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**Returns to digital skills around the world:
Evidence from PIAAC's Second Cycle (2022-2023)**

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Abstract: Using microdata from the second cycle of the OECD Programme for the International Assessment of Adult Competencies (PIAAC 2022-2023), this paper estimates wage returns to digital skills across twelve countries. Digital skills are measured as the use of ICT at work, and their effects are assessed through Mincer-type earnings regressions estimated separately for entry-(25-34), prime-(35-54), and exit-age (55-65) workers, controlling for education, experience, gender, and cognitive skills (i.e., literacy, numeracy, and adaptive problem solving).

Results show that ICT use is positively and significantly associated with earnings in most countries, with returns ranging from 3 to 16 per cent – comparable to, and in many cases exceeding, those of formal education. Returns to ICT use persist across the life course, while numeracy remains the strongest cognitive predictor of wages. Cross-country patterns suggest complementarity between ICT use and education returns, but variation in their link with numeracy. These findings highlight digital skills as a distinct form of human capital and a key source of emerging digital inequality.

Keywords: digital skills; human capital; ICT use; labor markets; PIAAC; wage returns; digital divide; digital inequality

JEL codes: J24, J31, I26, O33

1. Introduction

A lot of research in economics concentrates on evaluating returns to education and skills using the Mincer-type earnings model. Nowadays, not only the generic literacy or numeracy skills are important on the labour market, but also the ICT skills that are more and more often evaluated in large-scale surveys. The ICT skills are related to the concept of digital divide that emerged in the early 1990s as a binary division between those with and without Internet access (Dewan & Riggins, 2005; Hoffman et al., 2000). Soon it became clear that this was “a complex and dynamic phenomenon” (J. Van Dijk & Hacker, 2003), see also (Bruno et al., 2011; Shakina et al., 2021). The notion evolved to capture broader processes of digital inclusion and exclusion, being redefined as digital inequality (Drabowicz, 2014b, 2017; E. J. Helsper, 2017; Park, 2026) or socio-digital inequalities (E. Helsper, 2021; see also DiMaggio & Hargittai, 2001; van Dijk, 2005; J. A. G. M. Van Dijk, 2006).

Three levels of the digital divide are now widely recognized (DiMaggio et al., 2004; Hargittai, 2008; Lythreathis et al., 2022; Ragnedda & Muschert, 2013; Scheerder et al., 2017; J. Van Dijk, 2010). The first level concerns access to computers and the Internet (E. Helsper, 2021, pp. 32–33; Hilbert, 2016; Newhagen & Bucy, 2005), which has been studied extensively: between 1990 and 2000, it generated over 14,000 publications ((Arquette, 2002 in: Hongladarom, 2004; see also Yu, 2006). Access inequalities by age, gender, socioeconomic status, ethnicity, and geography remain persistent (Castells, 2000; Espín & Rojas, 2024; Mossberger et al., 2003; A. J. Van Deursen & Van Dijk, 2019). The second level highlights disparities in digital skills (Hargittai, 2002), initially measured through self-reports (Hargittai, 2005, 2008, 2009; Hargittai & Hsieh, 2010; Hargittai & Walejko, 2008) and later through direct assessments (Calvani et al., 2012; Gui, 2007; Gui & Argentin, 2011; Pagani et al., 2016; A. J. A. M. Van Deursen et al., 2016; A. J. A. M. Van Deursen & Van Dijk, 2009; A. Van Deursen & Van Dijk, 2011). Large-scale programs such as PISA and PIAAC enabled systematic measurement of digital skills among adolescents and adults (Drabowicz, 2014a, 2021; Gui et al., 2014; Hämäläinen et al., 2014, 2015; OECD, 2014; Palczyńska & Rynko, 2021; Perkins & Shiel, 2014; Zilian & Zilian, 2020). The third level refers to inequalities in the outcomes of technology use, including employment, earnings, education, social engagement, and health (Ragnedda, 2017; Selwyn, 2004; A. J. A. M. Van Deursen & Helsper, 2015; Wei et al., 2011), describing differences in the extent to which people can reap offline benefits from ICT use (Van De Werfhorst et al., 2022) and aligning with Helsper’s definition of digital literacy as the ability to use ICTs to achieve beneficial outcomes (E. Helsper, 2021). To use (Bourdieu, 1986) terms,

one can argue that in this stage one moves from capitals (access, skills) to their conversion – transforming digital resources into economic and social returns (E. J. Helsper, 2012; López-Sintas et al., 2012; Ragnedda, 2018; Ragnedda et al., 2020, 2020; Ragnedda & Ruiu, 2020). The third level thus captures how foundational digital capabilities (Castells, 2004) translate into tangible outcomes such as employment and wages.

Our paper focuses on this third level, treating digital skills as a component of human capital (Becker, 1962; J. Mincer, 1970; J. A. Mincer, 1974) essential for labour-market success. One can argue that skills represent Senian capabilities (Sen, 1992, 1999, 2004) whose returns depend on context (Acemoglu & Autor, 2012; Bowles et al., 2001; Hanushek & Woessmann, 2008; Woessmann, 2025). In this paper, we build on theories of Skill-Biased Technological Change (SBTC) and the Task-Based Approach (TBA) (Akerman et al., 2015; Autor et al., 2003), which posit that technology complements nonroutine, abstract tasks while substituting for routine ones. (Falck et al., 2021) used PIAAC's PS-TRE (problem solving in technology rich environments) measure to demonstrate a causal 24% return to digital skills, largely mediated by occupational sorting into abstract-task jobs. Our study tests the persistence of this mechanism using new PIAAC Cycle 2 measures.

Prior PIAAC studies show high correlations among literacy, numeracy, and digital skills, all predicting earnings although numeracy has the largest impact (Hanushek et al., 2015, 2017; Woessmann, 2025). Average returns to numeracy range from 13% in Norway, Sweden, and Czechia to 47% in Singapore, shaped more by institutional context than by skill inequality. Regarding direct returns to digital skills, (Falck et al., 2021) estimated a 24% international and 31% West German wage premium per one SD increase in PS-TRE, while (De La Rica & Gortazar, 2016) found ICT use explains more wage variance than any other job attribute. (Eden & Gaggl, 2020) and (De La Rica et al., 2020) showed ICT capital mitigates routine-task wage penalties. Longitudinal EU-SILC data (Richiardi et al., 2025) reveal modest but persistent effects of digital skills on earnings: digital competence aids job entry more than retention, supporting the 'conveyor-belt hypothesis' and stressing the need for lifelong up- and re-skilling policies.

In light of the above-mentioned existing literature, in this paper we ask the following research question: To what extent are digital skills rewarded in contemporary labor markets, net of gender, education, experience, and cognitive skills; and how do such returns differ across age cohorts and countries?

