European Commission

JRC TECHNICAL REPORTS

INSTITUTE FOR PROSPECTIVE TECHNOLOGICAL STUDIES DIGITAL ECONOMY WORKING PAPER 2015/10

E-skills Mismatch: Evidence from International Assessment of Adult Competencies (PIAAC)

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2015

Joint Research Centre

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This publication is a Working Paper by the Joint Research Centre of the European Commission. It results from the Digital Economy Research Programme at the JRC Institute for Prospective Technological Studies, which carries out economic research on information society and EU Digital Agenda policy issues, with a focus on growth, jobs and innovation in the Single Market. The Digital Economy Research Programme is co-financed by the Directorate General Communications Networks, Content and Technology

JRC Science Hub
https://ec.europa.eu/jrc

JRC98228

ISSN 1831-9408 (online)

How to cite:
Michele Pellizzari, Federico Biagi, Barbara Brecko (2015). E-skills Mismatch: Evidence from PIAAC. Institute for Prospective Technological Studies Digital Economy Working Paper 2015/10. JRC98228

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Abstract

In this report we produce measures of skill mismatch in the domain of problem solving in technology-rich-environments using PIAAC data for the 13 countries of the European Union participating in the programme (plus the US), extending the methodology developed in Pellizzari and Fichen (2013).

In practice, we define every worker as well-matched if his/her ICT skills fall in between the minimum and maximum requirement of the occupation in which he/she is observed, as under-skilled if they fall below the minimum and over-skilled if they are above the maximum. Our results indicate that, on average, about 87% of the workers in our final sample are well-matched, about 10% are over-skilled and 3% under-skilled. Ireland and the Slovak Republic are the countries with the highest incidence of over-skilling (mostly at the expenses of the well-matched) whereas Poland and the Netherlands only have about 5%. Under-skilling is highest in Sweden and Belgium but there seems to be quite a bit less variation in the incidence of under (relative to over)-skilling. These findings contrast sharply with results obtained using other popular methods adopted in the literature.

1. Introduction

The issue of skill-mismatch has been ranking high on the European policy agenda for a long time and even more so in the most recent years due to the prolonged economic recession. As more and more jobs vanish, more and more workers face long periods of joblessness during which their skills deteriorate, making it even more difficult for them to find employment.

In spite of the strong interest on skill mismatch, research on this topic has not been able to effectively guide the policy debate, mostly due to the difficulty in defining and measuring mismatch. Different authors use the term to indicate different phenomena, sometimes linked to each other and sometimes very different. For a large part this confusion arises from the fundamental fact that skill mismatch is essentially the outcome of the interaction between labour supply and labour demand, whereas most of the data used to measure it are collected exclusively from the supply side of the market, namely individuals who are either employed, unemployed or inactive.

A major advancement in the definition and measurement of mismatch has recently been possible thanks to the availability of the OECD Skill Survey, part of the large *Programme for the International Assessment of Adult Competencies* (PIAAC). This survey contains very detailed information on education and employment for a collection of comparable representative samples of 24 OECD and OECD partner countries (gathered with a background questionnaire) and in addition it administers tests of competencies to all respondents in three key areas: literacy, numeracy and problem solving in Technology Rich Environments (TRE).

Elaborating this information through the lenses of a simple theoretical model of optimal skill deployment, the OECD proposed a new measure of skill mismatch that was presented in the first OECD Skills Outlook (OECD, 2013) and further detailed in Pellizzari and Fichen (2013). However, both these publications focus exclusively on mismatch in the literacy and numeracy domains and do not extend the analysis to problem solving in Technology Rich Environments. This is because the structure of this last test is slightly different from the previous ones. Specifically, while respondents who could not use a computer could take the literacy and the numeracy modules of PIAAC on paper, they would simple drop out of the problem solving in TRE test, which could only be taken on a PC. Although this is an important concern, it is certainly one that can be addressed under appropriate assumptions.

The PIAAC module on problem solving in TRE is particularly interesting because it essentially asked respondents to solve problems on a computer, like searching a reference in an electronic library or finding the quickest route between two locations using electronic maps. Competence in this domain is thus informative about the degree of ICT knowledge of the labour force and it can be used to produce measures of e-skill mismatch adapting the same framework used in OECD (2013) and Pellizzari and Fichen (2013).

This report is organized as follows. In Sect. 2 we briefly introduce PIAAC and its measurement of numeracy, literacy and e-skills. In Sect. 3 we document the distribution of e-skills in the EU countries for which PIAAC data are available. In Sect. 4 we discuss how to measures skill mismatch in the PIAAC domain of problem solving in TRE, hence extending Pellizzari and Fichen (2013). In Sect. 5 we explain how we deal with the issue of missing observations for those who did not take the test in TRE. In Sect. 6 we present our estimates for e-skills mismatch using data for the 13 countries of the European Union participating in the test (plus the US), while in Sect. 7 we perform robustness analysis. Sect. 8 concludes our work.

Throughout the report we will refer to the competences tested in the PIAAC problem solving in TRE module as e-skills or ICT skills.

2. Assessing E-Skills in PIAAC

PIAAC is a broad research and policy programme managed by the OECD in collaboration with the governments of the participating countries and a number of other international organisations. One of the key elements of such programme is the Skills Survey, i.e. a collection of nationally representative samples (for the adult population aged 16 to 65) in each participating country. The samples are constructed according to harmonised guidelines designed to guarantee the comparability of data across national boundaries. The interviews were conducted between the summer of 2011 and the spring of 2012 in 24 countries.

Sampled individuals are administered a very detailed, but otherwise relatively standard, background questionnaire collecting information on family composition, employment, incomes and, interestingly, a battery of questions on the use of skills at work. The most innovative feature of the OECD Skill Survey is the skill assessment module. After answering the background questionnaire, survey participants are asked to take a test of their competence in three skill domains: literacy, numeracy and, in the PIAAC terminology, problem solving in Technology Rich Environments.

The first two domains are relatively straightforward and they cover: a) standard competences in reading, writing and understanding (for literacy) and b) counting and making calculations or more sophisticated mathematical and statistical operations (for numeracy). Problem solving in TRE refers to the ability to solve specific problems using modern ICT tools, typically a personal computer and its associated functions. Examples of the type of questions that are asked in this module include searching books in the archive of an electronic library, finding the quickest route between two locations on an online map. OECD (2013) provides a wealth of details on the structure of the test. For the purpose of this report, we will define e-skills as the score results from the problem solving in TRE module of PIAAC.

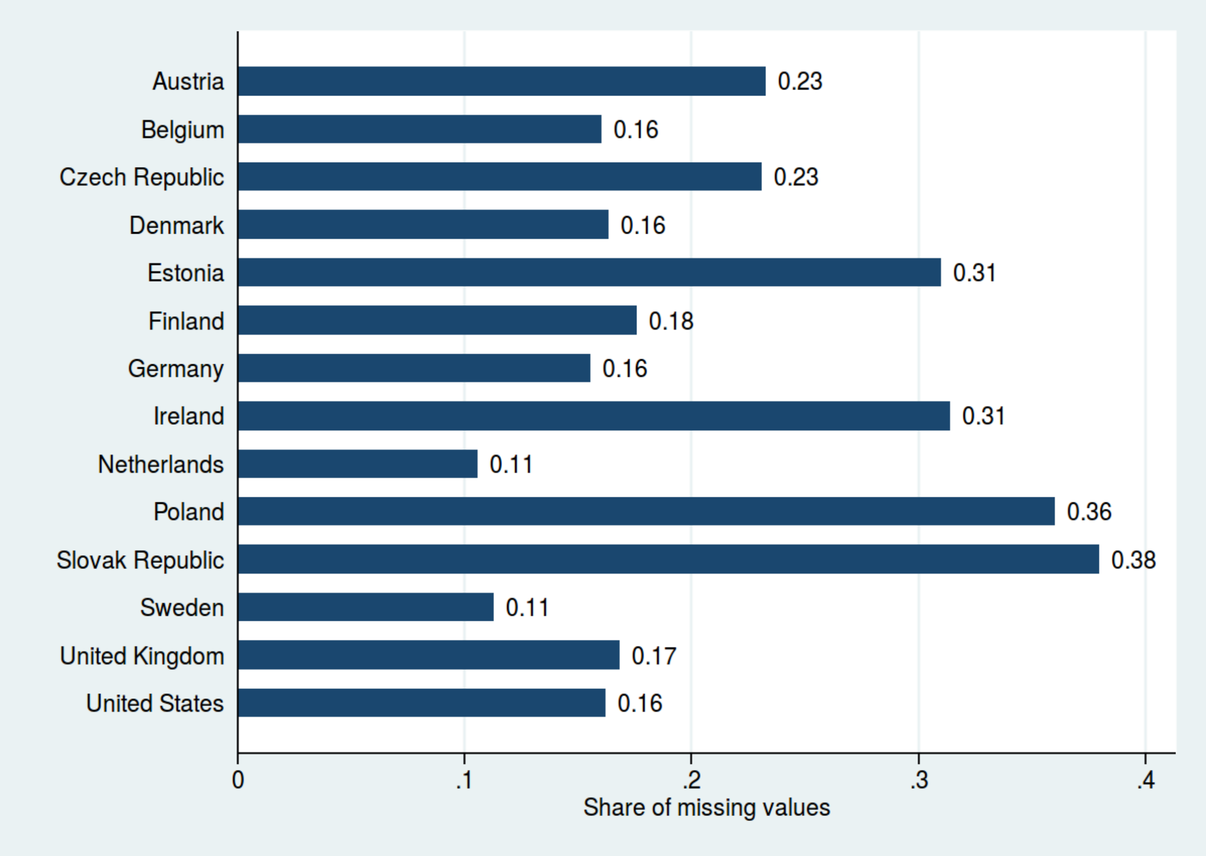
All three modules of the PIAAC assessment exercise, by default, were administered on a computer, however, for those who could not use a PC, the literacy and numeracy tests could also be taken on paper. Given the specific nature of the problem solving in TRE module, this possibility was not offered and those who were completely computer illiterate were simply routed out. More specifically, one could be routed out of the problem solving module for three reasons. First, the background questionnaire asked about one's familiarity with personal computers and those who reported not to be able to use a computer where automatically excluded from the problem solving exercise. Second, before engaging in any of the skill tests respondents were required to answer a very short set of core questions on computer use, such as how to switch it on and use a keyboard and a mouse. Those failing these core questions were given paper-based versions of the literacy and numeracy tests but were excluded from the problem solving in TRE test. Finally, some of those who passed the first two "theoretical" steps ended up opting out of the test if they were not able to perform the requested tasks.

