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Working Paper 193

FEBRUARY 2021

Breaking Through the Digital Ceiling:

ICT Skills and Labour Market Opportunities

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Abstract

This paper analyses the impact of ICT-skills on individuals' labour market mobility patterns, in particular job-to-job, employment- to-unemployment and unemployment-to-employment transitions. Based on the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) and longitudinal EU-SILC data, individuals' labour market outcomes are examined over the period 2011-2017 in nine EU countries and the UK. Our results indicate that individuals with strong ICT skills have better opportunities and are therefore not only more likely to change jobs more frequently but are also less likely to face unemployment. Furthermore, ICT skills support unemployment exit towards medium and high digital occupations. A certain minimum level of ICT skills also supports unemployment exit towards low digital occupations but seems to make employment in such occupations less likely once this threshold is crossed. Overall, ICT skills have less predictive power for transition towards medium digital occupations. Thus, while ICT skills appear to improve labour market opportunities significantly, it seems that there are still jobs that require relatively few ICT skills.

Keywords: digital skills, labour market transitions

JEL classification: C25, J23, J24

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1. Introduction

In their time, ground-breaking innovations such as the steam engine, the railway and electricity created a variety of new jobs often not imagined before the diffusion of these technologies. But as they became cheaper and ubiquitous in the work processes, such technological changes made certain skills redundant. Workers whose skills were no longer demanded by the labour market were not always successful in finding new opportunities and often faced unemployment and income cuts. Nowadays, digital technologies generate opportunities for those who possess the level of ICT skills demanded by the labour market, but they limit the options for those who do not possess these skills or have failed to upgrade them accordingly. As the pace of innovation in ICT technologies accelerates and their diffusion increases, workers are coming under growing pressure to adjust continuously.

Therefore, the objective of this research is to identify how the labour mobility of workers with different ICT skills varies. In view of the fact that there are still many jobs which require no or few digital skills, our study analyses job transitions from and to occupations with different degrees of digital task content. Based on these distinctions, we study job-to-job transitions, the probability of facing unemployment spells, and the exit to unemployment. In order to address these questions empirically, we link data from the OECD's Survey of Adult Skills (PIAAC), which provides information on ICT skills, with the longitudinal EU-SILC survey, which records individuals' labour mobility over time. Prior to the PIAAC, comprehensive cross-country analyses of the returns of ICT skills were non-existent or came with significant limitations (DiNardo and Pischke, 1997). Our analysis, which encompasses nine EU countries[1] and the United Kingdom, was conducted over the period 2011-2017.

The study presents evidence that indeed individuals tend to settle into jobs based on their own skills and the jobs' task content. Consequently, we observe that job changes between different occupational groups are rather rare, which supports the concepts of task-specific and occupation-specific human capital (Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010). Furthermore, the study finds that individuals who possess strong ICT skills tend to have greater opportunities in the labour market. ICT skills increase the probability to progress towards a new job, and especially towards jobs which are characterised by ICT-intensive tasks. These jobs tend to be better paid and are more likely to offer permanent contracts. When analysing the relationship between ICT skills and unemployment, we find that individuals with high ICT skills are less likely to be unemployed and tend to exit unemployment more quickly. Moreover, an increase in ICT skills is associated with a reduced risk of unemployment for individuals who are employed in low digital occupations. This relationship, however, holds only for individuals who exceed a certain minimum level of digital skills. An increase up to this threshold is associated with an increased probability of facing an unemployment spell. Thus it appears that individuals at the very bottom of the ICT skills level are the most affected by the shift in demand towards digital skills. Still, there are many jobs which do not require strong ICT skills. We find, therefore, that on average ICT skills tend not to facilitate job transitions towards medium digital occupations and do not make transitions towards low digital occupations less likely.

1 Belgium, Czechia, Denmark, Greece, Lithuania, Poland, Slovakia, Slovenia and Sweden.

This paper is structured in the following way. First, literature related to ICT skills and labour mobility is summarised. The data sources used and how occupations are classified as low, medium and high digital are described in Section 3. The method of linking PIAAC data with EU-SILC and the employed linear probability model are explained in Section 4. Section 5 presents the econometric results, and Section 6 concludes.

2. Literature

ICT skills are known to be distributed unevenly across the population. Access to computers with internet connection only grew rapidly during the 1990s (Losh, 2003). Although individuals acquire digital skills both through informal and formal education (Van Deursen and Van Dijk, 2014), it is unsurprising that younger cohorts perform better in a digital environment (Desjardins et al., 2013). In the early 2000s numerous studies pointed out that there exists a big digital divide between the genders. Women tended to have less access to the internet, and if they did have access, they had fewer occasions to use it and tended to use it for different reasons than males (Kennedy et al., 2003). According to Desjardins et al. (2013), the gap between access and use has narrowed significantly over time, at least in developed economies. These differences are particularly small among younger cohorts and more persistent among older generations.

Similar to other skills, such as literacy and numeracy, digital skills vary significantly across educational levels. There appears to be a link between the general ability of individuals and their digital skills. Thus, different educational outcomes seem to contribute to the digital divide (Desjardins et al., 2013). Van Deursen and Van Dijk (2014) elaborate that unequal access and varying digital skills directly impact the degree of participation in a wide range of society. Higher digital skills can lead to improved access to healthcare, more social relationships and memberships in organisations and even increased voting or other political activities. Furthermore, digital skills can affect labour market outcomes through various channels. Lindsay (2005), for example, stresses that the use of the internet helps to expand social networks, which are essential for finding opportunities on the labour market. Furthermore, the internet is a crucial tool for the job seeker. Green et al. (2012) find that in the UK, in particular, older individuals with lower levels of education use internet tools less often to search for jobs. ICT literacy is generally associated with higher labour market participation and wages (Desjardins et al., 2013). When controlling for a number of other individual characteristics correlated with ICT skills such as education, age etc., several studies indicate that there exists a premium for ICT skills (Hampf et al., 2017; Falck et al., 2016).

The present study draws on the Survey of Adult Skills, part of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC). Hanushek et al. (2015) were among the first to explore the PIAAC skills data to analyse workers' return according to the different levels of skill measured. The authors highlight that their data set allows an estimation of the benefits associated with human capital at a more granular level compared with other studies that identify education as the closest available proxy for skills. They find large cross-country variations in income associated with different skill levels. The returns to skills, for example, are much higher in the US than in the Nordic countries. Based on PIAAC data, Falck et al. (2016) find that variation in ICT skills can explain differences in workers' income. The size of the ICT skills premium, however, varies significantly across different occupations. Unsurprisingly, the returns to ICT skills are higher in occupations that rely heavily on such skills and are not insignificant in elementary occupations. This indicates that the benefits of the ICT revolution are distributed unequally and will continue to be so.

The objective of this research is to analyse to what extent ICT skills determine individuals' labour market transitions. A large strand of the literature has addressed the drivers and costs of job-to-job transitions. Bechichi et al. (2018) argue that in the literature two topics have been addressed prominently: first, the factor of workers' human capital, and second, labour market institutions. According to the literature, human capital that has been accumulated throughout an individual's career is not perfectly transferable from one job to another. Firm-specific human capital was first studied extensively by Becker (2009). The consequences of firm-specific human capital on wage developments remain inconclusive (Farber, 1999; Altonji and Williams, 2005). A series of literature has also emphasised the importance of industry-specific human capital (Neal, 1995) and occupation-specific human capital (Kambourov and Manovskii, 2009). More recently, task-based human capital has received considerable attention in labour economics (Ingram and Neumann, 2006; Gathmann and Schönberg, 2010). In the context of labour mobility, the theory implies that differences in wages between a new job and an old one are greatly dependent on the differences in the task content of the job. As highlighted by the literature, some skills pay a premium in a specific firm, occupation or industry, but this premium cannot be easily transferred from one to another. McQuaid and Lindsay (2005) argue that basic ICT skills can be considered as a key transferable skill along with other competences such as team work, problem solving or interpersonal skills. To put it differently, the absence of basic ICT skills could constrain labour market opportunities severely.

In order to explain the pattern of decreasing employment and wages for the middle class, particularly in the US (Autor and Dorn, 2013; Cortes, 2016) and the UK (Goos and Manning, 2007; Gardiner and Corlett, 2015) and to a lesser extent in other European countries (Goos et al., 2009; Oesch and Rodríguez Menés, 2011), studies have argued that this can be attributed to a large extent to falling demand for routine jobs. Technological progress has accelerated the automation of routine tasks in such jobs and has therefore contributed to the falling demand for workers employed in such occupations (Goos et al., 2011). In the US, for example, such jobs have mainly been filled by middle-income workers since World War II. The development of machines and algorithms and improvements in other organisational processes has consequently lowered the demand for their skills (Autor et al., 2003). Holmes and Tholen (2013) have analysed the job mobility of two cohorts in the UK, who were initially employed in routine occupations. They find that the shift towards non-routine occupations was supported by the increased job mobility of the older cohort. Linking this observation to the context of ICT development, the demand for workers without basic or low ICT skills is likely to decline. Several factors, such as economic shocks or fast technological progress, could accelerate this process. Workers could then either remain in such occupations until they retire or they may have to adjust and change jobs. As the research on human capital suggests, a change in jobs can have a significant impact on wage developments, depending on the mismatch between the task composition in the new job compared with the old one. This development could call for active labour market policies in order to avoid higher rates of long-term unemployment and higher poverty rates.