2. Conceptual framework

When making the case for their task-based approach to skill-biased technological change (SBTC) (Autor et al., 2003), after empirically analyzing the impact of computerization on the U.S. 1960s-1990s labor market, argued that computers – and the skills needed to work on them – are complementary to high-skilled, non-routine abstract tasks and substitute for routine tasks. This complementarity allowed the high-skilled American workers to select themselves into abstract jobs and to benefit from the higher wages such jobs pay. More recently (Akerman et al., 2015) found similar complementarity of high, abstract skills and broadband uptake in firms when they analyzed the 2000-2008 Norwegian data. A critical finding of (Falck et al., 2021, p. 2) comparative study of the First Round (2011-2012) PIAAC data in 19 countries is showing that occupational selection explains about two-thirds of the wage increase caused by higher digital skills as measured by the older and more narrow PS-TRE index. Our paper directly builds on this finding and advances our knowledge on task-based approach to SBTC.

2.1 From PS-TRE to APS: What Does It Mean and Why Does It Matter?

Problem Solving in Technology Rich Environments (PS-TRE) index, a measure of digital skills developed for and available in the First Cycle of the PIAAC (2011-2018), was conceptually static and narrow. PS-TRE focused on goal setting, monitoring, and planning in technology-rich environments (OECD, 2012) and assessed proficiency in the use of specific digital applications to access, search, manage, interpret, and evaluate information. In short, PS-TRE measured how well people used widely available and already familiar digital applications. Meanwhile, APS “involves the capacity to achieve one’s goals in a dynamic situation, in which a method for solution is not immediately available” (OECD, 2021, p. 157). It shifts the measurement focus to adaptability and cognitive flexibility in unknown and changing circumstances.

Our present study cannot be a simple follow-up of (Falck et al., 2021) for one very simple reason. Although the measures of literacy and numeracy are completely comparable across the First (2011-2018) and the Second (2022-2023) Cycle of the PIAAC, it is not the case with the third domain of cognitive skills. Namely, in the latest PIAAC’s Cycle, the problem solving in technology-rich environments (PS-TRE) scale which could be considered as a direct measurement of one’s digital skills was replaced with direct measures of adaptive problem solving (APS) (OECD, 2024b, p. 37). Even though digital aspects as a mode of problem solving

play an important role in APS, results from its assessment are nevertheless not comparable with results on PS-TRE from the first cycle of the survey (OECD, 2024b, p. 105). The underlying conceptual model for APS was developed by (Greiff et al., 2017). APS “involves the capacity to achieve one’s goals in a dynamic situation, in which a method for solution is not immediately available. It requires engaging in cognitive and metacognitive processes to define the problem, search for information, and apply a solution in a variety of information environments and contexts” (OECD, 2021, p. 159). As such, it can be considered as a measure of an individual’s general ability which is – for all intents and purposes – conceptually, operationally, and psychometrically indistinguishable from the measures of general ability (IQ) known in psychology. Throughout this paper, we will consider APS precisely as such a measure of individual general ability.¹

Estimating the wage effect of a specific skill domain, such as digital skills, is difficult in the Mincerian framework because it is unknown whether a person’s level of digital skills is simply a reflection of general ability, as (Falck et al., 2021, p. 1) rightly note. In their seminal analysis based on self-reported measures of on-the-job computer use coming from the West German *Qualification and Career Survey* and from the U.S. *Current Population Survey* (CPS), (DiNardo & Pischke, 1997, pp. 297–300) concluded that returns to computer use at work are biased by unobserved skills of users. From another analysis of data coming from 21 countries that took part in the first round of PIAAC (2011-2012) we also know that educational attainment (harmonized according to the International Standard Classification of Education, ISCED) cannot be taken as a cross-nationally comparable proxy for human capital in terms of literacy (Massing & Schneider, 2017).

Thus, because the PIAAC’s measures of literacy, numeracy, and APS can be considered as a measure of individual’s general ability, by including them as control variables in our own estimations of wage effects of digital skills on individual earnings we address the “unobserved skills of the users” bias discussed both by (DiNardo & Pischke, 1997) and (Falck et al., 2021). Additionally, our model indirectly tests Richiardi et al.’s (2025) “conveyor belt hypothesis”: do returns to ICT Use at Work (on-the-job practice) decline sharply for older workers (55-65) who may have accumulated obsolete skills? (Such a decline would support the depreciation part of Richiardi et al.’s (2025) hypothesis). These, we argue, are our two major contributions to the literature on the third level of digital divide.

¹ Our interpretation of APS follows OECD’s psychometric rationale, although we acknowledge that this interpretation can be a subject of further debates.

3. The PIAAC data and our empirical model

We use data coming from the Programme for the International Assessment of the Adult Competencies (PIAAC) coordinated by the OECD. The PIAAC population survey was conducted in 31 countries in the years 2022-2023. The 2023 PIAAC is a continuation of the 2011 PIAAC and both surveys are comparable to a big extent – as mentioned above, alas, with the exception of PS-TRE and APS. The conceptual, technical and statistical details of the 2023 PIAAC may be found in the OECD's publications (OECD, 2024a) (OECD, 2024b) (OECD, 2025a) (OECD, 2025b).

We obtained the Public Use Files (PUF) from the OECD website for 30 countries. In the next step we selected these countries for which the information on exact amount of earnings and years of education was available in the datasets. This selection resulted in the subset of nearly 65 thousands respondents interviewed in 12 countries: Chile, Croatia, Czechia, France, Ireland, Israel, Italy, Latvia, Lithuania, New Zealand, Poland and Spain. The exact information on earnings was also available for Estonia, but this country did not provide the information on years of education.

For the remaining 17 countries only the information on the decile of earnings distributions was available in the PUFs. The variable capturing the information on deciles is of ordered character, therefore, instead of a benchmark linear regression model, we should use the ordered logit (or probit) models. The interpretation of the results of such specifications becomes more difficult and not straightforward, therefore we decided to exclude these countries from the analysis.²

For the 12 countries analyzed, we have information on the gender and age of the respondents (exact age or in 10-years age groups), years of education, employment status, labour market experience (measured in years), hours worked, earnings, occupational class, the information on the use of selected skills at work and the directly measured levels of literacy, numeracy, and adaptive problem solving skills. We included only these individuals in the econometric analysis, who are employed at the time of the survey and who work at least 30

² We requested the information on the medians of deciles of earnings distributions for each of these countries from the OECD, which would allow for a linear regression specification. We have not obtained any answer from the OECD before the submission of this paper.

hours per week. The basic descriptive statistics for the variables included in the analysis are presented in Table 1.