This peculiarity of the problem solving module leads to a relatively large and heterogeneous incidence of non-responses, making the analysis of the results particularly cumbersome.[1] Moreover, while the literacy and numeracy modules were administered in all participating countries, problem solving in TRE was optional and Cyprus, France, Italy and Spain opted out. Since our focus here is on the EU, once we take into account non-participation to problem solving in TRE, we end up with data on the tests scores from the following countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, Germany, Ireland, the Netherlands, Poland, the Slovak Republic, Sweden, the United Kingdom (plus the US when we compute e-skills mismatch).

[1] Which is the reason why both OECD (2013) and Pellizzari and Fichen (2013) only focus on literacy and numeracy.

Notice that the share of PIAAC respondents not taking the ICT module for any of the previously mentioned reasons varies extensively among countries: it ranges from around 10% in the Netherlands and Sweden to 38% in the Slovak Republic and 36% in Poland.

***Figure 1*: Share of PIAAC respondents not taking the ICT module**



Most of the non-response is due to participants failing the core ICT questions rather than self-reporting being unable to use a computer (only less than 1% say so in the pooled sample).

As customary in skills surveys, the answers to the test items are elaborated through a psychometric *Item Response Model* (IRT) to derive scores for all survey participants. The PIAAC scores range on a scale 0 to 500.

3. The distribution of E-skills in the EU

We here summarize the main statistics on problem solving in TRE for the EU countries available in PIAAC. Notice that the summary statistics presented here are based on the scores obtained by those who performed the problem solving in TRE [2], and hence do not reflect the distribution of e-skills within the overall population. Moreover, since not all the EU countries in PIAAC actually performed the ICT tests, the EU average in the context of

[2] I.e. those that are completely computer illiterate or those who were routed out of the ICT test are not reflected in these statistics. More specifically, Column 1 in Table 1 represents those who reported not to be able to use a computer, while Column 2 in Table 1 reflects those who were not able to answer a very short set of core questions on computer use, such as how to switch it on and use a keyboard and a mouse. Finally, Column 3 in Table 1 reflects those who passed the first two "theoretical" steps but opted out of the test because they were not able to perform the requested tasks.

test scores refers to a set of countries different from the one referred to when we consider responses to the background questionnaire[3].

The table below presents the demographics for adults, in the age interval 16-65, aggregating all the EU countries participating in PIAAC.

***Table 1*: Basic statistics (by age, education, gender, occupation)**

	Adults with no computer experience	Adults failed ICT core	Adults who "opted out" of taking the computer based assessment	Adults who took computer based assessment	Overall EU
Age group (%)					
16-24 year-olds	1,5	15,5	10,3	23,6	19,5
25-34 year-olds	4,9	18,1	13,8	22,1	19,4
35-44 year-olds	12,1	19,3	18,7	21,3	20,1
45-54 year-olds	27,2	22,0	24,0	18,1	19,9
55-65 year-olds	54,3	25,0	33,2	14,9	21,1
Educational attainment (%)					
Less than upper secondary	56,0	32,6	25,4	17,4	27,0
Upper secondary, post-secondary non tertiary	40,3	47,1	54,2	45,9	43,4
Tertiary	3,6	20,3	20,4	36,7	29,5
Occupational level (%)					
Elementary occupation	25,8	16,7	13,5	7,3	9,7
Semi-skilled blue collar occupation	45,3	30,2	29,3	17,0	20,9
Semi-skilled white collar occupation	21,3	29,3	30,2	29,7	29,2
Skilled occupation	7,7	23,8	27,0	46,0	40,2

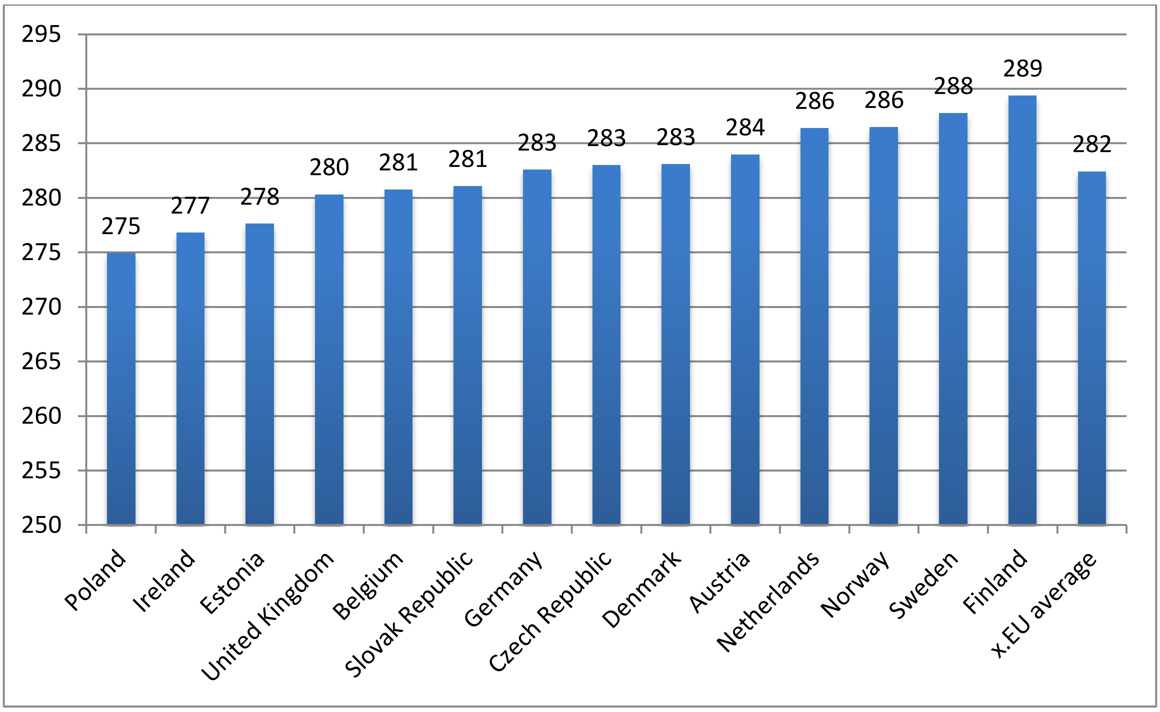
The first thing we notice is the clear generational gap among non-users (Column 1): 54.3% of those that do not have prior computer experience are in the age group 55-65 (and only 1.5% are in the age group 16-24). Older generations are also over-represented among those that either opted out (Column 3) or failed the test (Column 2). However, when we look only at those that actually performed the computer based tests (Column 4), we can see that the different age groups account for more similar shares (the values are lower for the older groups).