3. Data

3.1. DATA SOURCES AND ICT SCORES

The OECD's Survey of Adult Skills (PIAAC), which forms the basis of this analysis, was first conducted in 2010-2011 in 23 OECD countries. Fourteen more countries participated in the second and third rounds (2014-2015 and 2017). The survey is conducted every ten years, and thus only a cross-section is available so far. The PIAAC survey collects information on the skills of around 5,000 individuals per country: literacy, numeracy and problem solving in technology-rich environments. A measure of our main variable of interest, ICT skills, results from a computer-based test taken by every interviewee.[2] The test consists of a series of tasks which require different levels of computer and internet skills. Each participant receives a final test score, which we use as a proxy for ICT skills. In addition, the survey contains information on the interviewees' labour market activity, such as current occupation and income as well as socioeconomic background variables.

The objective of this research is to observe how ICT skills determine the labour market mobility of individuals. Since PIAAC data do not provide information on employment history, this data set alone does not allow us to answer the stated research question. Therefore, the PIAAC is linked with the longitudinal structure of the EU Statistics on Income and Living Conditions (EU-SILC). The EU-SILC survey is a four-year rotating panel, in which individuals are interviewed for a maximum of four years. It contains information on, for example, employment status, income and household characteristics. Unfortunately there is no unique identifier publicly available that makes it possible to match individuals from the PIAAC with other sources. Therefore, we apply statistical methods to link PIAAC data with EU-SILC data. The main idea is to find a model that predicts the ICT skills of individuals in the PIAAC and employ the same model for individuals in the EU-SILC. The respective model is described in Section 4.1.

The PIAAC data reveal that a majority of adults possess only basic ICT skills. This allows them to conduct only simple tasks, and they are therefore unable to evaluate and solve problems in a "technologically rich environment" (Chung and Elliott, 2015; see also OECD, 2016a and OECD, 2013 for a detailed analysis of digital skills distributions across countries and demographic characteristics). Our analysis confirms the main trends. Table 6 presents the estimates of a model that predicts the ICT score for individuals based on PIAAC data[3] and therefore highlights the most important determinants of ICT skills. First, cross-country differences are large. The shares of participants who lacked the operational skills to conduct the computer-based test range from 12% in Sweden to around 50% in Poland. Similarly, the average ICT score obtained is highest in Sweden and lowest in Greece, with 293 and 260 points, respectively. In our sample of ten EU countries the score for women is on average around six points lower than for men. Furthermore, individuals aged between 16 and 24 performed best in the computer test. The difference between this cohort and the 25-34 age group is significant and amounts to

2 There are three main groups that did not take the computer-based test. First, those who indicated they had no previous computer experience (10.1% in the first round). Second, 9.5% who opted out from the test and 5% who failed in an attempt to conduct the computer-based test (OECD, 2016b).

3 See Section 4.1 for details.

eight points, while the score of individuals aged between 55 and 64 is on average 42 points lower. It is also well known that higher education is associated with higher ICT skills. The difference between individuals who attained less than primary education compared with upper secondary education amounts to 19 points and increases to 29 points compared with individuals with tertiary education. In contrast, ICT skills are not linearly correlated with higher ICT scores. Individuals in the bottom decile of income distribution, for example, have the same level of digital skills as individuals between the 25th and 50th percentile. Employees in the top decile scored on average 20 points more than the bottom decile controlling for a series of individual characteristics.

3.2. LABOUR TRANSITIONS

3.2.1. Data on labour market transitions

As outlined above, we use data from the longitudinal component of the EU-SILC to record individuals' labour market activity over time. The survey is designed in such a way that interviews are conducted on an annual basis. Consequently, many variables are evaluated only at a certain point of the year (at the time of the interview). Such variables include measures on living conditions, but also variables related to the current job, such as occupation and usual hours worked. The remaining variables, mostly measuring income and benefits, do not refer to the income an individual earns at the time of the interview, but rather to how much the individual earned during the so-called *income reference period*. For most countries, the income reference period is the calendar year preceding the interview. For example, the reference period for an individual interviewed in September 2018 covers 1 January 2017 to 31 December 2017.[4]

In order to study labour market transitions, information on the labour market status and the corresponding characteristics should be available at frequent intervals. In the EU-SILC, individuals report their labour market status at the time of the interview and for each month of the reference period. Employment details, such as occupation or hours worked, however, are not available for the reference period but are reported for the time of the interview only. Therefore, transitions from employment to unemployment and vice versa can be easily identified at monthly intervals. Changes in jobs or contracts, however, cannot be identified. Therefore, in order to detect job-to-job transitions, we exploit a variable that indicates whether an individual has changed jobs or signed a new contract with the same employer.[5] This measure is imperfect in several ways. First, it does not indicate whether the individual has changed employer or occupation/tasks, or whether he/she has simply signed a new contract with the same employer. Second, a positive reply indicates that at least one change has occurred, but it does not reveal several job changes.

The objective of this paper is to study how digital skills alter labour market prospects. Due to the diverse reasons for labour market transitions, not every single change in labour market status can be interpreted as a change in labour market prospects. To avoid such ambiguous transitions, we only study labour market transitions that are not considered temporary. More precisely, transitions from employment

4 For Ireland and the United Kingdom, the reference period are the 12 months preceding the interview.

5 This variable asks whether the individual "left a job or changed from one job to another since the last interview (or last 12 months for the first year of data collection). For employees, a change of job means a change of employer, not moving from one set of duties to another with the same employer. Nevertheless, a change of contract with the same employer is still considered as a change of job". Binary answer option: yes, no. (Eurostat, 2019).

(unemployment) to unemployment (employment) are only recorded if the individual experiences an unemployment (employment) spell of at least six months after six consecutive months of employment (unemployment).[6] In our analysis of job-to-job transitions, it is not possible to exclude individuals who hold mainly temporary jobs.

3.2.2. Patterns of labour market transitions

In our analysis we focus mainly on three kinds of labour market transitions. First, job-to-job transitions are analysed, i.e. the probability that an individual employed at time t and t 1 changes jobs between the two periods. Second, we study the probability to become unemployed for at least six months following an employment period of at least six months. And third, the probability to find a job that lasts for at least six months after an unemployment spell of at least six months is investigated. It is likely that individuals with strong ICT skills search for jobs that demand such skills, in particular because several papers have found that there is a positive skill premium for ICT skills (Hanushek et al., 2015). Similarly, workers who lack ICT skills are less likely to be employed in jobs that require a strong knowledge of such skills. Therefore, in addition to the general case,[7] labour market transitions from and to occupational groups of different levels of ICT intensity (low, medium and high) are studied.

The occupational ICT intensity of each 2-digit ISCO occupational group is derived based on the PIAAC's "skill use at work" indicators. In particular, we exploit information on the frequency with which an individual uses seven different ICT-related tasks at work. These encompass email; searching for work-related information on the internet; conducting online transaction; use of spreadsheets; use of Microsoft Word or similar; use of programming language; and conducting real-time discussions. The frequencies interviewees could indicate were: 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. A number from 1 to 5 is attributed to each of the frequencies in ascending order. Thus, if an individual never uses emails at work the value is zero, compared with 5 if emails are used every day. Based on this information, an average is first calculated at the individual level and then summed within each 2-digit occupation group and country. Thus, the occupational ICT intensity measure is country-specific. Consequently, the bottom, middle and top 12 occupational groups (there are 36 in total) are classified as low, medium and high digitally intensive occupations, respectively. (See Table 7 in the Appendix for details.)

In terms of income, employees are significantly better off in high digital occupations. Median gross wages are on average 59% higher in high digital occupations than in low digital occupations. This difference is particularly pronounced in the UK, where the median employee in a high digital occupation earns twice as much as an employee in a low digital occupation. The difference is smallest in Slovakia, where the gap is around 25%. It is also interesting to note that individuals who are employed in low digital occupations are more likely to have temporary contracts. While 22% of employees in low digital occupations are employed based on a temporary contract, only 9% of employees in high digital

[6] This is in contrast to Tøge and Blekesaune (2015), who exploit the same data source to study changes in self-rated health around the event of becoming unemployed. In their paper, the authors include unemployment spells of at least three months that follow an employment spell that lasted at least three months.

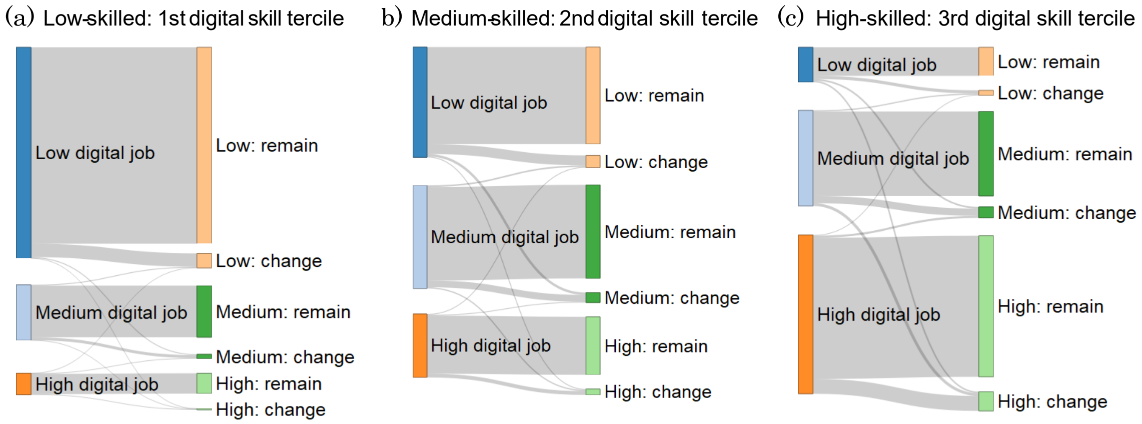
[7] Transition to any kind of job; unemployment spell after employment in any job; employment in any job after unemployment.

occupations have temporary contracts. Thus it appears that digital occupations are not only better paid but also provide more stable employment conditions.

