |
| | (0.237) | (0.217) | | (0.213) | (0.167) | | (0.306) | (0.228) |

**N**ote: Outcome variables are either the country-specific return to the overall skills ('Overall') or the difference between contractual and wage returns to overall skills ('Rel CW'). 'Invol PT' refers to involuntary part-time employment. Social expenditure excludes old age and survivor benefits. See the appendix for more details on the independent variables. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A11: The relation between skills and job security: all contract statuses

| | Fixed-term | Agency | No contract | Other |
|---|---|---|---|---|
| Base model | | | | |
| Numeracy | -0.069*** | -0.070* | -0.090*** | 0.009 |
| | (0.016) | (0.036) | (0.022) | (0.040) |
| Literacy | -0.014 | -0.074** | -0.079*** | -0.076* |
| | (0.016) | (0.035) | (0.022) | (0.041) |
| N | 82,239 | 80,734 | 82,239 | 82,239 |
| Pseudo-$R^2$ | 0.059 | 0.169 | 0.323 | 0.141 |
| ISIC/ISCO FE | | | | |
| Numeracy | -0.046*** | -0.052 | -0.052** | 0.041 |
| | (0.016) | (0.036) | (0.023) | (0.040) |
| Literacy | -0.007 | -0.048 | -0.052** | -0.069* |
| | (0.016) | (0.035) | (0.023) | (0.042) |
| N | 82,169 | 79,453 | 82,004 | 80,358 |
| Pseudo-$R^2$ | 0.088 | 0.214 | 0.366 | 0.186 |
| Mean prevalence | 0.126 | 0.022 | 0.073 | 0.016 |

**N**ote: The table reports results for the main model specification (including the full set of controls), separately for all types of temporary employment status. Outcome variable takes value 1 for the specified contract status, and 0 otherwise. "Agency" combines apprenticeships and temp agency work. The lower panel adds ISIC and ISCO fixed effects. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A12: The relation between skills and job security: other age ranges

| | 18-60 | 18-55 | 25-60 | 25-55 | 30-55 |
|---|---|---|---|---|---|
| Base model | | | | | |
| Numeracy | 0.083*** | 0.083*** | 0.105*** | 0.108*** | 0.105*** |
| | (0.013) | (0.014) | (0.014) | (0.015) | (0.017) |
| Literacy | 0.049*** | 0.047*** | 0.050*** | 0.047*** | 0.063*** |
| | (0.013) | (0.014) | (0.014) | (0.015) | (0.016) |
| N | 82239 | 74321 | 74278 | 66360 | 57171 |
| Pseudo-$R^2$ | 0.152 | 0.153 | 0.134 | 0.134 | 0.139 |
| ISIC/ISCO FE | | | | | |
| Numeracy | 0.046*** | 0.048*** | 0.062*** | 0.066*** | 0.061*** |
| | (0.014) | (0.014) | (0.015) | (0.015) | (0.017) |
| Literacy | 0.032** | 0.029** | 0.028** | 0.024 | 0.041** |
| | (0.013) | (0.014) | (0.014) | (0.015) | (0.017) |
| N | 82,214 | 74,288 | 74,231 | 66,308 | 57,095 |
| Pseudo-$R^2$ | 0.182 | 0.183 | 0.166 | 0.166 | 0.173 |

**N**ote: The table reports results for the main model (including the full set of controls), for different age ranges. The lower panel adds ISIC and ISCO fixed effects. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A13: The relation between skills and job security: using plausible values

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Numeracy | 0.261*** | 0.220*** | 0.189*** | 0.108*** | 0.057** | 0.052** |
| | (0.020) | (0.021) | (0.021) | (0.022) | (0.022) | (0.022) |
| Literacy | 0.004 | 0.069*** | 0.088*** | 0.057*** | 0.044** | 0.042* |
| | (0.021) | (0.021) | (0.022) | (0.022) | (0.022) | (0.022) |
| Age | | 0.138*** | 0.140*** | 0.047*** | 0.046*** | 0.043*** |
| | | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) |
| Age sq | | -0.002*** | -0.002*** | -0.001*** | -0.001*** | -0.001*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Female | | | -0.188*** | -0.101*** | -0.078*** | -0.074*** |
| | | | (0.022) | (0.023) | (0.026) | (0.027) |
| 1st gen migrant | | | -0.165*** | -0.074* | -0.051 | -0.077* |
| | | | (0.040) | (0.041) | (0.042) | (0.042) |
| 2nd gen migrant | | | -0.037 | -0.022 | -0.056 | -0.065 |
| | | | (0.041) | (0.042) | (0.043) | (0.043) |
| Experience | | | | 0.114*** | 0.112*** | 0.113*** |
| | | | | (0.005) | (0.005) | (0.005) |
| Exper. sq. | | | | -0.001*** | -0.002*** | -0.002*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Yrs of schooling | | | | 0.074*** | 0.051*** | 0.047*** |
| | | | | (0.005) | (0.005) | (0.005) |
| N | 82,231 | 82,231 | 82,231 | 82,231 | 82,231 | 82,206 |
| Pseudo-$R^2$ | 0.097 | 0.131 | 0.133 | 0.153 | 0.175 | 0.182 |