[3] The EU countries for which we have data from the background questionnaire are Austria, Belgium, Czech republic, Cyprus, Denmark, Estonia, Finland, France, Germany, Ireland, , Italy, the Netherlands, Poland, the Slovak Republic, Spain, Sweden, and the United Kingdom. Of these, Cyprus, France, Italy and Spain opted out from the test of problem solving in TRE.

When we consider the educational composition, we see that -among those who have no ICT skills- the group with the lowest educational attainment (less than upper secondary) takes up the highest share (56%), followed by the group with completed upper secondary, post-secondary non-tertiary education, while only 3.6% of those who have no ICT skills have completed tertiary education. Among the two other categories of those who did not take the ICT test (Columns 2 and 3 in Table 1), we notice that the group with completed upper secondary, post-secondary non-tertiary education has higher shares (47.1 % and 54.2%), followed by the group with less than secondary education (32.6 and 25.4) and then by the group with completed tertiary education (20.3% and 20.4%). Finally, when looking at the occupational/skills composition, we notice that among those with no computer experience, almost the entirety is made by individual in elementary or semi-skilled occupations (92.3%). These groups are dominant also among those that either failed (76.2%) or opted out the ICT test (73%). Among those that actually took the ICT test, the (relative) majority is made by individual in skilled occupations.

Figure 2 presents the assessment scores for problem solving in TRE[4] for the EU countries for which PIAAC provides data. The mean scores range from 275 in Poland to 289 in Finland, with the EU average being 282.

***Figure 2*: Mean PV problem solving in technology reach environment (PS – TRE)**

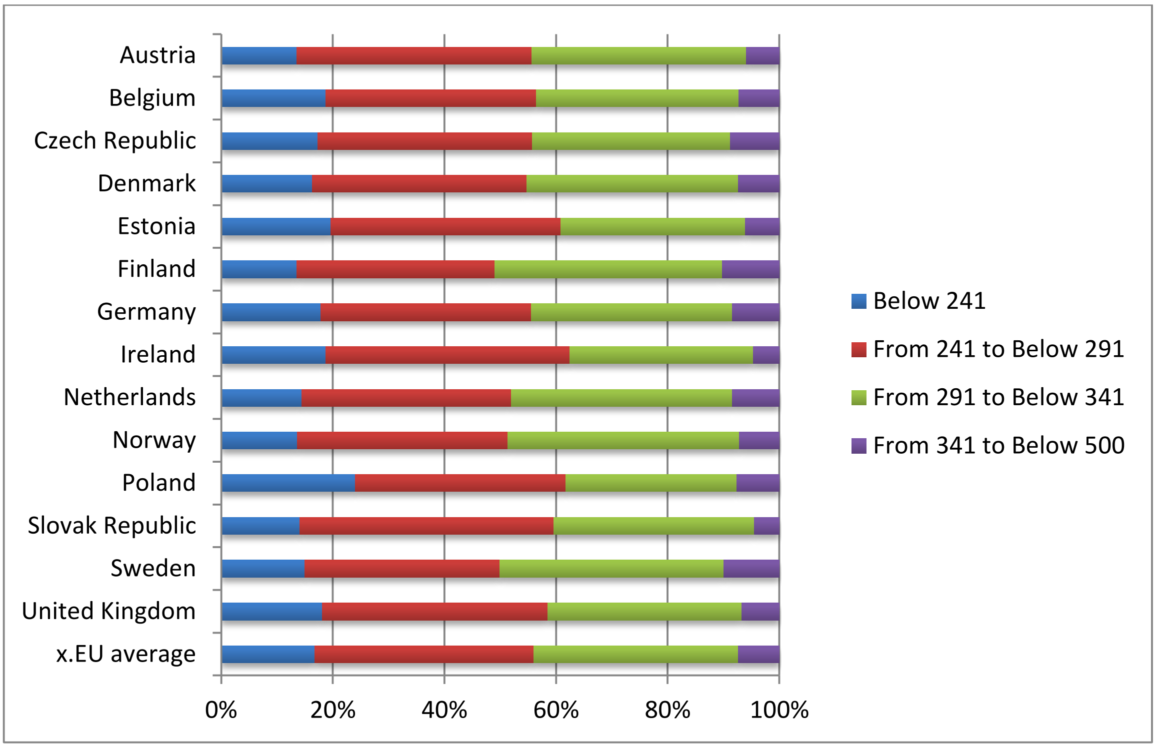


When looking at the distribution of test scores[5] across countries (see also Table A1), Figure 3 shows that in all countries there is only a minority of respondents in proficiency level 3, and the vast majority is in levels 1 and 2. However, some countries clearly show signs of better test results. In particular, Finland, Norway, Sweden, the Netherlands and Austria have both above average test outcomes and a larger than average share of level 3 test scores. The largest percentage of adults with below level 1 test outcomes is found in Poland (24%), Estonia (19.6%), Belgium (18.8%), Ireland (18.7%) and UK (18%).

[4] See the Appendix for an explanation of how to interpret the different scores obtained in the test for problem solving in TRE.

[5] Test scores are defined as Plausible Values (PV), due to the methodology used by PIAAC. For additional info please see OECD (2015) and OECD (2013).

***Figure 3*: Distribution of PV; PS-TRE**



The PIACC questionnaire contains a set of self-reported question that are very useful for better understanding the relationship between ICT skills, computer use and job performance.

The first of such questions directly asks "***Do you think you have the computer skills you need to do your job well?***" This provides very important sources of information for our analysis and it is further explored in our estimate of e-skill- mismatch.

The data show large across-country differences. While the EU share of positive answers is 7.54%, the country specific values range from 16.2 % in Norway, 11.1% in Finland and 9.9% in Denmark, to only 3.2% in the Czech Republic, 3.7% in Austria, 4% in the Slovak Republic, and 5% in Germany (a value that is less than half the one recorded for Norway).

When we relate the answer to this question to the educational attainment, we find that percentage of those who answered positively tend to rise with the level of educational attainment (see Table 2A, see also Fig 5).

Figure 4: **Positive answers to the question: "Do you think you have the computer skills you need to do your job well?"; PS-TRE**

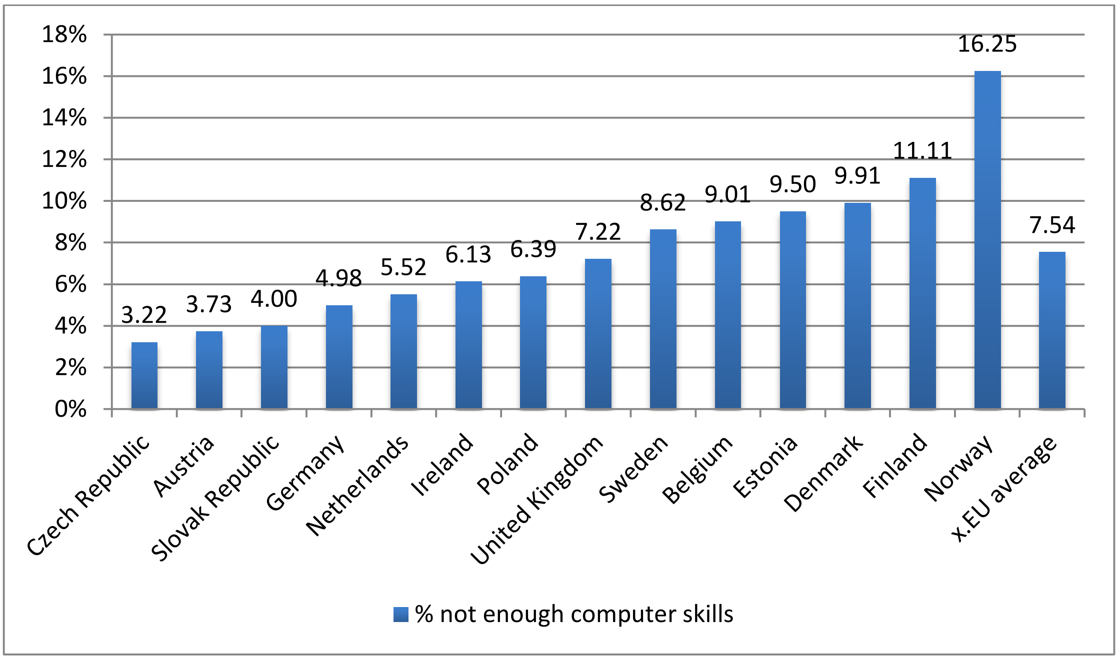
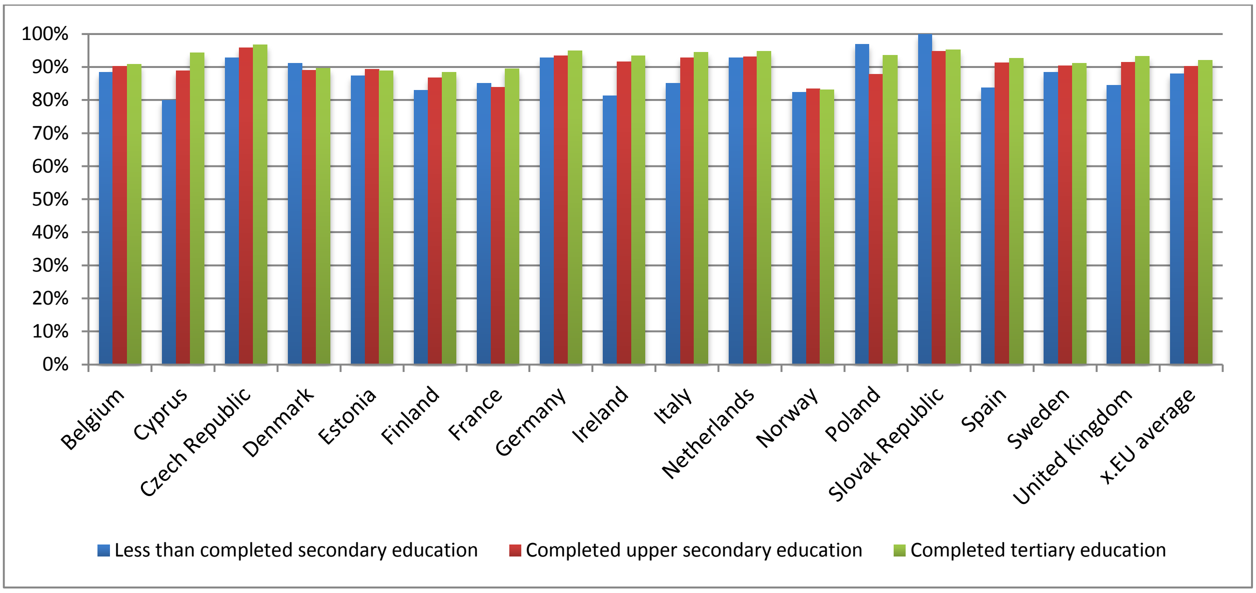