Figures 1 and 2 depict the labour market dynamics by ICT skill tercile for our sample of ten EU countries between 2011 and 2017; Table 5 in the Appendix presents the underlying data. It is unsurprising to observe that employees settle for jobs based on the skills-task match, that is, employees with low digital skills seek out occupations with relatively little ICT task content. Employees located in the second ICT skill tercile are employed across all three occupation categories, albeit with a bias towards low and medium digital occupations. More than half of the individuals in the top skill tercile work in high digital occupations, and around one-third work in medium digital occupations.

Figure 1 shows that a large majority of individuals employed in period $t-1$ remain in the same job at time t. Overall around 13% of individuals in our sample changed jobs or contracts at least once between two interviews (job-to-job transition). The data reveal that individuals with higher digital skills are changing jobs more often than those with fewer digital competences. While 14.5% of all (digitally) high-skilled workers change jobs within one year, only 10.3% of all low-skilled workers do so. Both low- and medium-skilled employees change mainly to low digital occupations, although half of the job changes of medium-skilled employees are to medium or high digital occupations. Furthermore, half of the job-to-job transitions of employees in the third skill tercile target high digital occupations, and another third transit to medium-skilled jobs.

Figure 1 / Labour market mobility of employees, by skill tercile and occupation group



Note: This figure shows the job mobility of employees (self-employed are excluded). The vertical axis is normalised - see Table 5 for absolute numbers. The sample encompasses the nine EU countries and the UK between 2011 and 2017 and covers individuals who were employed at time *t*1 and remained employed in period *t*. An individual is assumed to be still employed in the same job if he/she has not indicated a job change between the two periods. Similarly, an individual is assumed to have changed jobs if he/she stated such a change occurred between the two interviews. ICT scores are predicted based on model 1 presented in Section 4.1.
Sources: EU-SILC (longitudinal component); own estimations.

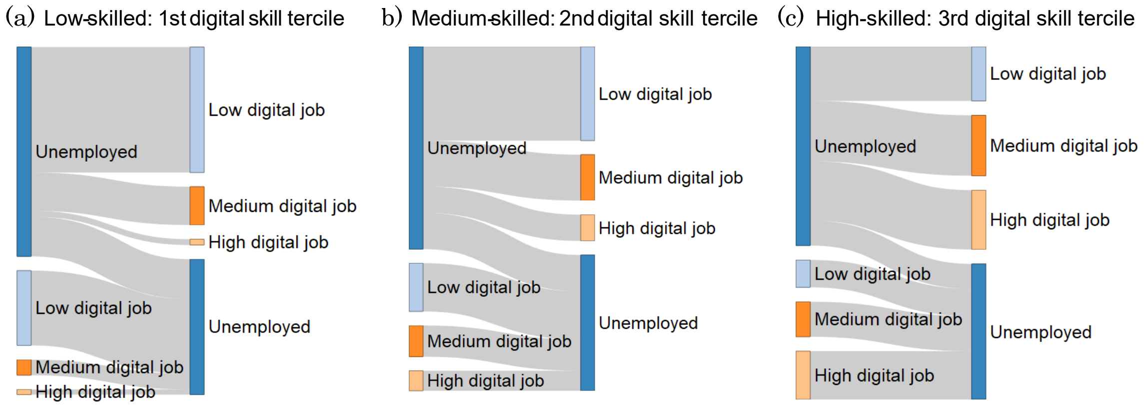
The EU-SILC survey also records the reasons for job changes, with 45% of respondents who changed jobs declaring that the reason to change was to take up or seek a better job. Thus, for almost one-half of respondents the change was motivated by the desire to find a better opportunity in the labour market. Another 28% changed jobs due to the end of a temporary contract or the termination of the contract by the employer.

Furthermore, the figures show that upward transitions, that is, transitions from low- or medium-skilled work to an ICT-intensive occupation, are rather rare. Indeed, this could indicate that the lack of digital skills imposes a ceiling on employees and/or the job-specific human capital that workers have accumulated during their career, which deters the transition to a different occupation.

Transitions from and to unemployment are depicted in Figure 2.[8] Table 5 indicates that the share of unemployed individuals located in the first digital skills group is twice as high as the share of individuals in the top tercile. During the period 2011-2017 on average 4.3% of the former group were unemployed, compared with 1.9% of the latter. Around 3.4% were unemployed in the second skill tercile.[9] The significant differences in labour market opportunities can also be seen from the share of individuals who transit from employment to unemployment. While only 2.2% of individuals in the top tercile were unemployed in period t given employment in period $t-1$, 3.8% of the bottom tercile transited to unemployment. Furthermore, individuals in the top tercile were almost twice as likely to exit unemployment as the bottom tercile.

To summarise, the data exhibit that individuals with stronger digital skills differ in their transition pattern from those with low digital skills. The former group is more likely to change jobs, less likely to be affected by unemployment spells, and more likely to find a job when unemployed. Figures 4 to 6 show the correlation between the ICT score and the probability to experience one of the three labour market transitions. These figures will be discussed further in Section 5.

Figure 2 / Transition to and from unemployment, by skill tercile and occupation group



Note: This figure shows transitions to and from unemployment. The vertical axis is normalised - see Table 5 for absolute numbers. The sample encompasses the nine EU countries and the UK between 2011 and 2017 and covers individuals who were unemployed in *t* 1 or t or both. Note that transitions to and from unemployment are recorded if the reported labour market status changed from “employed” to “unemployed” and from “unemployed” to “employed” between *t* 1 and *t*, respectively. Individuals who were never employed during the time covered by the EU-SILC are not included. This differs from our definition used in the regression analysis - see 3.2. ICT scores are predicted based on model 1 presented in Section 4.1
Sources: EU-SILC (longitudinal component); own estimations.

[8] Note that in Figure 2 all transitions from and to unemployment are recorded. This is in contrast to our definition in Section 3.2, which we use for our estimations. Table 4 shows the transitions based on this definition.

[9] Note that this number is significantly smaller than the official unemployment rate published by the national statistical offices. This is because individuals who were never employed during the time covered by the EU-SILC are excluded because the ICT score was not predicted for unemployed individuals.

4. Method

4.1. PREDICTION OF ICT SKILLS IN THE PIAAC AND EU-SILC

As indicated in Section 3.1, it is impossible to study the relationship between ICT skills and labour market transitions based on PIAAC data alone owing to their cross-sectional character. Therefore, we combine information from the PIAAC and EU-SILC to empirically analyse this relationship. This is achieved in several steps. First, predictors that determine an individual's ICT score are identified.[10] The individual's ICT score is regressed on a set of socioeconomic and occupational variables X_{ic} and a set of country dummies α_c as represented in equation (1). The control variables include gender, age, education, income and occupational group. The sample excludes countries that did not conduct the computer-based test within the PIAAC (Spain, France and Italy), do not provide information on the 2-digit ISCO code in EU-SILC (Austria, Estonia and Finland) or do not provide data for the longitudinal component of EU-SILC (Germany). Since work-specific characteristics are used as predictors, individuals who were not employed at the time they were interviewed in the PIAAC survey are excluded from the sample. Population coefficients are estimated based on PIAAC weights.

$$ICTscore_i = \beta X_{ic} + \alpha_c + \varepsilon_{ic} \tag{1}$$

Table 6 in the Appendix presents OLS estimates of model 1. A cross-country comparison of the actual and predicted distribution of the ICT score can be found in Figure 3. The figure exhibits that our approach tends to generate a distribution characterised by a smaller standard deviation. Therefore, the ICT score for individuals who are located in the tails of the original distribution cannot be predicted accurately.[11] The results are in line with the study conducted by Chung and Elliott (2015), who provide a descriptive analysis of the determinants of ICT skills. Controlling for age, education, income, occupation and country-specific effects, women perform on average worse in the computer-based problem-solving test. Furthermore, younger cohorts outperform older cohorts significantly. The ICT score of individuals with primary education is not statistically different from individuals with less than primary education; the attainment of secondary and tertiary education is associated with higher ICT scores. For a more detailed discussion of the determinants of ICT skills, please refer to Section 3.1

In a second step, these results are used to predict ICT scores for each individual in the EU-SILC data. To this end, the estimated coefficients from model 1 are multiplied by the respective variables for each individual and year in the EU-SILC. Since this approach would create different values of ICT scores for individuals across time, depending on time-variant characteristics, the maximum value is assumed for

[10] Individuals who failed to take part in the PIAAC ICT test due to a lack of operational skills are excluded from our sample. This number ranges from 12% of all individuals who were surveyed in Sweden to almost 50% in Poland.

[11] We tested several methods and specifications to estimate model 1. The cross-validated Lasso and Ridge estimator yields very similar results as plain OLS. Furthermore, the model was estimated on a country-by-country basis, but the results did not change relative to our results presented in Section 5.

each individual in the baseline regressions.[12] This assumption does not allow the ICT score to vary over the observed period.

The ICT scores can only be predicted for individuals in the EU-SILC who were employed at least once while participating in the panel survey, since work-specific characteristics are included in equation (1). The data are also restricted to individuals aged 15-64 and exclude the self-employed.