**N**ote: Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). Skills are measured by taking PIAAC's first plausible value. A logit specification is applied. Column (6) adds fixed effects for ISIC and ISCO at the one-digit level. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A14: Instrumental variable estimation

| | OLS no HC | OLS Main | YoS | Avg YoS | Par. educ | Nr books |
|---|---|---|---|---|---|---|
| Skills | 0.032*** | 0.017*** | 0.121*** | 0.471*** | 0.070*** | 0.025** |
| | (0.002) | (0.002) | (0.005) | (0.091) | (0.016) | (0.010) |
| N | 82,239 | 82,239 | 82,239 | 82,239 | 78,227 | 81,676 |
| Fstat | | | 9464.07 | 47.51 | 689.50 | 1824.85 |

**N**ote: The table reports coefficients for an OLS model without educational attainment and experience controls, an OLS model with educational attainment and experience controls, and four IV specifications. Instruments are: years of schooling, average years of schooling by country and age cohort, parental years of schooling, and number of books present at age 16. Standard errors are robust. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A15: The relation between skills and job security: OLS model

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Numeracy | 0.034*** | | 0.029*** | 0.024*** | 0.012*** | 0.007*** |
| | (0.002) | | (0.002) | (0.002) | (0.002) | (0.002) |
| Literacy | | 0.025*** | 0.009*** | 0.013*** | 0.007*** | 0.005*** |
| | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Age | | | | 0.026*** | 0.008*** | 0.008*** |
| | | | | (0.001) | (0.001) | (0.001) |
| Age sq | | | | -0.000*** | -0.000*** | -0.000*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Female | | | | -0.029*** | -0.016*** | -0.011*** |
| | | | | (0.003) | (0.003) | (0.004) |
| 1st gen migrant | | | | -0.036*** | -0.016** | -0.008 |
| | | | | (0.007) | (0.006) | (0.006) |
| 2nd gen migrant | | | | -0.004 | -0.001 | -0.005 |
| | | | | (0.006) | (0.006) | (0.006) |
| Experience | | | | | 0.020*** | 0.019*** |
| | | | | | (0.001) | (0.001) |
| Exper. sq. | | | | | -0.000*** | -0.000*** |
| | | | | | (0.000) | (0.000) |
| Yrs of schooling | | | | | 0.014*** | 0.010*** |
| | | | | | (0.001) | (0.001) |
| ISIC-1/ISCO-1 | | | | | | X |
| N | 82,239 | 82,239 | 82,239 | 82,239 | 82,239 | 82,239 |
| $R^2$ | 0.108 | 0.105 | 0.108 | 0.146 | 0.169 | 0.191 |

**N**ote: Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). A logit specification is applied. Column (6) adds fixed effects for ISIC and ISCO at the one-digit level. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A16: The relation between skills and job security: probit model

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Numeracy | 0.121*** | | 0.104*** | 0.091*** | 0.049*** | 0.028*** |
| | (0.006) | | (0.007) | (0.007) | (0.008) | (0.008) |
| Literacy | | 0.087*** | 0.032*** | 0.046*** | 0.028*** | 0.021*** |
| | | (0.006) | (0.007) | (0.007) | (0.008) | (0.008) |
| Age | | | | 0.083*** | 0.027*** | 0.026*** |
| | | | | (0.002) | (0.004) | (0.004) |
| Age sq | | | | -0.001*** | -0.001*** | -0.001*** |
| | | | | (0.000) | (0.000) | (0.000) |
| Female | | | | -0.111*** | -0.061*** | -0.045*** |
| | | | | (0.012) | (0.013) | (0.015) |
| 1st gen migrant | | | | -0.144*** | -0.078*** | -0.052** |
| | | | | (0.022) | (0.023) | (0.023) |
| 2nd gen migrant | | | | -0.025 | -0.014 | -0.034 |
| | | | | (0.023) | (0.023) | (0.024) |
| Experience | | | | | 0.067*** | 0.065*** |
| | | | | | (0.003) | (0.003) |
| Exper. sq. | | | | | -0.001*** | -0.001*** |
| | | | | | (0.000) | (0.000) |
| Yrs of schooling | | | | | 0.047*** | 0.031*** |
| | | | | | (0.002) | (0.003) |
| ISIC-1/ISCO-1 | | | | | | X |
| N | 82,239 | 82,239 | 82,239 | 82,239 | 82,239 | 82,214 |
| Pseudo-$R^2$ | 0.093 | 0.090 | 0.094 | 0.130 | 0.152 | 0.175 |

**N**ote: Outcome variable is equal to 1 for those on an indefinite contract and 0 otherwise (fixed-term, employment agencies, apprenticeships, no contract or other). A logit specification is applied. Column (6) adds fixed effects for ISIC and ISCO at the one-digit level. Standard errors are robust.
$*p < 0.10, **p < 0.05, ***p < 0.01$