Figure 5: **Positive answers to the question: "Do you think you have the computer skills you need to do your job well?" by level of educational attainment; PS-TRE**



The EU average shows that, among respondents with less than completed upper secondary education, 12% of respondents feel they do not have the computer skills to do the job well, (10% among respondents with completed upper secondary, post-secondary non tertiary education and 8% among those with completed tertiary education).

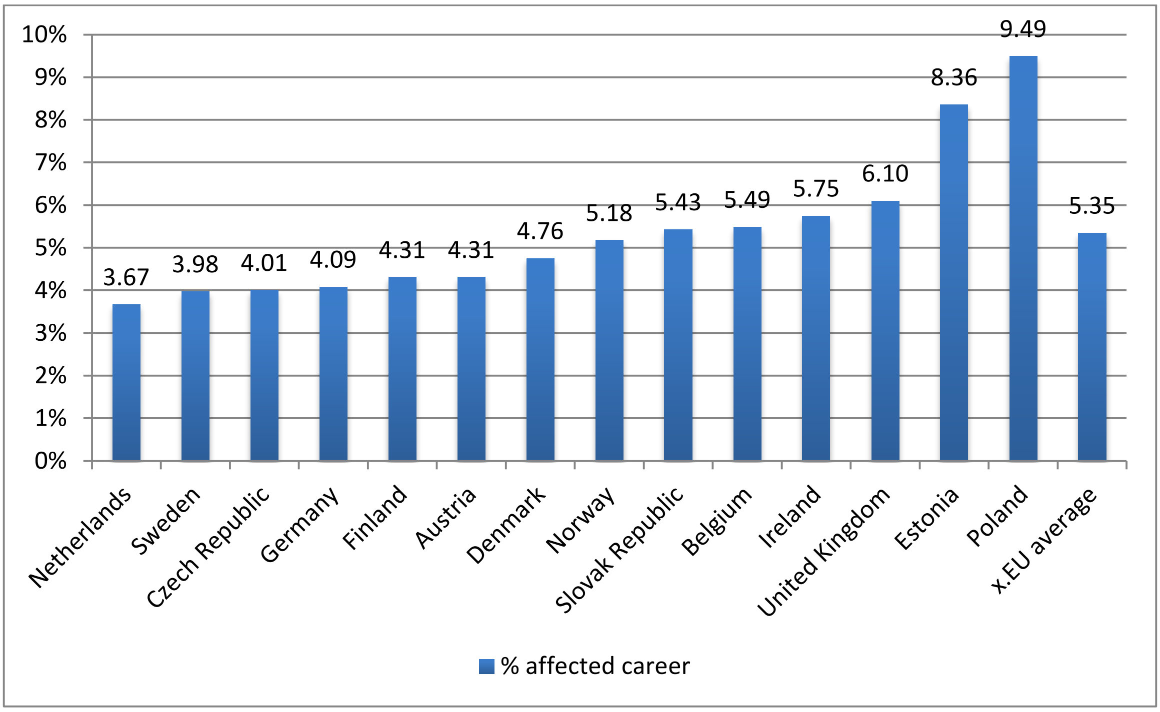
The extreme cases are represented by Cyprus, where roughly 20% of respondents with less than completed high school think they lack the computer skills needed for the job and the Slovak Republic where all the respondents with less than completed high school declare to have the required ICT skills. Overall the data show large across-country variation (in part due to the varying sample size).

Lack of computer skills not only affects the productivity and efficiency at work place, it also affects the possibility of getting a job, getting a promotion or a pay raise. PIAAC data allow us to focus on this issue by looking at the responses to the following question: "***Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?***"

In the EU (overall) 5.35% of respondents reported that lack of computer skills has affected their career.

The percentage of positive answers to this question is the highest in Poland (9.5%), Estonia (8.3%), U.K. (6.1%) and Ireland (5.8%), while it is the lowest in Netherlands (3.6%), Sweden (3.9%), Czech Republic (4%) and Germany (4.1%) (Figure 6).