4.2. ESTIMATION OF LABOUR MARKET TRANSITION MODEL

In order to identify the role ICT skills play in labour market transitions, model 2 is estimated for the different kinds of labour market transitions denoted by $LMtransition_{it}$. The set of transitions considered encompasses those reported in Section 3.1: job-to-job transition, transition to unemployment, and unemployment exit. The dependent variable is a dummy variable equal to 1 if the individual experiences the respective labour market transition between t and $t-1$ and zero otherwise. The respective base groups are discussed in more detail in Section 5.

$$LMtransition_{it} = \beta ICTscore_i + \delta X_{ict} + \alpha_c + \varepsilon_{ict} \quad (2)$$

The random-effects model in equation 2 is estimated using OLS. In the context of binary-dependent variables, Hellevik (2009) argues that linear and logistic models can deliver practically indistinguishable results, especially when the distribution of the dichotomous dependent variable is not extreme, that is, in the absence of large proportions near 0 or 1. However, as Horrace and Oaxaca (2006) argue, OLS assumptions of a normal distribution and homogeneous error variance are violated in the context of binary-dependent variables. Furthermore, OLS can lead to biased and inconsistent estimates. Therefore, we also estimate a logistic model with the same set of control variables.[13]

As Cameron and Miller (2015) have highlighted, standard errors can be misleadingly small if clusters are ignored by the researcher. In this cross-country analysis with a relatively large sample size, it is therefore crucial to cluster standard errors at the country level.

Model 2 is estimated based on EU-SILC data and includes the predicted ICT scores as described in Section 4.1 for a set of nine EU countries[14] and the UK for the period 2011-2017.[15] Note that a natural log transformation for the ICT score is used throughout all regressions and coefficients should therefore be interpreted as semi-elasticities, except in the logistic model, where coefficients are presented as odds ratios. Since ICT scores are only estimated in EU-SILC for individuals who were employed at least once between 2011 and 2017, the sample excludes individuals who were unemployed throughout this period, as explained above.

X_{ict} is a set of control variables. In our regression analysis we combine the controls into four broad groups: demographics, household characteristics, labour market characteristics at time t, and labour

12 This is based on the assumption that workers are generally more likely to be overqualified than being employed in a job where they lack the required ICT skills (Groot and Van Den Brink, 2000; Pellizzari et al., 2015).

13 Results are presented in Tables 9, 11 and 13 in the Appendix.

14 Belgium, Czechia, Denmark, Greece, Lithuania, Poland, Sweden, Slovenia, and Slovakia.

15 Changes in the ISCO classification in 2011 make a comprehensive analysis for the years before 2011 impossible.

market characteristics at time $t-1$. Demographic variables encompass sex, age and education. Variables related to household characteristics include the number of children, the number of children below the age of seven, marital status, home ownership characteristics, the degree of urbanisation, and a household poverty measure. Labour market variables encompass the share of years in employment since the highest level of education has been attained and the country-specific income percentile.[16] (If a person is employed, this is the wage percentile; if a person is unemployed, the percentile in the distribution of unemployment benefits is considered.) Finally, labour market indicators related to part-time, type of contract and the 1-digit ISCO code are included with one lag.

16 In order to alleviate the issue of unobserved heterogeneity, the individual's position in an intra-group income quintile is added to the model in addition to the position in the overall income distribution. Income distributions are calculated at the sub-groups level to proxy idiosyncratic heterogeneity. The groups are generated along five dimensions, leading to 2,700 subgroups based on around 425,000 observations of employees. The five dimensions are: country, one-digit ISCO group, three education groups, five age groups, and sex. Similarly, an individual's unemployment income quintile position is calculated within four dimensions, leading to 300 subgroups based on 90,000 observations of unemployed individuals. The groups are the same as for wage, excluding the one-digit ISCO group.

5. Results

This section presents the results of the empirical analysis investigating the impact of ICT skills on individuals' labour mobility. Each sub-section focuses on one of the three transitions: (i) job-to-job transition, (ii) transition to unemployment, and (iii) unemployment exit. As outlined in the previous section, the random effects model is estimated using OLS. We are aware of the potential limitations of the linear probability model as highlighted, for example, by Horrace and Oaxaca (2006), and therefore estimate effects are additionally based on a logit model - see discussion in Section 3.2. Although the estimations of the logistic model are broadly in line with OLS estimates,[17] we decided to present mainly coefficients from OLS owing to the simpler interpretation (Hellevik, 2009). Furthermore, since the ICT score is transformed using the natural logarithm, the coefficients should be interpreted as semi-elasticities. All regressions include country dummies, and standard errors are clustered at the country level.

5.1. JOB-TO-JOB CHANGES

The first labour transition considered is the move from one job to another at time t conditional on the person being employed at time $t-1$. The dependent variable is a dummy variable equal to 1 if the interviewee's change of job has occurred since the last interview (or in the last 12 months if the interviewee has not been questioned previously). The reference group (dummy variable equal to zero) are workers who are employed at time t but did not record any change in jobs since the last interview.

Figure 4 summarises the relationship between ICT score and the probability of experiencing a job-to-job transition. Each dot in the scatter plots represents a group of individuals of equal size. The figure reveals that job changes to low digital occupations become less likely the higher the ICT score, while the opposite is true for the relationship between job-to-job transitions towards medium digital occupations. Furthermore, the ICT score is positively associated with the probability of job changes towards high digital occupations and suggests that the probability is particularly high for individuals at the top of the ICT score distribution.

[17] OLS and the logistic regression yield conflicting results only two cases - see discussion about a potential non-linear effect in Sections 5.1 and 5.3.

Table 1 / Regression results: impact of ICT skills on probability of job change

	(1)	(2)	(3)	(4)
	job to job			
ICTscore	−0.075*	−0.051	0.053*	0.220***
	(0.041)	(0.037)	(0.028)	(0.057)
Number of observations	308,502	279,185	255,951	139,591
Mean dependent variable	0.088	0.087	0.084	0.071
	job to low digital job			
ICTscore	−0.293***	−0.272***	−0.220**	−0.012
	(0.088)	(0.084)	(0.086)	(0.031)
Number of observations	292,477	264,948	243,476	133,624
Mean dependent variable	0.038	0.038	0.037	0.030
	job to medium digital job			
ICTscore	0.011	0.020	0.074***	0.084***
	(0.017)	(0.020)	(0.026)	(0.031)
Number of observations	289,257	261,935	240,615	132,582
Mean dependent variable	0.027	0.027	0.026	0.022
	job to high digital job			
ICTscore	0.212***	0.204***	0.209***	0.158***
	(0.071)	(0.072)	(0.072)	(0.048)
Number of observations	288,785	261,394	240,213	132,610
Mean dependent variable	0.026	0.025	0.024	0.022
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.
Note: ICTscore in logs; all regressions include country dummies.

The top panel in Table 1 shows the estimates of job-to-job transitions for the entire sample. The results indicate that employees with higher ICT scores are more likely to switch jobs once we include all labour market controls. A 10% increase in the ICT score increases the probability of a job change by 2.2 percentage points. This effect is sizeable, considering that on average around 7% of the employed population change jobs at least once in a given year.

The second panel in the table indicates that workers with a higher ICT score are less likely to move to low digital jobs. This result, however, turns insignificant once we include the full set of control variables (specification 4). In Appendix Table 8 we also test a quadratic relationship and find significant and robust evidence: an increase in the ICT score to around 230 seems to facilitate a job change to a low digital occupation, but an increase beyond this threshold,[18] which is located at the 8th percentile of the ICT

[18] Thresholds are calculated based on the obtained estimates which are presented in the respective tables. The threshold is defined as the level of ICT score, where the linear and squared effects offset each other. That is, in a first step we find the derivative of the function with respect to the natural log of ICT score $\frac{\partial y}{\partial \ln(ICTscore)} = \beta_1 + 2\beta_2 \ln(ICTscore)$ and set it to zero. Note that β_1 and β_2 are the coefficients for the linear and squared ICT term, respectively. Then we solve $\ln(ICTscore) = -\frac{\beta_1}{2\beta_2}$.

score distribution, reduces the probability to change to a low digital job significantly. This result could be driven by at least two channels. First, a certain minimum level of digital skills is believed to be useful for all individuals because it facilitates online job searches and the participation in online networks (Lindsay, 2005; Green and McIntosh, 2007). Second, the results could indicate that an increase in digital skills up to a certain level could be seen as an advantage even in a job where the digital task content is low.

The third and fourth panels confirm a strong positive relation between the ICT score and mobility towards medium and high digital jobs. A 10% increase in the ICT score increases the probability to change to a medium and high digital job by 0.8 and 1.6 percentage points, respectively. Note that the reason for lower coefficients compared with the top panel is probably due to the sample restrictions. While the top panel includes all individuals who changed jobs in general, panel four, for example, includes only individuals who changed jobs to a high digital occupation. The base group remains unchanged across all panels.

Panel c in Figure 4 suggests that ICT skills could have a non-linear effect on the probability to change to a high digital occupation. The figure depicts that job transitions of individuals with an ICT score of less than 260 are minuscule and seem to be independent of the ICT score. Thereafter the probability increases with the ICT score, and the relationship becomes even stronger for ICT scores above 300. This pattern could indicate that job transitions to high digital occupations are not linear in ICT skills. Appendix Table 8 exhibits that a quadratic relationship is indeed statistically significant. After a threshold of 237 the effect of the ICT score on the probability to experience a job change increases. The threshold of 237 is close to the first decile of the average ICT score distribution but lies only in the second percentile of the skills distribution of individuals employed in high digital occupations. Columns 2 and 4 in Table 9 support this result, but the estimates based on the logistic model are contradictory. Column 6 suggests a quadratic relationship too, but with opposite signs. Thus, although the linear relationship appears to be robust, no clear-cut conclusion can be drawn from the test of the quadratic functional form.