Table 1. Descriptive statistics for the analysed PIAAC sample

	Country ID					
	Chile	Croatia	Czechia	France	Ireland	Israel
Observations	1750	1772	2396	2974	1761	2000
Earnings	7976.2 (41691.2)	50.7 (22.7)	208.2 (96.1)	19.1 (15.5)	48.2 (486.3)	734.9 (8110.2)
Years schooling	13.3 (3.3)	13.0 (2.6)	13.8 (2.5)	13.3 (2.8)	16.5 (2.7)	13.9 (2.4)
Experience	16.0 (10.5)	18.8 (10.7)	21.6 (10.7)	20.8 (10.8)	20.8 (11.0)	20.0 (10.6)
Index of use of ICT skills at work	2.2 (1.1)	2.0 (1.2)	1.8 (0.9)	2.1 (1.0)	2.4 (1.1)	2.3 (1.0)
Literacy	223.2 (54.8)	260.9 (49.9)	268.3 (47.9)	265.0 (54.4)	269.8 (46.3)	252.5 (57.1)
Numeracy	221.9 (58.2)	261.6 (46.3)	278.4 (49.3)	267.8 (57.1)	269.7 (50.5)	256.3 (57.8)
Adaptive Problem Solving	221.3 (46.4)	241.5 (41.7)	255.9 (41.1)	256.5 (47.3)	254.1 (41.7)	243.0 (50.4)
Female	43.0%	52.4%	42.2%	47.0%	41.6%	46.7%

	Country ID					
	Italy	Latvia	Lithuania	New Zealand	Poland	Spain
Observations	1403	3315	2837	2064	1803	2488
Earnings	13.9 (7.1)	7.5 (20.9)	8.0 (6.4)	39.3 (19.9)	28.3 (22.2)	15.9 (12.4)
Years schooling	12.4 (3.6)	14.0 (2.5)	14.1 (2.3)	14.6 (2.6)	13.3 (2.6)	12.8 (3.2)
Experience	20.9 (10.8)	21.6 (11.1)	20.8 (11.0)	22.1 (12.1)	18.9 (10.6)	19.6 (10.5)
Index of use of ICT skills at work	1.9 (1.1)	2.1 (1.0)	1.8 (0.9)	2.5 (1.0)	1.7 (0.9)	2.4 (1.2)
Literacy	254.1 (50.7)	253.4 (49.9)	242.1 (42.2)	270.1 (59.1)	241.7 (48.1)	256.9 (46.8)
Numeracy	257.3 (52.2)	270.0 (50.3)	251.4 (43.4)	267.6 (60.2)	246.9 (52.7)	261.0 (48.5)
Adaptive Problem Solving	239.2 (40.4)	248.0 (43.9)	234.2 (35.8)	258.6 (55.2)	232.1 (40.8)	249.4 (41.3)
Female	39.9%	50.8%	51.9%	43.5%	47.7%	44.9%

Source: own elaboration based on PIAAC 2023.

Note: Standard deviations reported in parentheses.

Our dependent variable is the variable capturing the hourly earnings including bonuses for wage and salary earners reported in the national currency and derived by the consortium as the raw information on earnings was reported differently by different respondents (e.g. weekly, monthly, piece rate). Our main independent variable is the index of use of ICT skills at work. This index was estimated using the IRT methodology based on the information coming from five items, to which the respondents were requested to report the frequency of the listed activities (“never”, “less than once a month”, “less than once a week but at least once a month”, “at least once a week but not every day” and “every day”). The exact wording of the questions was as follows: “In your current job, how often do you usually use a computer or digital device such as a tablet or smartphone for the following purposes?:

- To communicate with others (e.g. via emails, social networking sites, or internet calls). Exclude normal phone calls using a mobile phone.
- To access information (e.g. use a search engine, find information, or read documents).
- To create or edit electronic documents, spreadsheets or presentations (using Microsoft Word, Excel, PowerPoint, or similar software).
- To use specialized software (e.g. for computer-aided design, the processing or analysis of data, sound and images, or quality control).
- To use a programming language to program software (e.g. applications) or websites.”

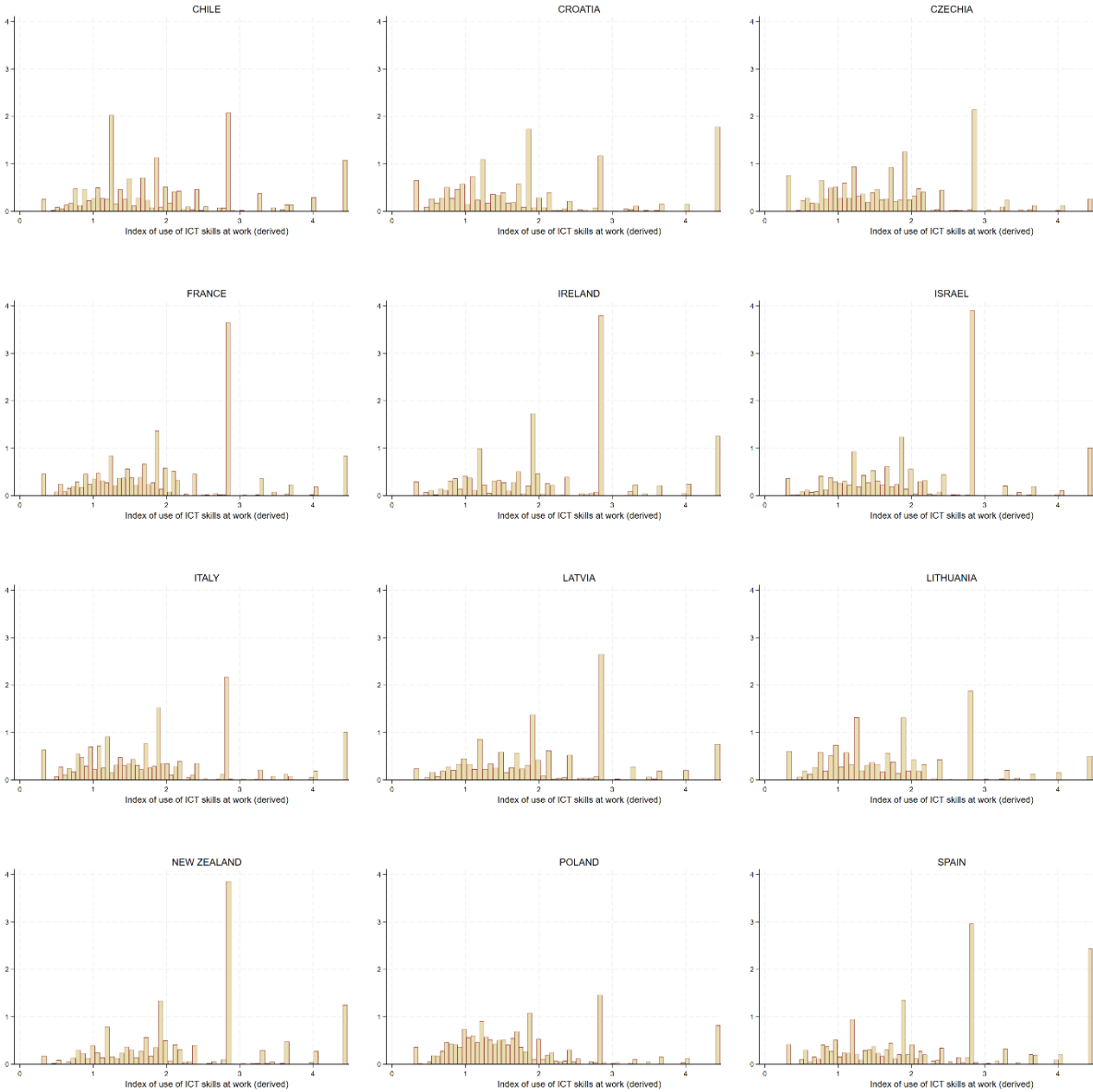
The distribution of index of use of ICT skills at work in the twelve countries analyzed is presented in Figure 1.