***Figure 6*: Positive answers to the question: "Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?"**

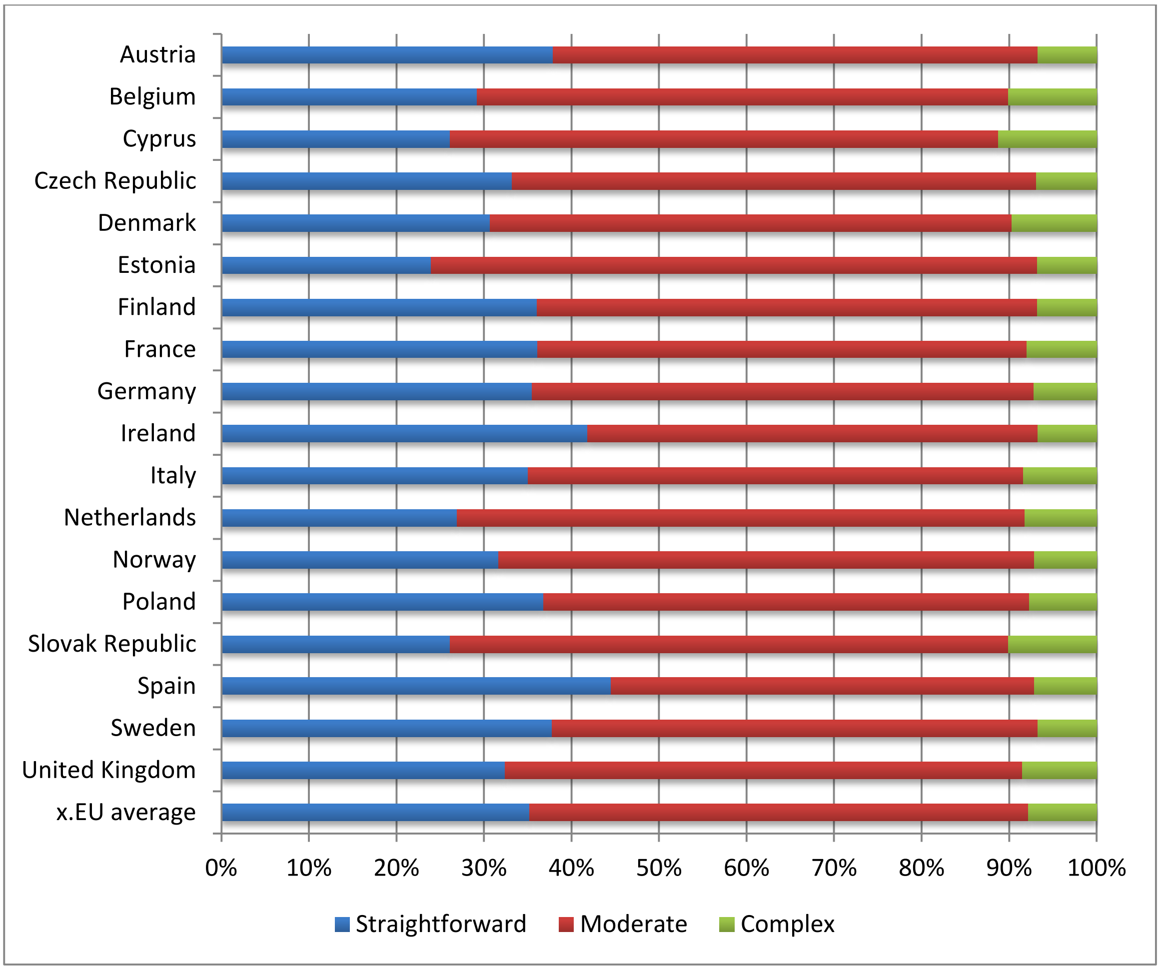


It is interesting to relate the answers to the question "Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?" with individuals' educational attainment. When we consider the EU average we find (see Table A3) that respondents with lower education are more likely to be affected than those with higher education, but the differences across educational attainment groups are quite small. Results also indicate large across-country variation. Among those with the lowest educational attainment, the countries with the largest share of positive responses to such question are Cyprus (22.32%), Ireland (15.54%) and U.K. (12.61%), while the countries with the smallest share the Czech Republic (3.25%), Finland (3.26%) and Denmark (3.97%), with an EU average of 8.76%. Among those with average educational attainment, the countries with the highest share of positive responses are Cyprus (14.94%), Estonia (10.51%) and Poland (10.13%), while the lowest values are found in Finland (3.5%), the Netherlands (3.6%) and Sweden (4.15%), with a EU average of 7.01%. Finally, in the group with the highest educational achievement, the highest shares of positive answers are found in Poland (10.24%), Estonia (7.43) and Italy (6.92%), while the lowest shares are found in the Czech Republic (2.72%), Germany (3.1%) and the Netherlands (3.42%), with a EU average of 5.3%.

Respondents of the problem solving questionnaire in TRE were also asked what level of computer skills were needed to perform their job (Figure 7). Three different levels are provided in PIAAC questionnaire: **Straightforward** (such as using a computer for straightforward routine tasks such as data entry or sending and receiving e-mails), **Moderate** (for example word-processing, spreadsheets or database management) and **Complex** (such as developing software or modifying computer games, programming using languages like java, SQL, Php or Perl, or maintaining a computer network).

In the EU (overall) the vast majority of respondents report the need for a Moderate level (on average 61,4%) while 30,4% declare the need for a Straightforward level and only 8,2% report the need for Complex computer skills (see Table A4). Once again the data show large across country variation. The countries in which the share of requested Complex use is higher are Slovak Republic (10.10), Belgium (10.10%), Denmark (9.07%), while the countries with the lowest shares are Sweden (6.7%), Austria (6.7%), Finland (6.80%), Estonia (6.80%). Finding Sweden, Finland and Norway among the countries with the lowest shares of Complex use requirements might surprise some readers, but we think that this result is due to the fact that the answer to such question might be affected by the skills possessed by individuals[6] (in fact, Finland and Norway are the two countries for which the share of positive responses to the question "Do you think you have the computer skills you need to do your job well" are highest).

***Figure 7*: Answers to the question: "What level of computer use is needed to perform your job?"**

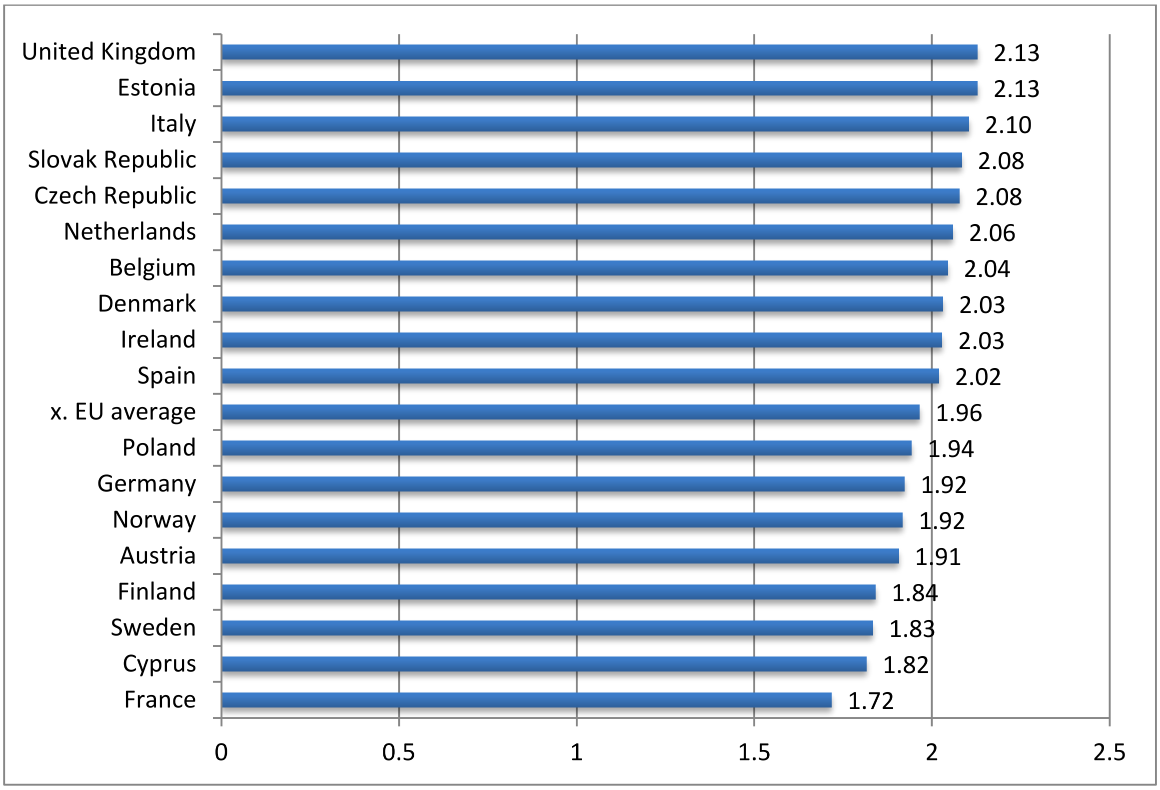


6 In other words, individual with high ICT skills are more likely to consider Moderate, rather than Complex, the ICT tasks in which they are involved.

We also notice in Table A4 that test scores in problem solving in TRE tend to grow as we move from Straightforward (273), to Moderate (294) and then to Complex (309).

PIAAC data also allows us to better understand how individuals use their ICT skills (measured through an ad hoc index[7]) at work (Figure 8). The index is generated by Item Response Theory using the following variables: the frequency of using e-mail, Internet, spreadsheets, word processors, programming languages; conducting transactions online; participating in online discussions (conferences, chats). At the individual level, the minimum value for the index is -2.26 and the maximum value is 6.5, with the mean value 1.96 (s.d=0.98).

***Figure 8*: Index of use of ICT skills at work**



The highest values for the index of ICT use at work are recorded in the UK and Estonia (2.13), followed by Italy (2.10) the Slovak and the Czech Republic (2.08). The lowest values are found in France (1.72), Cyprus (1.82) Sweden (1.83) and Finland (1.84).

4. The OECD measure of skill mismatch

The theoretical set-up used in this note is entirely borrowed from Pellizzari and Fichen (2013) and is briefly summarized in this section. The methodology is based on a simplified theoretical framework that rationalises the notion of skill mismatch and provides guidance about how to use observable worker data to recover features of the production process.

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7 Item Response Theory is a measurement framework used in the design and analysis of educational and psychological assessments (achievement tests, rating scales, inventories, or other instruments) that measure mental traits. Item response theory, is based on establishing a model that specifies the probability of observing each response option to an item as a function of the target trait being measured by the assessment, which is often a knowledge, skill, or ability.

The theory assumes heterogeneity of both jobs and workers. Workers are heterogeneous in their skill endowments, whereas jobs are heterogeneous in their production technologies. Operationally, we will assume that all jobs within the same occupational group share the same production technology and the empirical definition of an occupation will depend crucially on the structure of the sample. As is customary, the production technology is characterised by means of a production function which takes skills as inputs and has goods or services as outputs. However, in order to rationalize the existence of skill requirements across jobs, such a function is assumed to have two kinks, one towards the bottom, generated, for instance, by fixed costs, and one towards the upper part, induced by a decline in productivity at higher level of skill input. Fixed costs arise, for example, when jobs need some capital stock to become operational and, until the job can produce enough output to repay the rental cost of such capital, its overall productivity is null. Hence, a minimum skill input is required to activate the job. Maximum requirements assume, instead, that productivity declines discontinuously at some given skill level, thus generating a kink in the production function.