To summarise, these results suggest strongly that workers with better ICT skills change jobs more often and in favour of occupations with a higher digital task content. This indicates that strong ICT skills could be a competitive advantage in the race for jobs, in particular to better-paid jobs. This finding is in line with Hampf et al. (2017) and Falck et al. (2016), who find a premium for digital skills in the labour market. Furthermore, as mentioned in Section 3.2.2, for almost one-half of respondents the change of jobs was motivated by the desire to find a better opportunity. Therefore, our results suggest that ICT skills can indeed increase the labour market opportunities available for employees.

5.2. TRANSITION TO UNEMPLOYMENT

This subsection depicts whether ICT skills determine the probability that a worker transits to unemployment, given being employed in $t-1$. In this case, the dependent variable equals 1 if an individual faces an unemployment spell of at least six months after an employment period of at least six months in a given year.[19] The control group consists of individuals who indicate continuous employment during the reference period and who are employed in the respective digital occupation group at $t-1$.

Table 2 / Regression results: impact of ICT skills on probability of transition to unemployment

	(1)	(2)	(3)	(4)
	employment to unemployment			
ICTscore	−0.099***	−0.080***	−0.019	−0.013
	(0.023)	(0.024)	(0.020)	(0.021)
Number of observations	322,407	276,283	250,670	141,245
Mean dependent variable	0.016	0.016	0.016	0.010
	low digital job to unemployment			
ICTscore	−0.150***	−0.121***	−0.044	−0.030
	(0.034)	(0.035)	(0.043)	(0.032)
Number of observations	72,614	63,746	58,698	55,239
Mean dependent variable	0.026	0.027	0.026	0.015
	medium digital job to unemployment			
ICTscore	−0.171***	−0.140***	−0.041	−0.011
	(0.043)	(0.041)	(0.030)	(0.018)
Number of observations	63,268	54,801	49,147	46,966
Mean dependent variable	0.018	0.017	0.018	0.009
	high digital job to unemployment			
ICTscore	−0.109**	−0.066*	−0.007	0.017
	(0.046)	(0.034)	(0.031)	(0.016)
Number of observations	51,752	45,113	40,195	39,040
Mean dependent variable	0.011	0.010	0.010	0.005
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.
Note: ICTscore in logs; all regressions include country dummies.

The scatter plot in Figure 5 exhibits a negative and rather linear relationship between the ICT score and the share of workers who report an unemployment spell across all three occupation groups. Table 3, however, shows that when controlling for individual labour market characteristics in addition to demographic and household characteristics, we fail to identify a statistically significant effect of ICT skills on the probability of an unemployment transition. In Appendix Table 10 we test the quadratic relationship. ICT skills appear to have no effect in preventing individuals from entering unemployment spells of at least six months if they are employed in medium digital occupations. Higher ICT skills for

[19] In a single EU-SILC wave the monthly employment status can be observed for one entire year (usually the calendar year preceding the interview). Unsurprisingly, only few cases could be observed where the first six months of employment are followed by six months of unemployment. Therefore, the dependent variable has been designed such that information on the monthly employment status can be sourced from two interviews/waves. The pattern "six- month-employment, six-month unemployment" can take place within a period of 24 months: the last six months of the preceding interview + 12 months of the current interview + the first six months of the succeeding interview.

employees in low digital occupations appear to reduce the risk of unemployment, albeit only for individuals who exceed the lowest skill quintile within the low digital occupation group (ICT score of 235). Thus it appears that incremental improvements in the ICT score for employees who possess the lowest ICT skills contribute little to preventing unemployment. However, once an employee possesses a certain digital skills set which exceeds a minimum standard, the probability of unemployment decreases. Two possible reasons for this phenomenon seem plausible. First, digital skills are useful to the employer, and therefore the individual is less likely to be made redundant. Second, ICT skills offer more opportunities in the labour market, as suggested by the results for job-to-job transitions, and help the individual to find a job more quickly (potentially in a medium digital occupation).

For employees in highly skilled occupations, the quadratic relationship becomes significant only when we include the entire set of control variables. The estimates suggest that after a threshold ICT score of 303 ICT skills help to prevent transitions to unemployment spells of at least six months relative to colleagues in similar occupations. The threshold is located at the 60th percentile of the ICT score distribution of employees in the high digital occupation group. Thus, an increase in the ICT score reduces the risk of unemployment once an individual belongs to the top third of the ICT skills distribution in high digital occupations.

5.3. UNEMPLOYMENT TO EMPLOYMENT TRANSITION

Finally, we consider unemployment exits. Following our definition in Section 3.2, such a transition is recorded for individuals who return to employment for a period of at least six months after having being unemployed for at least six months. The control group consists of individuals who were unemployed continuously during the reference period. Note that individuals who were unemployed throughout the time they were covered by EU-SILC, such as long-term unemployed individuals, are not included. Figure 6 shows a positive correlation between ICT skills and the chance of exiting unemployment for individuals who exit medium and high digital occupations. ICT skills seem to increase the probability of exiting unemployment and transitioning to a low digital occupation up to a level of around 275. Individuals with a higher ICT score become less likely to find a job in a low digital occupation.

The estimates in the top panel in Table 3, which include the entire sample, suggest an overall positive relationship. The significance of such an effect, however, vanishes when all control variables are included.

Considering the estimates for unemployment exit towards the three occupational groups reveals that the effect of ICT scores is not homogeneous. The results indicate that transitions from unemployment to low digital jobs are less likely for people possessing higher ICT scores. In contrast, there is strong evidence that people with higher ICT scores are more likely to move towards medium and high digital jobs. A 10% increase in the ICT score increases the probability to find a job in a medium digital and high digital occupation by 5 and 6 percentage points, respectively. Table 12 in the Appendix presents results for regressions which include the squared term of the ICT score. The table exhibits a significant quadratic relationship for unemployment exits towards low digital occupations and high digital occupations. As Table 13 indicates, the quadratic relationship is not significant for unemployment exits towards high digital occupations in the logistic model. The coefficients for unemployment exits towards low digital occupations suggest that an increase in the ICT score initially increases the probability, but this decreases after a certain level. The calculated threshold, however, lies below the first percentile of the ICT skills distribution. This indicates that ICT skills are negatively associated with unemployment exits towards low digital occupations, and this effect increases with the ICT score.

Table 3 / Regression results: impact of ICT skills on probability of unemployment exit

	(1)	(2)	(3)	(4)
	unemployment to employment			
ICTscore	0.409***	0.342***	0.112**	0.121
	(0.092)	(0.082)	(0.057)	(0.087)
Number of observations	21,341	18,388	12,904	8,691
Mean dependent variable	0.336	0.347	0.285	0.394
	unemployment to low digital employment			
ICTscore	−0.344***	−0.383***	−0.431***	−0.612***
	(0.112)	(0.114)	(0.121)	(0.191)
Number of observations	17,951	15,421	11,198	7,134
Mean dependent variable	0.211	0.221	0.177	0.261
	unemployment to medium digital employment			
ICTscore	0.516***	0.523***	0.317***	0.502***
	(0.064)	(0.074)	(0.051)	(0.062)
Number of observations	16,093	13,722	10,212	6,183
Mean dependent variable	0.119	0.125	0.097	0.148
	unemployment to high digital employment			
ICTscore	0.648***	0.598***	0.376***	0.612***
	(0.138)	(0.141)	(0.091)	(0.128)
Number of observations	15,063	12,759	9,630	5,646
Mean dependent variable	0.059	0.059	0.043	0.066
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.
Note: ICT score in logs; all regressions include country dummies.

6. Conclusions

Where the labour market is concerned, few policy reports refrain from highlighting the importance of a digital upskilling of the labour force. This paper provides econometric evidence of how ICT skills or the lack thereof affect individuals' labour market opportunities. Based on the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) and longitudinal EU-SILC data, individuals' labour market outcomes are examined over the period 2011-2017 in nine EU countries and the United Kingdom. In order to analyse labour market transitions in more detail, occupations are classified based on their digital task content into low, medium and high digital occupations.

Overall, our results suggest that ICT skills increase labour market opportunities for employees significantly. Higher ICT scores are associated with a higher probability of changing jobs in favour of medium or high digital employment. As the survey data suggest, almost half of all job changes are because individuals have found a better job. Furthermore, ICT skills increase the probability of unemployed individuals finding medium or high digital jobs, which are on average better paid and more often offer permanent contracts. To put it differently, the lack of ICT skills clearly limits labour market opportunities and can therefore function as a ceiling to find well-paid jobs. It is important to note that low digital occupations can still pay relatively well in some economies. In Slovakia, for example, the median income in low digital occupations is on average around 19% lower than in high digital occupations. Moreover, an increase in the ICT score for individuals who are employed in low digital occupations is associated with a lower risk of facing periods of unemployment that last longer than six months. This, however, is only true for individuals who exceed a certain minimum level of digital skills. Thus it appears that individuals at the very bottom of the ICT score distribution are the most affected by the shift in demand towards digital skills. It is clear that there are still numerous jobs that do not require strong digital skills. Our study suggests that ICT skills mainly facilitate job transition towards a particular kind of job, i.e. mainly medium and high digital occupations. Therefore, strong ICT skills may not be helpful for every individual in the labour market.