This operationalization of digital skills is based on observation that “proficiency in cognitive skills (...) [is] not fixed for life, and life paths, interests and individual circumstances affect how [digital] skills are gained and lost. Adults enhance or maintain their skills by (...) using information and communication technologies (ICT) at work (...). Proficiency and practice are mutually reinforcing, with practice positively affecting the level of proficiency and proficiency having a positive impact on practice.” (OECD, 2024b, pp. 65–66) It is also worth noting that (Richiardi et al., 2025, p. 12), using Eurostat’s Community Survey on ICT usage in households and by individuals, also constructed their index of digital skill based on 22 binary variables measuring if the individual has carried out a particular task pertaining to one of four areas: information skills, communication skills, problem solving skills, and software skills.

All countries provided the information on estimates of literacy, numeracy and adaptive problem solving skills. For each of these domains, 10 plausible values (PV) are available in the

datasets. We use only the first PV, but we tried also specifications with the consecutive PVs and the results remain robust.

Figure 1. The distribution of index of use of ICT skills at work in 12 countries analyzed.



Source: Own elaboration based on the PIAAC 2023 (Public Use Files)

4. Returns to digital skills around the world

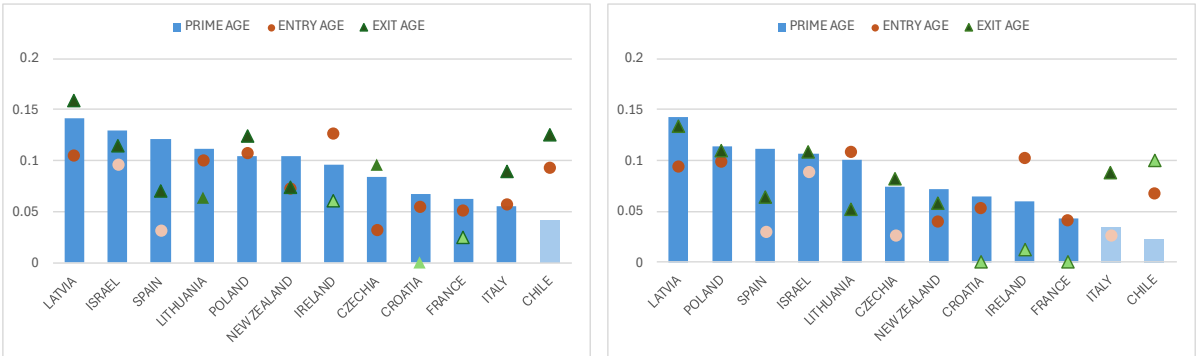
We model the logarithm of earnings as a function of the use of ICT skills at work, controlling for gender, education, cognitive skills measured in PIAAC (literacy, numeracy,

adaptive problem-solving), and experience. Experience enters the model in quadratic form to capture potential non-linear effects. The ICT use index and all PIAAC skill measures are standardized, so their coefficients can be interpreted as the percentage change in earnings associated with a one-standard-deviation increase in each variable (within-country standardization).

Regression models are estimated separately for each of the 12 countries and for three age groups: entry age (25–34 years), prime age (35–54 years), and exit age (55–65 years). This follows the methodological approach of Hanushek et al. (2015) and allows us to test Richiardi et al. (2025)’s “conveyor-belt hypothesis,” which posits that digital skills are less crucial for those already employed (“on the belt”) but vital for those trying to re-enter the labour market (“jumping on the belt”). Thus, the entry-age group captures the initial market valuation of digital and problem-solving skills as “entry tickets,” while comparing prime-age and exit-age groups sheds light on the depreciation or maintenance of digital competencies over the life course.

We estimate both a baseline model, which includes the above variables, and an extended model, which additionally controls for job type (skilled, semi-skilled white-collar, semi-skilled blue-collar, and elementary occupations). Detailed estimation results are reported in Appendix 1, while Figure 2 presents the estimated coefficients next to the ICT skills use at work index (standardized).

Figure 2. Returns to ICT skills use



Source: Own elaboration based on PIAAC 2023 data (PUF).
 Notes: The plots present the estimated parameters next to ICT skills use index in the Mincerian regressions estimated separately in prime age, entry age and exit age groups. The index on ICT skills use at work was standardized within each country. The left plot presents estimates in the baseline specification and the right plot in the extended specification (when occupational groups are also controlled for). The bars or dots marked in lighter colors denote estimate not statistically significant (p-value > 0.1).

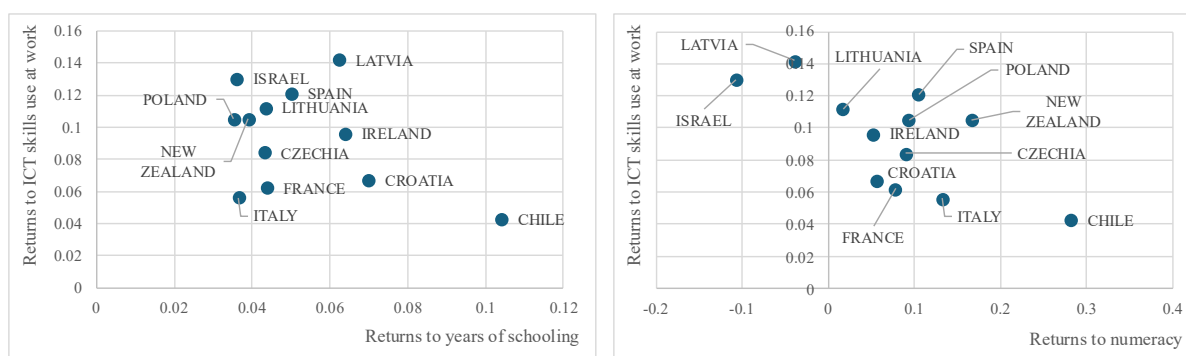
Prime age (35-54)

We begin with prime-age workers, where digital skill returns are expected to be strongest given full labor-market integration. Among prime-age workers (35–54), the estimates point to the consolidation of digital and educational returns, reflecting the phase in which accumulated experience, stable employment, and technological proficiency combine to yield the highest and most consistent wage differentials. More specifically, for this age bracket returns to ICT skills use at work range from 4.3 % in Chile to 14.2 % in Latvia in the baseline model. By comparison, returns to education (an additional year of schooling) lie between 3.5 % in Poland and 10.4 % in Chile.