Workers are assumed to be exogenously allocated to jobs and, once the match is formed, they endogenously decide how much of their endowments to deploy in their jobs. Such a decision is based on a standard utility maximization process where deploying skills is costly. Additionally, in order to allow for the existence of under-skilling in equilibrium, workers are allowed to deploy more skills than their endowment at an especially high cost.

In such setting, it is then possible to formally define skill mismatch. Over-skilled workers are workers who possess more skills than the maximum requirement in their jobs. Under-skilled workers are those whose endowment is below the minimum requirements. All others are well-matched.

In this setting, Pellizzari and Fichen (2013) show that only the workers who are well-matched deploy their entire endowments of skills on their jobs and it is from them that one should start the empirical implementation of the definition of skill mismatch. Specifically, one can make use of the following two questions that are commonly asked in many surveys, included the OECD Skills Survey:

1. "*Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?*"
2. "*Do you feel that you need further training in order to cope well with your present duties?*"

These questions have been extensively used in the previous literature to produce self-reported measures of mismatch but they have also been heavily criticised due to the extent to which the answers are affected by measurement error. Specifically, most persons appear to be overconfident and answer "yes" to question 1. At the same time, positive answers to question 2 do not necessarily indicate under-skilling, as workers may feel that additional training may help them do things better even if they are effectively well-matched. Finally, there is a fair share of respondents in all countries answering "yes" to both questions. The approach proposed in Pellizzari and Fichen (2013) only uses information on those workers who answer "no" to both questions, i.e. those who self-reported themselves as well-matched. These answers are neither affected by overconfidence nor by an extensive interpretation of the need for training. Moreover, the theoretical model suggests that well-matched workers deploy their entire endowment of skills on their jobs. Hence, one can use the minimum and the maximum of the skills of the self-reported well-matched to identify the minimum and maximum requirements within each occupation and then recode all other workers accordingly.

5. The imputation of the missing values

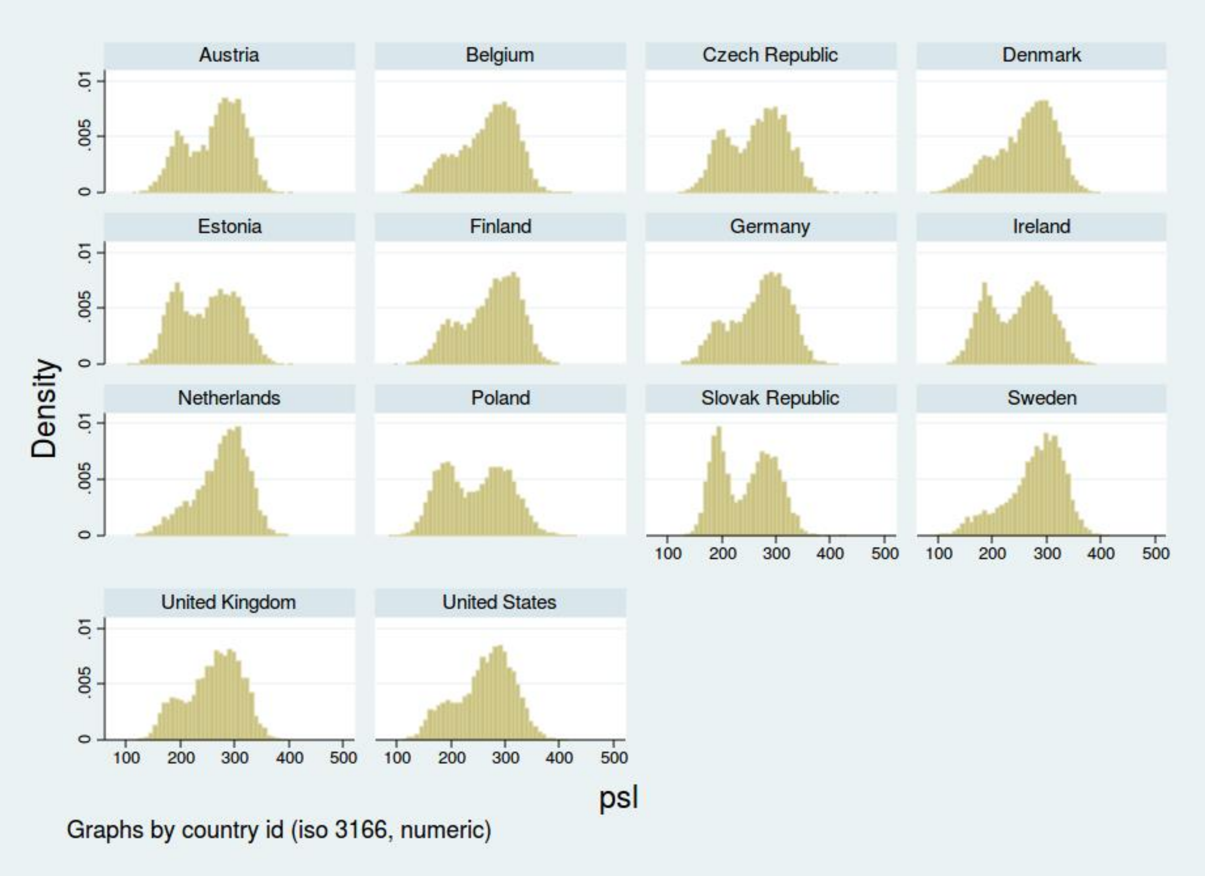
The single most important difficulty when extending the work of Pellizzari and Fichen (2013) to ICT skills is the treatment of the missing values. Given the large heterogeneity across countries shown in Figure 1, disregarding them would heavily bias comparisons across countries. One might also be tempted to simply recode these missing values with zeros. However, not being able to switch on a calculator may not necessarily correspond to a zero on the skill score scale derived from the IRT model. There is no alternative to impute these missing values on the basis of some reasonable procedure. The alternative is simply to abandon the very intent to compute skill mismatch indicators in the ICT area.

To make the imputation all the more important is the fact that, since the imputed values will necessarily be located in the lowest part of the distribution it will very often occur that the minimum skill requirements in several occupations will coincide with an imputed value. Hence, the details of the imputation procedure will matter for the final results.

After experimenting with various possible solutions, in this section we discuss the methodology that we consider to be the most reasonable and that we suggest adopting. However, we obviously do not exclude the possibility that other procedures may be equally or even more reasonable to some readers.

Our proposed imputation procedure rests on the observation that the 3 skill domains tested in PIAAC are highly correlated with one another and that respondents with missing values on ICT skills do have scores on literacy and numeracy. When focusing on the subset of individuals with valid scores on all 3 domains we find that literacy and numeracy alone predict over 50% of the variation in ICT skills. We then run country-by-country linear regressions of ICT skills on literacy, numeracy and a set of standard demographic controls (age, gender and education) using only observations in the bottom quartile of the country-specific ICT distribution. We then take the linear predictions of such regressions and, to avoid producing imputed distributions with abnormal mass points, we add a random noise drawn from a normal distribution with zero mean and variance equal to the estimated variance of the OLS residual in the country specific regressions. This leads to a predicted value of ICT skills for all observations in the sample, including those who were routed out of the ICT assessment module. Finally, in order to account for the fact that these respondents are presumably less skilled than their counterparts with the same demographic characteristics and the same skill levels in literacy and numeracy who do have a non-imputed ICT score, we impute the missing values using the predictions obtained from such estimation (augmented by the normal random noise) and we multiply them by 0.8. The choice of this value is clearly arbitrary but it reflects the idea that the non-respondents should score at a lower level than the least able respondents. In Section 7 we present some robustness checks to document the important implications of the imputation method on the final results and we show that our main finding do not depend crucially on the arbitrary choice of the 0.8 value (see Figure 12).

***Figure 9*: Distribution of ICT imputed scores**



The resulting distribution of ICT scores, imputed and non-imputed, is shown in Figure 9. In some countries the bimodal feature due to the imputation is quite evident, especially in those countries with a particularly strong incidence of missing values, like the Slovak Republic. It should be noted, however, that the bimodality of the distribution may not be a problem, to the extent that the underlying correct distribution is itself bimodal.

6. E-skill mismatch in European countries

In this paragraph we apply the methodology of OECD (2013) and Pellizzari and Fichen (2013) to the data on ICT skills, with the missing values imputed according to the procedure described in the previous section.