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Appendix

Table 4 / Frequencies of labour market transition, in % of number of employed/unemployed, by digital skill tercile

	average	**low skilled** 1st digital skill tercile	**medium skilled** 2nd digital skill tercile	**high skilled** 3rd digital skill tercile
job change	12.730	10.260	12.799	14.485
to low digital job	5.191	7.685	6.301	2.425
to medium digital job	3.811	1.982	4.232	4.799
to high digital job	3.728	0.592	2.265	7.261
transition to unemployment	1.530	2.208	1.700	0.881
from low digital job	0.823	1.640	0.783	0.245
from medium digital job	0.487	0.462	0.675	0.347
from high digital job	0.220	0.105	0.242	0.289
unemployment exit	32.924	28.291	34.973	38.868
to low digital job	19.311	22.021	20.472	11.915
to medium digital job	9.266	5.266	10.770	14.837
to high digital job	4.347	1.003	3.731	12.116

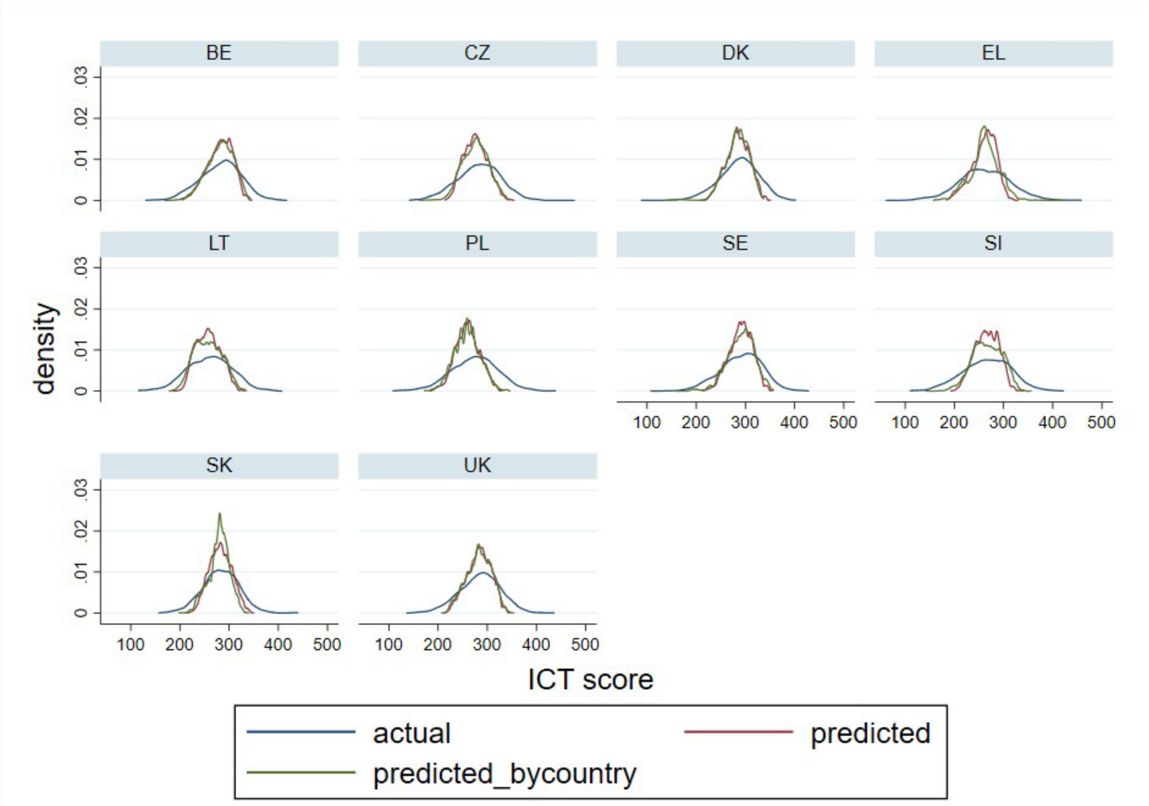
Note: Job change is recorded based on interviewee's response to question if respondent changed job since last interview or since last 12 months in case of first interview. The response is binary: yes, no. Job change requires that individual is employed in two consecutive interviews or for 12 months in case of the first interview. Transition to unemployment is only recorded if interviewee is unemployed for at least six months after at least six months of employment. The concept is analogously applied to unemployment exit. Thus, not all transitions between employment and unemployment are counted. See Section 3.2 for details.
Source: EU-SILC longitudinal component, ten EU sample countries.

Table 5 / Frequencies of labour market transition between low, medium and high digital job and unemployment, % of labour force of respective skill group

	Low digital job	Medium digital job	High digital job	Unemployment	No transition
1st digital skill tercile					
Low digital job	4.3	0.3	0.2	1.6	63.7
Medium digital job	0.3	0.9	0.1	0.3	16.8
High digital job	0.1	0.2	0.2	0.1	6.6
Unemployment	2.6	0.8	0.1		0.8
Total	7.3	2.2	0.6	2.0	87.9
2nd digital skill tercile					
Low digital job	3.4	0.8	0.3	0.8	33.3
Medium digital job	0.5	2.3	0.4	0.5	32.0
High digital job	0.3	0.3	1.3	0.3	19.9
Unemployment	1.6	0.8	0.4		0.6
Total	5.8	4.2	2.5	1.7	85.8
3rd digital skill tercile					
Low digital job	1.0	0.6	0.5	0.3	9.6
Medium digital job	0.4	2.4	0.9	0.3	28.3
High digital job	0.3	0.7	5.0	0.5	47.3
Unemployment	0.5	0.6	0.6		0.2
Total	2.2	4.3	7.0	1.1	85.4

Note: This table provides the underlying data for Figures 1 and 2.
Source: EU-SILC longitudinal component, ten EU sample countries.

Figure 3 / Comparison of actual and predicted ICT-score distribution in PIAAC, by country



Note: This figure compares the actual distribution of ICT scores (blue line) based on PIAAC data relative to the distribution which results from our predictions based on the model described in Section 4.1 (see regression output in Table 6). The red line shows the distribution based on a pooled regression of equation 1 and the green line is based on a country-by-country estimation of equation 1.
Sources: PIAAC; own estimations.

Figure 4 / Scatter plot: share of individuals who changed jobs, by ICT score and destination occupation

(a) Job change to low digital occupation

(b) Job change to medium digital occupation

(c) Job change to high digital occupation

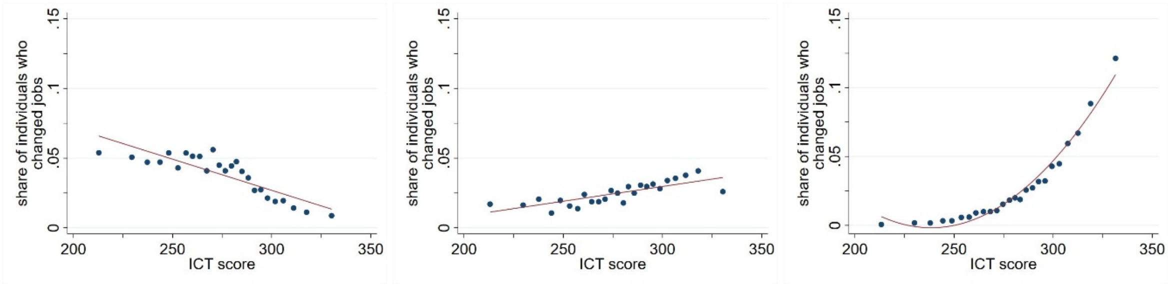


Figure 5 / Scatter plot: share of individuals who transited to unemployment, by ICT score and departing occupation

(a) Transition to unemployment from low digital occupation

(b) Transition to unemployment from medium digital occupation

(c) Transition to unemployment from high digital occupation

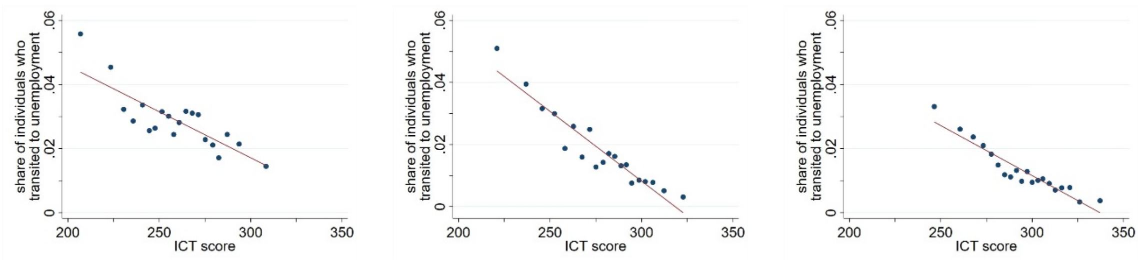


Figure 6 / Scatter plot: share of individuals who exited unemployment, by ICT score and destination occupation