The effects of cognitive skills differ across domains: returns to literacy and adaptive problem-solving are mostly insignificant, while numeracy shows the strongest association with earnings – ranging from 5.6 % (Croatia) to 28.2 % (Chile)—and is insignificant in only four countries (Ireland, Israel, Latvia, and Lithuania).

Across countries, there is no clear relationship between returns to education and ICT use. A compensation effect (high education returns, low ICT returns) appears only in Chile. A similar pattern emerges for numeracy and ICT, though in Israel and Latvia the situation is reversed: both show relatively high ICT and insignificant numeracy returns (Figure 3).

Figure 3. The relation between the returns to ICT skills use at work, years of schooling and numeracy.



Source: Own elaboration based on PIAAC 2023 data (PUF).

Notes: The plots present the estimated parameters next to ICT skills use index, years of schooling and numeracy skills in the Mincerian regressions (baseline specification) estimated for prime age group (35-54 years).

Entry age (25-34)

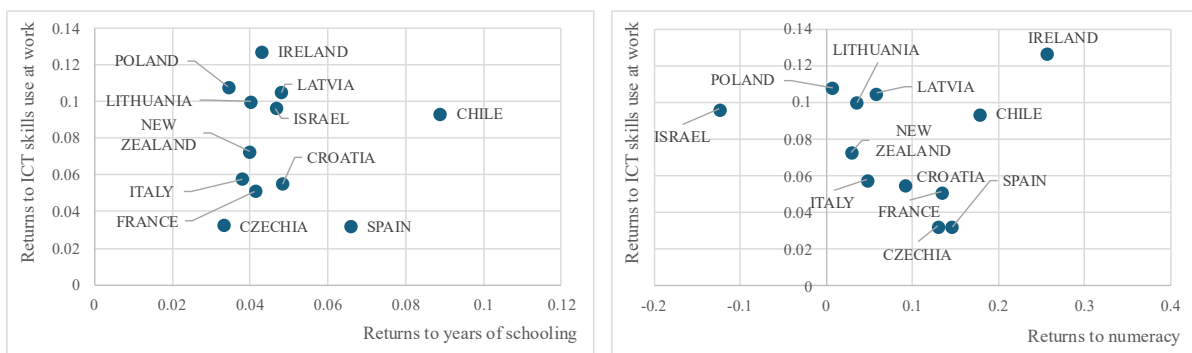
Among entry-age workers (25–34), the estimates reveal the early formation of digital and educational wage advantages, indicating how initial labor-market positioning increasingly depends on the interplay between formal education and workplace digital engagement. More specifically, in this age group returns to ICT skills use range from 3.2 % in Spain to 12.7 % in Ireland. Returns to education oscillate between 3.3 % (Czechia) and 8.9 % (Chile).

Cognitive skills again show mixed effects: literacy is insignificant across all countries, while adaptive problem-solving is statistically significant only in Latvia (11.0 %) and in Italy where its effect is negative at -10.5 %! Numeracy remains the strongest cognitive predictor of earnings, with returns between 9.2 % (Croatia) and 25.7 % (Ireland), and is statistically insignificant in six countries (Italy, Latvia, Lithuania, New Zealand, Poland, and Israel), the latter showing a negative association (-12.4 %).

The relationship between education and ICT returns follows a complementary pattern: in almost all countries, higher returns to schooling are accompanied by higher ICT returns. The only clear compensation case is Spain, where education effects are strong but ICT use is not rewarded (not statistically significant). In Israel, in turn, neither coefficient is statistically significant.

When comparing numeracy and ICT returns, a compensation pattern (the effect of numeracy being greater than that of ICT) appears in Chile, Croatia, Czechia, France, Ireland, and Spain, whereas the opposite pattern (the effect of ICT being greater than that of numeracy) is observed in Italy, Latvia, Lithuania, New Zealand, and Poland. In Israel, both effects are not statistically significant (Figure 4).

Figure 4. The relation between the returns to ICT skills use at work, years of schooling and numeracy.



Source: Own elaboration based on PIAAC 2023 data (PUF).

Notes: The plots present the estimated parameters next to ICT skills use index, years of schooling and numeracy skills in the Mincerian regressions (baseline specification) estimated for entry age group (25–34 years).

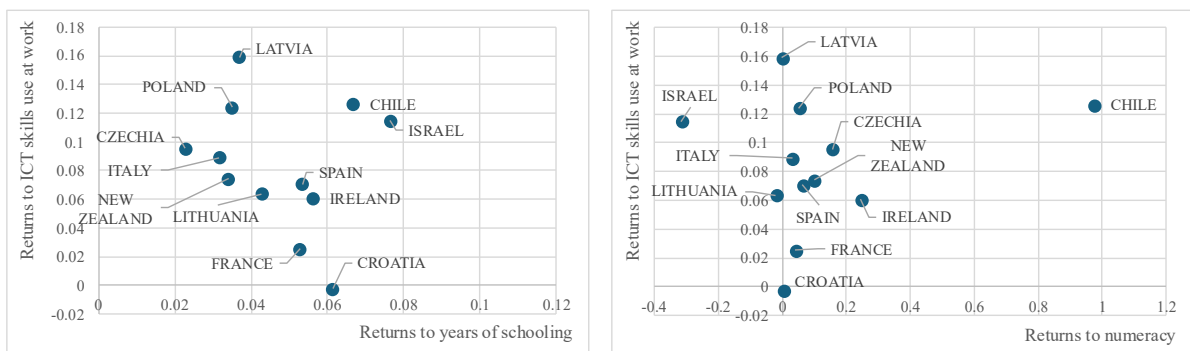
Exit age (55-65)

For exit-age workers (55–65), the results highlight the enduring value of digital competences in later career stages, suggesting that continued engagement with ICT mitigates skill depreciation and sustains earnings despite age-related declines in other forms of human capital. For the exit-age group, returns to ICT skills use remain substantial – ranging from 6.4 % in Lithuania to 15.9 % in Latvia – even without controlling for occupational type. Returns to education are smaller, between 2.3 % (Czechia) and 7.7 % (Israel).

Among cognitive skills, literacy has little impact except in Lithuania (9.7 %) and in Israel (50.3 %) where the effect is positive, and in Chile (-38.5 %) where it is negative. Adaptive problem-solving shows significant effects only in Latvia (9.3 %) and Chile (-37.5 %). Numeracy continues to yield the highest returns – up to 97.4 % in Chile and 24.4 % in Ireland – and is statistically significant in four countries (Chile, Czechia, Ireland, Israel) while being negative only in Israel (-31.7 %).