Practically, we proceed according to the following procedure:

1. we select only employed workers, excluding the self-employed and those holding more than one job;
2. we define occupations on the basis of the ISCO 1-digit coding, excluding those occupation-country cells with fewer than 50 observations;
3. in each occupation-country cell we identify those workers who self-define themselves as well-matched, namely those who answer "no" to both the question "*Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?*" and the question "*Do you feel that you need further training in order to cope well with your present duties?*";

4. we estimate the minimum and maximum ICT requirement in each occupation-country cell, which coincide, respectively, with the bottom and top 5% values of the distribution of the ICT skills of the self-reported well-matched;[8]
5. finally, we recode every worker as well-matched if her ICT skills fall in between the minimum and maximum requirement of the occupation in which she is observed, as under-skilled if they fall below the minimum and over-skilled if they are above the maximum.

All calculations are performed using the survey weights provided by the OECD. The exact same procedure can be replicated also for literacy and numeracy to produce comparable indicators of skill mismatch in the three skill domains.[9] The main results are reported in Table 2.

***Table 2*: E-skill mismatch across Europe**

	Under-skilled	Well-matched	Over-skilled
Austria	0.026	0.840	0.134
Belgium	0.048	0.884	0.068
Czech Republic	0.016	0.861	0.123
Denmark	0.035	0.890	0.076
Estonia	0.020	0.884	0.096
Finland	0.028	0.869	0.103
Germany	0.016	0.872	0.111
Ireland	0.034	0.808	0.158
Netherlands	0.027	0.919	0.055
Poland	0.038	0.913	0.049
Slovak Republic	0.044	0.762	0.193
Sweden	0.065	0.861	0.074
United Kingdom	0.030	0.855	0.115
United States	0.036	0.865	0.100
Total	0.032	0.868	0.100

On average, about 87% of the workers in our final sample are well-matched, about 10% are over-skilled and 3% under-skilled. Ireland and the Slovak Republic are the countries with the highest incidence of over-skilling (mostly at the expenses of the well-matched) whereas Poland and The Netherlands only have about 5%. Under-skilling is highest in Sweden and Belgium but there seems to be quite a bit less variation in the incidence of under (relative to over)-skilling.

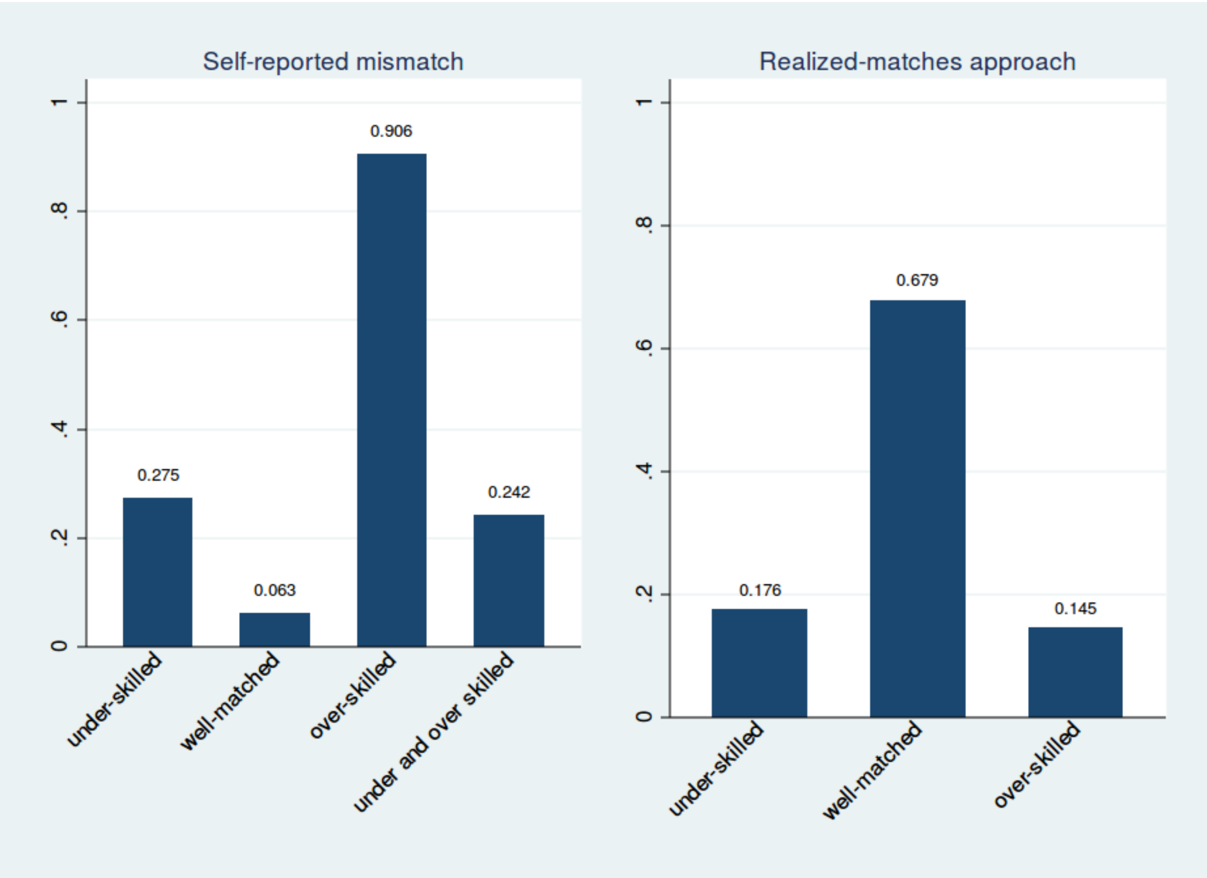
The findings in Table 2 contrast sharply with results obtained using other popular methods adopted in the literature, pooling all countries together. Figure 10 shows results based on two such alternatives. On the left-hand panel mismatch is measured using exclusively self-reported status (Allen and van der Velden, 2001; Green and McIntosh, 2007; Green and Zhu, 2010; Mavromaras, Mcguinness, and Fok, 2009; McGuinness and Wooden, 2009). Workers are classified as well-matched if they report both that they do not need training and do not feel able to perform more sophisticated tasks; they are under-skilled if they respond that they need training and do not feel they can do more

8 Using the bottom and top 5% instead of the actual minimum and maximum limits the impact of outliers, which is particularly important given the numerous imputed values in the distribution.

9 The results for literacy and numeracy do not match exactly those in OECD (2013) and Pellizzari and Fichen (2013) because these studies are based on the original PIAAC database which is only available for internal OECD use. This report uses the public use file, which is somewhat less detailed. The differences in the results are, however, minimal.

demanding tasks; finally, they are over-skilled if they report to feel able to do more complex jobs and not to need training. Further, a non-negligible faction of respondents reports both the need of training and the feeling that they can do more demanding jobs. Over 90% of the respondents end up in the over-skilled group according to this classification, confirming the intuition that overconfidence is widespread. Apparently almost one third of respondents falls into the under-skilled category. Finally, about one fourth of workers reports both to need training and to be able to do more demanding tasks, which is not necessarily a contradicting status but rather a signal of the inappropriateness of the self-reported methodology to measure mismatch.

***Figure 10*: Alternative measures of skills mismatch**



The left-hand panel of Figure 10 displays results based on another popular methodology, known in the literature as the *realized-matches approach* (Bauer, 2002; Kiker, Santos, and de Oliveira, 1997; Mendes de Oliveira, Santos, and Kiker, 2000; Verdugo and Verdugo, 1989). This approach does not make any use of the self-reported questions and, as such, is not affected by the measurement error induced by either over-confidence or training needs. It exploits the distribution of observed matches and, within each occupation-country cell, considers well-matched those whose skills are within a one-standard deviation range around the median. Those with skills above the median plus one standard deviation are classified as over-skilled and those with skills below the median minus one standard deviation are under-skilled. [10] The results are more reasonable than those obtained with the self-reported approach but they reflect more the heterogeneity of skills within a profession than some specific notion of mismatch. For

[10] Both the median and the standard deviations are computed separately for each occupation-country cell.

example, according to the *realized-matches approach* when the distribution of the skills within an occupation is degenerated onto a single mass point the method would mechanically classify every worker in that occupation as well-matched.