(a) Unemployment exit to low digital occupation

(b) Unemployment exit to medium digital occupation

(c) Unemployment exit to high digital occupation

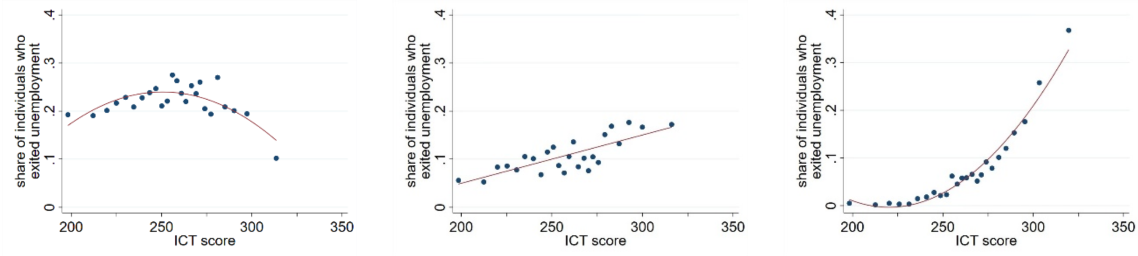


Table 6 / Regression results - predict ICT score based on PIAAC data

	(1)	(2)	(3)	(4)
female	−6.659***	−9.083***	−3.392***	−6.349***
	(0.968)	(0.934)	(1.008)	(1.046)
age 25-34	7.285***	−2.352	−6.274***	−7.996***
	(1.485)	(1.539)	(1.576)	(1.500)
age 35-44	−4.783***	−12.519***	−19.486***	−20.809***
	(1.515)	(1.564)	(1.634)	(1.591)
age 45-54	−18.518***	−24.150***	−31.685***	−32.926***
	(1.604)	(1.633)	(1.732)	(1.668)
age 55-64	−28.468***	−32.994***	−39.376***	−42.119***
	(1.839)	(1.857)	(1.946)	(1.861)
primary educ		−8.192	−3.720	−5.421
		(10.008)	(10.141)	(9.469)
lower secondary educ		9.708**	10.320**	8.309*
		(4.631)	(4.750)	(4.806)
upper secondary educ		25.597***	24.749***	18.859***
		(4.224)	(4.355)	(4.452)
post-secondary non-tertiary educ		36.102***	34.252***	25.744***
		(4.781)	(4.965)	(5.062)
tertiary educ		50.074***	42.264***	29.068***
		(4.212)	(4.396)	(4.563)
income percentile 10-24			−5.619***	−5.799***
			(1.823)	(1.748)
income percentile 25-49			0.672	−1.642
			(1.809)	(1.726)
income percentile 50-74			11.789***	6.837***
			(1.950)	(1.925)
income percentile 75-90			17.006***	8.790***
			(2.275)	(2.252)
income percentile >90			31.075***	20.031***
			(2.316)	(2.336)
adj R-squared	.105	.196	.239	.289
Number of observations	26,776	26,776	25,000	25,000
Country dummies	YES	YES	YES	YES
ISCO 2-digit dummies	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.
Note: Reference groups: male, aged 16-24, less than primary education, income percentile <10.
Source: PIAAC; sample includes Belgium, Czechia, Denmark, Greece, Lithuania, Poland, Sweden, Slovenia, Slovakia, United Kingdom.

Table 7 / Classification of digital occupations (1= low, 3= high), by country

occupation	BE	CZ	DK	EL	LT	PL	SE	SI	SK	UK
Chief executives, senior officials and legislators	3	3	3	3	3	3	3	3	3	3
Administrative and commercial managers	3	3	3	3	3	3	3	3	3	3
Production and specialised services managers	3	3	3	3	3	3	3	3	3	3
Hospitality, retail and other services managers	3	3	3	3	3	3	3	3	3	3
Science and engineering professionals	3	3	2	3	3	3	3	3	2	3
Health professionals	2	1	2	2	1	1	2	2	2	2
Teaching professionals	2	2	2	2	2	2	2	2	2	2
Business and administration professionals	3	3	3	3	3	3	3	3	3	3
ICT professionals	3	3	3	3	3	3	3	3	3	3
Legal, social and cultural professionals	2	3	3	3	3	3	3	2	3	2
Science and engineering associate professionals	2	2	3	3	2	2	3	2	2	2
Health associate professionals	2	2	2	1	1	2	2	1	1	1
Business and administration associate professionals	3	3	3	3	3	3	3	3	3	3
Legal, social, cultural, related associate professionals	3	2	2	2	2	2	2	2	2	2
Information and communications technicians	3	3	3	3	3	3	3	3	3	3
General and keyboard clerks	3	3	2	2	3	2	2	3	3	2
Customer services clerks	3	2	3	2	2	2	2	2	2	2
Numerical and material recording clerks	2	3	3	2	2	2	3	2	2	3
Other clerical support workers	2	2	2	2	2	2	1	1	2	2
Personal service workers	1	2	1	1	2	1	2	1	1	1
Sales workers	2	2	2	1	2	2	2	2	1	1
Personal care workers	1	1	1	2	2	2	1	1	1	1
Protective services workers	2	1	2	1	1	1	2	2	2	1
Market-oriented skilled agricultural workers	2	2	2	2	2	2	2	2	1	2
Building and related trades workers, excl electricians	1	2	1	2	1	1	2	2	2	1
Metal, machinery and related trades workers	1	1	1	1	1	1	1	1	1	1
Handicraft and printing workers	1	2	2	1	1	3	1	3	1	3
Electrical and electronic trades workers	2	2	2	2	2	2	2	2	2	2
Food processing, woodworking, garment	1	1	1	1	1	1	1	1	1	2
Stationary plant and machine operators	1	1	1	1	1	1	1	1	1	1
Assemblers	1	1	1			1	1	1	1	1
Drivers and mobile plant operators	1	1	1	1	1	1	1	1	1	1
Cleaners and helpers	1	1	1	1	1	1	1	1	3	1
Agricultural, forestry and fishery labourers	1	1	1		1	1	1			2
Labourers in mining, constr., manufact., transport	1	1	1	1	1	1	1	1	1	1
Food preparation assistants	2	1	1	1		3	1	1		

Note: The digital occupational indicator is developed for each 2-digit ISCO occupational group based on the “skill use at work” indicators from PIAAC data. The more frequent individuals use digital skills (email, search for work-related information on the internet, conduct online transaction, use of spreadsheets, use of Microsoft Word or similar, use of programming language and conduct real-time discussions) in an occupation, the higher the score. Occupations are divided into terciles based on their average score by country.
Source: PIAAC.

Table 8 / Regression results: impact of ICT skills on probability of job change, quadradtic form

	(1)	(2)	(3)	(4)
	job to job			
ICTscore	−3.231	−3.218	−2.763	−3.866*
	(2.198)	(2.012)	(1.935)	(2.143)
ICTscore_squared	0.283	0.284	0.252	0.366*
	(0.199)	(0.182)	(0.175)	(0.194)
Number of observations	321,596	291,958	268,065	139,933
Mean dependent variable	0.087	0.086	0.083	0.071
	job to low digital job			
ICTscore	5.475***	4.893***	4.978***	3.482***
	(1.692)	(1.552)	(1.532)	(1.209)
ICTscore_squared	−0.516***	−0.462***	−0.465***	−0.313***
	(0.157)	(0.144)	(0.144)	(0.110)
Number of observations	304,792	276,997	254,939	133,877
Mean dependent variable	0.037	0.036	0.035	0.029
	job to medium digital job			
ICTscore	1.270**	1.318**	1.473*	0.156
	(0.599)	(0.642)	(0.825)	(0.812)
ICTscore_squared	−0.113**	−0.116**	−0.126*	−0.006
	(0.054)	(0.058)	(0.073)	(0.074)
Number of observations	301,572	273,984	252,078	132,835
Mean dependent variable	0.026	0.026	0.025	0.022
	job to high digital job			
ICTscore	−9.679***	−9.172***	−8.775***	−7.776***
	(3.377)	(3.168)	(3.164)	(2.881)
ICTscore_squared	0.885***	0.839***	0.804***	0.711***
	(0.308)	(0.289)	(0.289)	(0.262)
Number of observations	301,100	273,443	251,676	132,863
Mean dependent variable	0.025	0.024	0.023	0.022
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 9 / Robustness checks, regression results: impact of ICT skills on probability of job change

	OLS, excl bottom decile		OLS, excl top decile		Logit, full sample	
	job to job					
ICTscore	0.257***	−5.329	0.220***	−5.217**	4.197***	−62.067***
	(0.072)	(3.565)	(0.049)	(2.357)	(0.956)	(13.742)
ICTscore_squared		0.497		0.490**		5.923***
		(0.318)		(0.214)		(1.238)
Number of observations	129,293	129,293	122,371	122,371	139,933	139,933
Mean dependent variable	0.073	0.073	0.068	0.068	0.071	0.071
	job to low digital job					
ICTscore	−0.025	5.761***	0.005	2.782*	−1.163	88.099*
	(0.047)	(1.935)	(0.037)	(1.656)	(0.791)	(48.379)
ICTscore_squared		−0.515***		−0.250*		−8.048*
		(0.173)		(0.152)		(4.395)
Number of observations	123,314	123,314	117,892	117,892	133,792	133,792
Mean dependent variable	0.028	0.028	0.032	0.032	0.029	0.029
	job to medium digital job					
ICTscore	0.084**	−0.082	0.101***	−1.727*	5.826***	89.735*
	(0.039)	(1.236)	(0.031)	(1.027)	(2.001)	(48.242)
ICTscore_squared		0.015		0.165*		−7.468*
		(0.111)		(0.093)		(4.368)
Number of observations	122,698	122,698	116,538	116,538	132,835	132,835
Mean dependent variable	0.023	0.023	0.021	0.021	0.022	0.022
	job to high digital job					
ICTscore	0.212***	−11.062**	0.128***	−7.205***	13.165***	236.265***
	(0.065)	(4.411)	(0.043)	(2.621)	(2.256)	(46.942)
ICTscore_squared		1.002**		0.661***		−19.622***
		(0.397)		(0.239)		(4.091)
Number of observations	122,751	122,751	115,874	115,874	132,778	132,778
Mean dependent variable	0.024	0.024	0.016	0.016	0.022	0.022

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.
Note: This table provides robustness checks for results in Table 1 and Table 8. Estimations based on full model, that is, including the full set of control variables. Note that coefficients estimated with OLS (column 1-4) can be interpreted as semi-elasticities. Coefficients estimated based on the logit model (column 5-6) are presented as odds ratios. Column 1-2 and column 3-4 exclude individuals in the bottom and top decile of the ICT score distribution, respectively.