In ten of the twelve countries, ICT returns exceed educational returns, two exceptions being Croatia and France. This indicates that digital proficiency retains or even increases its economic value late in workers' careers, whereas education-based returns tend to flatten. Regarding the relationship between numeracy and ICT, a compensation pattern (the effect of numeracy greater than that of ICT) emerges in Chile, Czechia, Ireland, and New Zealand, while the reverse pattern (the effect of ICT greater than that of numeracy) is found in Italy, Latvia, Lithuania, Poland, and Spain. In Croatia and France, both effects are statistically insignificant. In Israel, numeracy has a negative and ICT a positive effect, suggesting that on the Israeli labor market it is ICT proficiency rather than cognitive ability that drives wage differentials at older ages (Figure 5).

Figure 5. The relation between the returns to ICT skills use at work, years of schooling and numeracy.



Source: Own elaboration based on PIAAC 2023 data (PUF).

Notes: The plots present the estimated parameters next to ICT skills use index, years of schooling and numeracy skills in the Mincerian regressions (baseline specification) estimated for exit age group (55-65 years).

Summing up: individual wage returns to ICT use at work increase slightly from entry to prime age and they remain robust at exit age, suggesting durable value of workplace digital engagement.

5. Conclusions

5.1. Summary of empirical findings

This paper examined whether, and to what extent, digital skills – measured as the use of ICT at work – are rewarded in contemporary labor markets across twelve OECD countries. Using data from the second cycle of the OECD Programme for the International Assessment of Adult Competencies (PIAAC 2022–2023), we estimated Mincer-type wage equations separately for three life-course groups: entry age (25–34), prime age (35–54), and exit age (55–65). Each model controlled for gender, education, cognitive skills (literacy, numeracy, adaptive problem-solving), and experience.

The results show that ICT use at work is consistently and significantly associated with higher earnings in most countries, even when educational attainment and cognitive ability are taken into account. Among entry-age workers, the estimated returns to ICT use at work range between 3 % and 13 %, comparable to the wage premium of an additional year of schooling. For prime-age workers, ICT use at work continues to yield strong returns – often exceeding those of education – while literacy and adaptive problem-solving show little or no association with earnings. In the exit-age group, ICT use at work remains economically valuable, and in several countries (e.g., in Latvia) its returns even increase, suggesting that digital engagement may mitigate the depreciation of other forms of human capital later in life.

5.2. Cross-country and cross-skill relationships

Across the twelve countries analyzed, the relationship between returns to ICT use and education is predominantly complementary: countries that reward formal schooling also tend to reward workplace digital engagement. Only in a few cases, such as Chile (for prime age workers), Spain (for entry age workers), Croatia and France (for exit age workers) we do

observe a compensation pattern where higher returns to education coincide with weaker returns to ICT use.

The relationship between ICT use and numeracy skills is more heterogeneous. In countries such as Czechia, France (except for exit age group), and Ireland (but only among entry age workers) the two appear to reinforce each other, while in others – such as Italy, Latvia, Lithuania, and Poland – returns to ICT use remain strong even when numeracy effects are statistically insignificant. This variation points to the influence of national skill-formation systems, technological adoption rates, and labor-market institutions in shaping the way digital competences translate into earnings.

5.3. Theoretical implications

Our findings extend the Task-Based Approach and theories of Skill-Biased Technological Change by showing that ICT use constitutes a distinct and durable component of human capital. Persistent wage premia for digital engagement suggest that digital capital has become an independent dimension of economic inequality – complementary to, but not reducible to, educational attainment or cognitive ability.

This evidence also supports the concept of a *third-level digital divide*, in which inequalities emerge not from unequal access or skills themselves but from differences in the *economic conversion* of those skills into wage-derived income. The results lend partial support to the “conveyor-belt hypothesis” (Richiardi et al., 2025): digital skills are most valuable for younger and re-entering workers – those seeking to “jump onto the belt” – yet their continued rewards among older workers indicate that digital proficiency functions as a form of *maintenance capital*, necessary for sustaining employability and earnings throughout the working life course.

5.4. Policy implications

The persistence of digital-skill returns across all age groups highlights the importance of lifelong digital learning. Governments, employers, and training institutions should approach digital competences not as fixed assets obtained through formal schooling, but as evolving capabilities requiring continuous renewal. Policy responses should include:

- expanding adult-learning and reskilling programs aimed at maintaining digital adaptability;
- supporting mid- and late-career digital training to prevent skill obsolescence;
- improving access to digital infrastructure and training in small firms and non-urban regions; and
- ensuring that wage-setting and promotion systems recognize and reward digital proficiency.

Cross-country variation in ICT returns indicates that institutional factors – education systems, vocational structures, collective bargaining, and technology-diffusion policies – mediate how digital skills are converted into labor-market outcomes.

5.5. Limitations and future research

While robust and comparable across countries, our analysis faces certain limitations. The cross-sectional nature of PIAAC Cycle 2 data prevents causal inference on how digital skills accumulate or depreciate over time. Using a single plausible value for cognitive skills may slightly understate their effects, and the ICT-use indicator measures frequency rather than complexity or autonomy of digital tasks.

Future research could extend to the remaining 17 countries (provided we obtain the information on the medians of deciles of earnings distributions for each one of them from the OECD), apply full plausible-value estimation, link the PIAAC data with administrative or longitudinal datasets, and explore how automation exposure and workplace innovation interact with digital skills. Studies focusing on within-occupation or within-firm differences would further clarify how digital skills complement other forms of human capital in practice.

5.6. Concluding remarks

Taken together, our findings demonstrate that the economic value of digital skills endures across the life course. ICT engagement remains a strong determinant of earnings, complementing education and, in many contexts, exceeding traditional cognitive skills in its payoff. As digital technologies increasingly permeate all sectors of work, maintaining equitable opportunities to acquire, renew, and effectively use digital skills will be essential to preventing the widening of both digital and social inequalities in the years ahead.

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Appendix 1. Results of linear regression modelling, dependent variable=log(earnings)

Entry age. Baseline specification

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.123**	-0.177***	-0.0886**	-0.0508	-0.0398	-0.271*
Years schooling	0.0888***	0.0483***	0.0331***	0.0412***	0.0430**	0.0465
Experience	0.0225	0.0142	0.0374*	0.0262***	0.0556**	-0.126*
Experience2	-0.0759	-0.0689	-0.122	-0.0721*	-0.190*	0.554
ZCITWORK	0.0934***	0.0551**	0.0325*	0.0511***	0.127***	0.0963
ZPVLIT1	-0.0656	-0.0297	-0.0439	-0.0686	-0.0637	0.0208
ZPVNUM1	0.178**	0.0917**	0.130***	0.134***	0.257***	-0.124
ZPVAPS1	-0.00259	0.0430	0.0268	0.0149	-0.0795	0.0840
Constant	7.114***	3.454***	4.754***	1.988***	1.978***	4.775***
Observations	471	336	441	553	385	571
R2	0.385	0.318	0.293	0.221	0.232	0.0350

	ITALY	LATVIA	LITHUANI A	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.0654	-0.203***	-0.219***	-0.0858**	-0.160***	-0.0781*
Years schooling	0.0379***	0.0479***	0.0401***	0.0399***	0.0344**	0.0658***
Experience	0.104***	0.0205	0.125***	0.0184*	0.0306**	0.0345***
Experience2	-0.491***	-0.0171	-0.697***	-0.0417	-0.0637	-0.0821*
ZCITWORK	0.0577**	0.105***	0.0998***	0.0728***	0.108***	0.0321
ZPVLIT1	0.0926	-0.0208	0.0337	0.0429	0.0528	-0.0494
ZPVNUM1	0.0474	0.0581	0.0358	0.0291	0.00715	0.146**
ZPVAPS1	-0.105*	0.110*	0.0103	0.000752	0.00846	-0.0358
Constant	1.531***	1.572***	1.505***	2.849***	2.839***	1.395***
Observations	243	465	557	514	348	419
R2	0.208	0.268	0.211	0.223	0.215	0.272

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Entry age. Extended specification.

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.133**	-0.158***	-0.0743*	-0.0496	-0.0476	-0.270*
Years schooling	0.0575***	0.0303***	0.0248***	0.0275***	0.0185	0.0344
Experience	0.0297	0.0108	0.0451**	0.0248**	0.0457*	-0.101
Experience2	-0.116	-0.0512	-0.177*	-0.0659*	-0.145	0.438
Skilled occupations (ref)						
Semi-skilled white-collar	-0.424***	-0.174***	-0.151***	-0.167***	-0.263***	-0.194
Semi-skilled blue-collar	-0.271***	-0.106	-0.0506	-0.131*	-0.276**	-0.292
Elementary occupations	-0.297***	-0.0151	-0.192*	-0.176*	-0.414*	0.679
ZCITWORKC2	0.0670**	0.0526**	0.0270	0.0408**	0.102***	0.0897
ZPVLIT1	-0.0301	-0.0294	-0.0515	-0.0772*	-0.0485	-0.0396
ZPVNUM1	0.151**	0.0917**	0.107**	0.120**	0.230***	-0.0908
ZPVAPS1	-0.0444	0.0419	0.0501	0.0302	-0.0727	0.0751
Constant	7.756***	3.749***	4.907***	2.250***	2.541***	4.887***
Observations	463	331	436	522	384	552
R2	0.460	0.364	0.327	0.256	0.268	0.0469

	ITALY	LATVIA	LITHUANIA	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.0914*	-0.204***	-0.178***	-0.0978***	-0.142**	-0.0555
Years schooling	0.0288**	0.0379**	0.0461***	0.0252**	0.0148	0.0604***
Experience	0.108***	0.0189	0.126***	0.0127	0.0295**	0.0379***
Experience2	-0.510***	-0.0135	-0.716***	-0.0266	-0.0608	-0.0900*
Skilled occupations (ref)						
Semi-skilled white-collar	-0.136**	-0.193**	-0.0883	-0.250***	-0.189***	-0.206***
Semi-skilled blue-collar	-0.231**	0.0309	0.135*	-0.115**	-0.153*	-0.0843
Elementary occupations	-0.340*	-0.256	0.0707	-0.427***	0.0472	0.0110
ZCITWORKC2	0.0271	0.0941***	0.108***	0.0395**	0.0984***	0.0299
ZPVLIT1	0.0711	-0.0152	0.0228	0.0336	0.0486	-0.0442
ZPVNUM1	0.0536	0.0612	0.0568	0.0230	-0.00216	0.144**
ZPVAPS1	-0.0808	0.104	0.00590	0.00981	0.00963	-0.0442
Constant	1.767***	1.765***	1.347***	3.211***	3.196***	1.487***
Observations	242	458	553	511	343	414
R2	0.259	0.286	0.232	0.307	0.247	0.313

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Prime age. Baseline specification.

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.218***	-0.189***	-0.211***	-0.126***	-0.00262	-0.210**
Years schooling	0.104***	0.0699***	0.0432***	0.0438***	0.0639***	0.0361*
Experience	0.0345**	0.0348***	0.0272***	0.0185**	0.0301	0.0355
Experience2	-0.0739*	-0.0706***	-0.0497**	-0.0253	-0.0436	-0.0628
ZCITWORK	0.0427	0.0672***	0.0841***	0.0622***	0.0961***	0.130***
ZPVLIT1	0.0126	-0.0296	0.0348	-0.0105	0.142**	0.0781
ZPVNUM1	0.282***	0.0559*	0.0906***	0.0784**	0.0523	-0.107
ZPVAPS1	-0.0750	0.0307	-0.0264	0.0181	-0.0904	0.114
Constant	7.049***	2.985***	4.728***	2.113***	1.656***	3.691***
Observations	679	656	1179	1530	993	846
R2	0.437	0.370	0.309	0.250	0.0960	0.0797

	ITALY	LATVIA	LITHUANIA	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.203***	-0.337***	-0.236***	-0.133***	-0.202***	-0.101***
Years schooling	0.0366***	0.0624***	0.0434***	0.0390***	0.0353***	0.0501***
Experience	-0.00246	0.0172	0.0162	0.00573	-0.00780	0.0198*
Experience2	0.0255	-0.0338	-0.0396	-0.00291	0.0323	-0.0203
ZCITWORK	0.0560**	0.142***	0.112***	0.105***	0.105***	0.121***
ZPVLIT1	0.0305	-0.0172	0.0509	0.0302	-0.115**	-0.0425
ZPVNUM1	0.133**	-0.0390	0.0175	0.167***	0.0938*	0.105**
ZPVAPS1	-0.0650	0.155***	0.0233	-0.0614*	0.0514	0.0419
Constant	2.274***	1.596***	1.777***	3.114***	3.237***	1.678***
Observations	423	1301	995	944	610	1175
R2	0.211	0.261	0.291	0.333	0.167	0.269

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Prime age. Extended specification.