Table 10 / Regression results: impact of ICT skills on probability of transition to unemployment, quadratic form

	(1)	(2)	(3)	(4)
	job to unemployment			
ICTscore	−0.055	−0.076	−0.330	0.666
	(0.729)	(0.779)	(0.798)	(0.575)
ICTscore_squared	−0.005	−0.001	0.028	−0.061
	(0.066)	(0.071)	(0.072)	(0.052)
Number of observations	336,912	289,654	263,103	142,031
Mean dependent variable	0.017	0.017	0.017	0.011
	low digital job to unemployment			
ICTscore	2.773**	2.641**	2.386**	2.425***
	(1.238)	(1.067)	(1.066)	(0.715)
ICTscore_squared	−0.267**	−0.251***	−0.220**	−0.222***
	(0.112)	(0.097)	(0.096)	(0.066)
Number of observations	73,454	64,299	59,062	55,584
Mean dependent variable	0.028	0.028	0.027	0.016
	medium digital job to unemployment			
ICTscore	0.550	1.960	1.643	1.061
	(2.236)	(1.444)	(1.509)	(0.902)
ICTscore_squared	−0.066	−0.189	−0.151	−0.096
	(0.200)	(0.132)	(0.136)	(0.081)
Number of observations	63,859	55,200	49,371	47,182
Mean dependent variable	0.019	0.018	0.018	0.009
	high digital job to unemployment			
ICTscore	−0.413	0.919	0.853	1.737***
	(2.124)	(2.199)	(2.026)	(0.575)
ICTscore_squared	0.026	−0.088	−0.076	−0.152***
	(0.185)	(0.192)	(0.177)	(0.051)
Number of observations	52,284	45,485	40,425	39,265
Mean dependent variable	0.011	0.010	0.010	0.006
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 11 / Robustness checks, regression results: impact of ICT skills on probability of transition to unemployment

	OLS, excl bottom decile		OLS, excl top decile		Logit, full sample	
	job to unemployment					
ICTscore	−0.023	0.456	−0.001	0.766	−0.320	96.890***
	(0.020)	(0.752)	(0.015)	(0.675)	(0.650)	(25.975)
ICTscore_squared		−0.043		−0.069		−8.773***
		(0.068)		(0.061)		(2.381)
Number of observations	132,745	132,745	126,542	126,542	144,347	144,347
Mean dependent variable	0.010	0.010	0.012	0.012	0.011	0.011
	low digital job to unemployment					
ICTscore	−0.068**	3.064***	−0.024	2.398***	−1.253	179.014***
	(0.032)	(1.168)	(0.030)	(0.788)	(0.937)	(38.480)
ICTscore_squared		−0.280***		−0.220***		−16.374***
		(0.106)		(0.073)		(3.497)
Number of observations	46,586	46,586	54,636	54,636	55,536	55,536
Mean dependent variable	0.015	0.015	0.016	0.016	0.016	0.016
	medium digital job to unemployment					
ICTscore	−0.014	2.456*	−0.015	1.257	−0.490	104.278**
	(0.022)	(1.328)	(0.016)	(1.045)	(0.835)	(40.985)
ICTscore_squared		−0.220*		−0.114		−9.398**
		(0.118)		(0.094)		(3.699)
Number of observations	45,668	45,668	42,071	42,071	47,169	47,169
Mean dependent variable	0.009	0.009	0.010	0.010	0.009	0.009
	high digital job to unemployment					
ICTscore	0.008	1.014	0.043***	2.286**	1.450	237.401***
	(0.015)	(0.660)	(0.014)	(1.131)	(1.557)	(88.462)
ICTscore_squared		−0.089		−0.199**		−20.878***
		(0.059)		(0.101)		(7.865)
Number of observations	38,735	38,735	27,662	27,662	39,263	39,263
Mean dependent variable	0.005	0.005	0.006	0.006	0.006	0.006

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.
Note: This table provides robustness checks for results in Table 1 and Table 8. Estimations based on full model, that is, including the full set of control variables. Note that coefficients estimated with OLS (column 1-4) can be interpreted as semi-elasticities. Coefficients estimated based on the logit model (column 5-6) are presented as odds ratios. Column 1-2 and column 3-4 exclude individuals in the bottom and top decile of the ICT score distribution, respectively.

Table 12 / Regression results: impact of ICT skills on probability of unemployment exit, quadratic form

	(1)	(2)	(3)	(4)
	unemployment to employment			
ICTscore	−8.015*	−9.126*	−4.944	−9.269
	(4.723)	(4.738)	(4.665)	(6.074)
ICTscore_squared	0.763*	0.857**	0.458	0.850
	(0.422)	(0.423)	(0.418)	(0.542)
Number of observations	21,341	18,388	12,904	8,691
Mean dependent variable	0.336	0.347	0.285	0.394
	unemployment to low digital employment			
ICTscore	15.253***	12.425***	11.106***	11.438*
	(4.973)	(4.760)	(4.123)	(6.338)
ICTscore_squared	−1.414***	−1.161***	−1.045***	−1.092*
	(0.450)	(0.431)	(0.377)	(0.573)
Number of observations	17,951	15,421	11,198	7,134
Mean dependent variable	0.211	0.221	0.177	0.261
	unemployment to medium digital employment			
ICTscore	−6.618*	−6.058*	−3.928	−8.450*
	(3.431)	(3.238)	(2.972)	(4.524)
ICTscore_squared	0.646**	0.596**	0.384	0.810**
	(0.312)	(0.294)	(0.271)	(0.412)
Number of observations	16,093	13,722	10,212	6,183
Mean dependent variable	0.119	0.125	0.097	0.148
	unemployment to high digital employment			
ICTscore	−25.630***	−24.358***	−17.711***	−27.593***
	(4.563)	(4.011)	(4.107)	(6.207)
ICTscore_squared	2.378***	2.257***	1.637***	2.551***
	(0.425)	(0.375)	(0.379)	(0.571)
Number of observations	15,063	12,759	9,630	5,646
Mean dependent variable	0.059	0.059	0.043	0.066
Demographics	YES	YES	YES	YES
Household characteristics	NO	YES	YES	YES
Labour market controls I	NO	NO	YES	YES
Labour market controls II	NO	NO	NO	YES

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 13 / Robustness checks, regression results: impact of ICT skills on probability of unemployment exit

	OLS, excl bottom decile		OLS, excl top decile		Logit, full sample	
	unemployment to employment					
ICTscore	0.091	−27.501*	0.091	−7.840	0.603	−44.914
	(0.117)	(15.167)	(0.099)	(6.711)	(0.513)	(32.156)
ICTscore_squared		2.466*		0.720		4.118
		(1.349)		(0.603)		(2.867)
Number of observations	7,205	7,205	8,412	8,412	8,691	8,691
Mean dependent variable	0.408	0.408	0.388	0.388	0.394	0.394
	unemployment to low digital employment					
ICTscore	−0.960***	−3.730	−0.603***	14.186*	−4.036***	97.666**
	(0.271)	(9.804)	(0.182)	(7.434)	(1.176)	(44.763)
ICTscore_squared		0.248		−1.345**		−9.235**
		(0.869)		(0.670)		(4.046)
Number of observations	5,785	5,785	6,985	6,985	7,134	7,134
Mean dependent variable	0.263	0.263	0.264	0.264	0.261	0.261
	unemployment to medium digital employment					
ICTscore	0.533***	−9.910	0.586***	−13.635**	5.501***	−14.042
	(0.080)	(14.432)	(0.041)	(5.793)	(0.978)	(63.370)
ICTscore_squared		0.934		1.292**		1.761
		(1.292)		(0.527)		(5.676)
Number of observations	5,117	5,117	6,015	6,015	6,183	6,183
Mean dependent variable	0.167	0.167	0.145	0.145	0.148	0.148
	unemployment to high digital employment					
ICTscore	0.938***	−45.489***	0.458***	−22.810***	12.344***	29.754
	(0.205)	(13.505)	(0.145)	(6.757)	(1.983)	(117.281)
ICTscore_squared		4.146***		2.114***		−1.545
		(1.219)		(0.623)		(10.392)
Number of observations	4,629	4,629	5,439	5,439	5,630	5,630
Mean dependent variable	0.079	0.079	0.054	0.054	0.067	0.067

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.
Note: This table provides robustness checks for results in Table 1 and Table 8. Estimations based on full model, that is, including the full set of control variables. Note that coefficients estimated with OLS (column 1-4) can be interpreted as semi-elasticities. Coefficients estimated based on the logit model (column 5-6) are presented as odds ratios. Column 1-2 and column 3-4 exclude individuals in the bottom and top decile of the ICT score distribution, respectively.

IMPRESSUM

Herausgeber, Verleger, Eigentümer und Hersteller:
Verein „Wiener Institut für Internationale Wirtschaftsvergleiche“ (wiiw),
Wien 6, Rahlgasse 3

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Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.