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.179***	-0.155***	-0.166***	-0.129***	0.00107	-0.214**
Years schooling	0.0831***	0.0553***	0.0319***	0.0339***	0.0525***	0.0199
Experience	0.0244*	0.0318***	0.0268***	0.0161*	0.0270	0.0357
Experience2	-0.0511	-0.0655**	-0.0481**	-0.0214	-0.0392	-0.0644
Skilled occupations (ref)						
Semi-skilled white-collar	-0.408***	-0.164***	-0.173***	-0.202***	-0.299***	-0.379***
Semi-skilled blue-collar	-0.143	0.0144	-0.0596	-0.144***	-0.190*	-0.184
Elementary occupations	-0.423***	-0.224	-0.208**	-0.206***	-0.364*	0.319
ZCITWORKC2	0.0221	0.0651***	0.0736***	0.0428***	0.0599*	0.106**
ZPVLIT1	0.00741	-0.0288	0.0293	-0.0184	0.130*	0.0511
ZPVNUM1	0.243***	0.0636*	0.0886***	0.0559*	0.0169	-0.121
ZPVAPS1	-0.0486	0.0281	-0.0234	0.0265	-0.0760	0.136*
Constant	7.518***	3.226***	4.899***	2.361***	1.991***	4.020***
Observations	658	643	1170	1475	993	832
R2	0.471	0.405	0.336	0.286	0.114	0.101

	ITALY	LATVIA	LITHUANIA	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.213***	-0.302***	-0.182***	-0.132***	-0.122**	-0.0983***
Years schooling	0.0288**	0.0582***	0.0347***	0.0268***	0.0334**	0.0439***
Experience	0.000771	0.0144	0.0166	0.00414	-0.00482	0.0201*
Experience2	0.0148	-0.0284	-0.0404	-0.000206	0.0238	-0.0217
Skilled occupations (ref)						
Semi-skilled white-collar	-0.216***	-0.133**	-0.283***	-0.274***	-0.153**	-0.164***
Semi-skilled blue-collar	-0.155*	0.0822	0.0172	-0.178***	0.132*	-0.0698
Elementary occupations	-0.0998	-0.179	-0.262**	-0.416***	0.257	-0.250***
ZCITWORKC2	0.0341	0.143***	0.101***	0.0716***	0.114***	0.111***
ZPVLIT1	0.0244	-0.0200	0.0465	-0.0253	-0.121***	-0.0438
ZPVNUM1	0.123**	-0.0425	0.0146	0.181***	0.0947**	0.0984**
ZPVAPS1	-0.0573	0.163***	0.0247	-0.0479	0.0685*	0.0450
Constant	2.477***	1.648***	1.879***	3.414***	3.126***	1.838***
Observations	416	1292	992	940	593	1166
R2	0.248	0.271	0.350	0.389	0.200	0.292

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Exit age. Baseline specification

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.176	-0.0637	-0.136***	-0.202***	-0.0490	-0.418***
Years schooling	0.0668**	0.0614***	0.0227**	0.0528***	0.0563***	0.0765***
Experience	-0.00685	-0.0133	0.00657	-0.000258	0.0250	0.0446
Experience2	0.0195	0.0425	-0.0171	0.0234	-0.0520	-0.0682
ZCITWORK	0.126*	-0.00233	0.0956***	0.0254	0.0608	0.115*
ZPVLIT1	-0.385**	0.0440	-0.0699	0.0580	-0.101	0.503***
ZPVNUM1	0.974***	0.00322	0.156***	0.0390	0.244**	-0.317**
ZPVAPS1	-0.375**	0.0650	-0.0262	0.0552	-0.0742	-0.0915
Constant	7.827***	3.148***	5.199***	2.222***	2.241***	3.197***
Observations	175	185	380	427	236	223
R2	0.478	0.225	0.208	0.322	0.205	0.310

	ITALY	LATVIA	LITHUANIA	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.0949	-0.178***	-0.143***	-0.0970*	-0.109	-0.0742
Years schooling	0.0316***	0.0369***	0.0427***	0.0340***	0.0350*	0.0535***
Experience	0.0125	0.00988	0.00349	0.0103	-0.0172	0.0408**
Experience2	-0.0207	-0.00719	-0.00944	-0.0122	0.0520	-0.0367
ZCITWORK	0.0891**	0.159***	0.0637**	0.0743***	0.124*	0.0706*
ZPVLIT1	-0.0347	0.00605	0.0968*	0.0636	-0.0757	0.0195
ZPVNUM1	0.0295	-0.00249	-0.0211	0.0982	0.0517	0.0628
ZPVAPS1	0.0178	0.0934*	0.0354	-0.0134	0.0636	-0.0432
Constant	2.269***	1.490***	1.696***	3.044***	3.001***	1.193***
Observations	146	600	487	370	129	318
R2	0.208	0.298	0.183	0.304	0.228	0.301

Exit age. Extended specification

	CHILE	CROATIA	CZECHIA	FRANCE	IRELAND	ISRAEL
Person gender (ref=males)	-0.0717	-0.0479	-0.105**	-0.168***	-0.0967	-0.432***
Years schooling	0.0557*	0.0459**	0.0116	0.0406***	0.0465**	0.0716***
Experience	-0.00993	-0.00886	0.00212	-0.00351	0.0227	0.0537*
Experience2	0.0211	0.0300	-0.0132	0.0262	-0.0484	-0.0866*
Skilled occupations (ref)						
Semi-skilled white-collar	-0.193	-0.162*	-0.251***	-0.305***	-0.292***	-0.0300
Semi-skilled blue-collar	0.137	0.0146	-0.0482	-0.319***	-0.0312	-0.155
Elementary occupations	-0.354	-0.467*	-0.188	-0.317**	-0.549*	-0.630
ZCITWORKC2	0.0999	-0.0198	0.0819***	-0.0159	0.0125	0.108*
ZPVLIT1	-0.359*	0.0620	-0.0297	0.0329	-0.0822	0.506***
ZPVNUM1	0.925***	-0.0277	0.0985*	0.0556	0.195*	-0.334***
ZPVAPS1	-0.366**	0.0915	-0.0229	0.0389	-0.0274	-0.0804
Constant	7.974***	3.377***	5.517***	2.517***	2.594***	3.235***
Observations	172	179	380	417	234	222
R2	0.501	0.254	0.273	0.385	0.261	0.326

	ITALY	LATVIA	LITHUANIA	NEW ZEALAND	POLAND	SPAIN
Person gender (ref=males)	-0.0831	-0.170***	-0.135**	-0.0956*	-0.0644	-0.0790
Years schooling	0.0249*	0.0246**	0.0275**	0.0183*	0.0313	0.0443***
Experience	0.00679	0.00551	0.00388	0.0169	-0.0125	0.0388**
Experience2	-0.0123	-0.00108	-0.00969	-0.0258	0.0426	-0.0339
Skilled occupations (ref)						
Semi-skilled white-collar	-0.167*	-0.249***	-0.205***	-0.285***	-0.207*	-0.159**
Semi-skilled blue-collar	-0.0172	-0.0843	-0.0504	-0.152*	0.0531	-0.175*
Elementary occupations	0.0457	-0.172*	-0.302***	-0.403**	0.0680	-0.295**
ZCITWORKC2	0.0881*	0.134***	0.0519*	0.0581*	0.110*	0.0642*
ZPVLIT1	-0.0509	0.0119	0.0689	0.0402	-0.0823	0.0151
ZPVNUM1	0.0153	-0.00571	-0.00926	0.0976	0.0610	0.0587
ZPVAPS1	0.0508	0.0861*	0.0571	0.0157	0.0613	-0.0267
Constant	2.487***	1.779***	1.970***	3.318***	2.980***	1.454***
Observations	145	596	486	366	127	317
R2	0.243	0.326	0.234	0.377	0.282	0.329