***Figure 11*: Mismatch across skill domains**

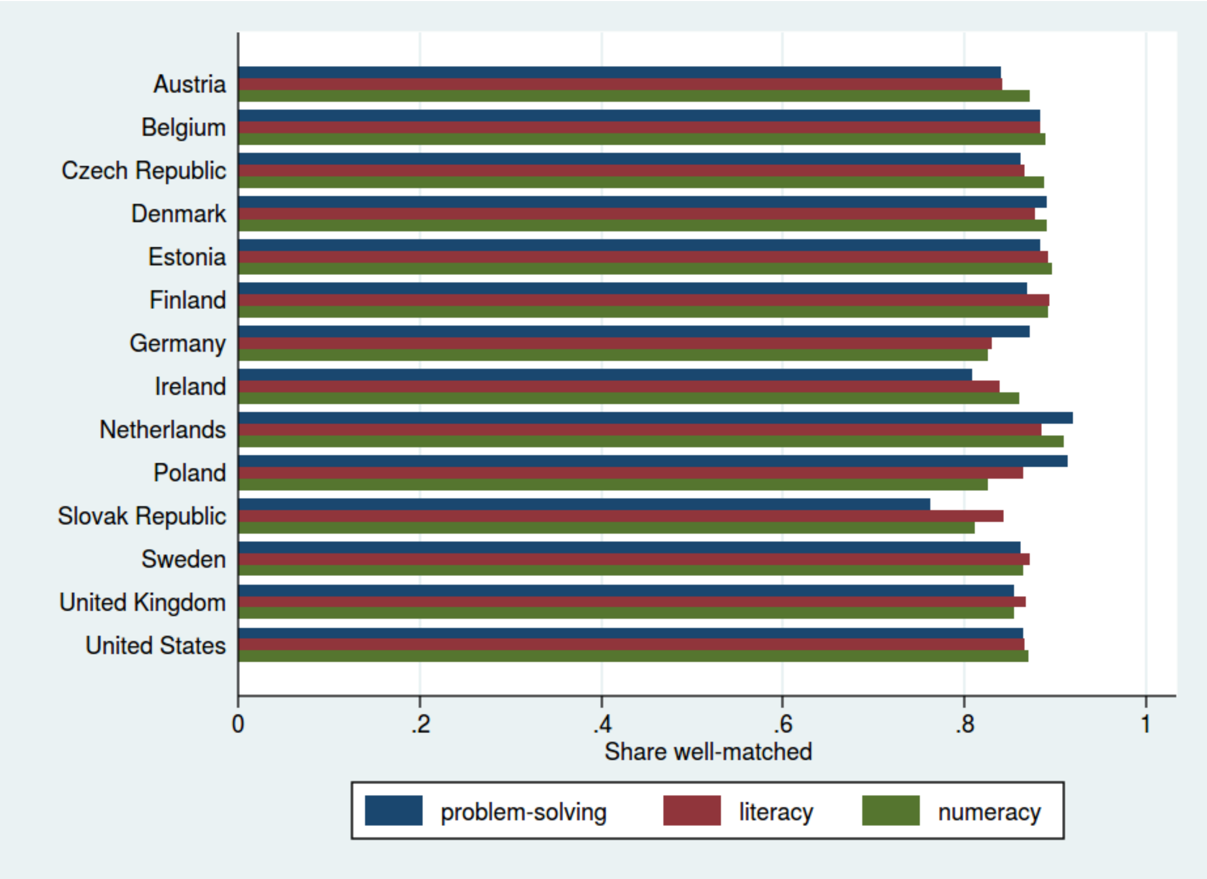


***Table 3*: Mismatch across skill domain**

	ICT	Literacy	Numeracy
Austria	0.84	0.84	0.87
Belgium	0.88	0.88	0.89
Czech Republic	0.86	0.87	0.89
Denmark	0.89	0.88	0.89
Estonia	0.88	0.89	0.90
Finland	0.87	0.89	0.89
Germany	0.87	0.83	0.83
Ireland	0.81	0.84	0.86
Netherlands	0.92	0.89	0.91
Poland	0.91	0.87	0.83
Slovak Republic	0.76	0.84	0.81
Sweden	0.86	0.87	0.86
United Kingdom	0.85	0.87	0.85
United States	0.86	0.87	0.87
Total	0.87	0.86	0.86

Fraction of workers classified as well-matched.

It might also be interesting to compare mismatch in different skill domains, as in Figure 11 and Table 3, where we report the incidence of well-matched workers in the areas of ICT, literacy and numeracy in all the countries considered. Results show a relatively strong correlation of all these measures, suggesting that workers who are well-matched in one skill domain tend to be so in other domains as well. This is also confirmed by the individual rank correlation of the mismatch indicators across skill areas. Over 90% of the workers who are well matched in the ICT domain are also well-matched in literacy and the same holds for numeracy.

6.1 Skill mismatch and skill usage

One of the important reasons why skill mismatch ranks high on the policy agenda is the idea that it must be associated with an inefficient use of workers' skills and thus may hinder economic growth. In order to investigate this issue, it is interesting to complement the analysis of skill mismatch with data on the use of skills at work. As mentioned earlier, the PIAAC survey includes a detailed battery of questions on the frequency with which certain tasks are performed on the job and a good number of such questions refers to the use of ICT tools such as email, internet, e-commerce, spreadsheets, word processors or programming. The original frequency questions allow respondents to answer on a discrete scale of 5 values: never (one), less than once a month (two), less than once a week but at least once a month (three), at least once a week but not every day (four) and every day (five). We aggregated these many questions into an indicators of ICT use using Cronbach alpha (Cronbach, 1951), which is essentially based on summing all the discrete frequency answers one on top of the other.[11] This procedure has the advantage of reducing the dimensionality of the information gathered in the survey, while at the same time maintaining a rather intuitive interpretation of the resulting scales, where a value of one signifies that none of the tasks considered is ever performed and a value of 5 corresponds to performing each of the tasks every day. According to this indicator, the mean use of ICT skills across the entire sample is 2.3 with a standard deviation of 1.1.

By comparing skill mismatch and skill use it is possible to construct indicators of skill under- and over-usage. The underlying idea is that over-skilled workers are not making full use of all their skills, while under-skilled workers find themselves in the difficult position of having to over-use their skills in order to keep their jobs. For each mismatched worker (either under- or over-skilled) we compare the use of skills with well-matched workers at their same level of proficiency and in the same country.

[11] Pellizzari and Fichen (2013) use the same methodology to construct indicators of skill use for literacy and numeracy.

***Table 4*: Overuse of ICT skills**

	Overuse of ICT skills	
	Under-skilled	Over-skilled
Austria	0.188	-0.151
Belgium	0.195	-0.145
Czech Republic	0.210	-0.149
Denmark	0.201	-0.142
Estonia	0.213	-0.150
Finland	0.189	-0.141
Germany	0.202	-0.144
Ireland	0.203	-0.154
Netherlands	0.189	-0.140
Poland	0.231	-0.146
Slovak Republic	0.187	-0.152
Sweden	0.180	-0.139
United Kingdom	0.198	-0.145
United States	0.212	-0.148
Total	0.208	-0.147

Table 4 shows that, on average across countries, the indicator of ICT use at work for individuals who are under-skilled is about 0.208 (about 20% of a standard deviation) higher than the corresponding indicator for similarly proficient workers who are well-matched, suggesting that they do actually over-use their skills with potentially sizeable consequences on the quality of their work and on their level of stress and well-being. Over-skilling is associated with a substantial waste of skills, as workers who are over skilled in ICT appear to use their skills at work substantially less than similarly proficient workers who are well-matched, namely 0.147 lower usage, corresponding to approximately 13% of a standard deviation.

6.2 From skill mismatch to skill shortages

The debate on skill mismatch is often linked to the notion of skill shortages. Mismatch, especially in the form of under-skilling, could in fact be due to the fact that employers cannot fill their vacant jobs with workers possessing the appropriate skills and fall back on hiring under-skilled workers. This may happen either because of labour market frictions or because there simply are not enough workers possessing the required skills.

In order to investigate this issue, Table 5 compares, for each country and each skill area, the sum of all the minimum or maximum requirements in all the active jobs observed in the data with the sum of the skill levels of all the employed workers. More specifically, the numbers in the table are constructed as ratios. In column 1, for example, the denominators are the sums of all the minimum ICT job requirements observed in the data and estimated according to the procedure described at the beginning of Section 6. More specifically, for each employed worker we construct the minimum required level of ICT skill in her job as the 5th percentile of the observed distribution of ICT skills among those workers who are self-reported well-matched in her country-occupation cell. The numerators are the sums of the ICT skills of all the employed workers, i.e. the workers who are employed in the jobs whose requirements are used to compute the numerators. Column two is computed in the exact same way with the exception that the denominators are now the sums of the maximum requirements. The following columns repeat the exercise using requirements and skills in the literacy and numeracy domains.

***Table 5*: Skill stocks relative to job requirements- employed workers**

	ICT		Literacy		Numeracy	
	min	max	min	max	min	max
Austria	1.52	0.84	2.08	1.24	2.32	1.22
Belgium	1.44	0.85	2.09	1.32	2.07	1.29
Czech Republic	1.70	0.91	2.47	1.59	2.49	1.54
Denmark	1.52	0.83	1.97	1.21	1.97	1.17
Estonia	1.55	0.82	2.02	1.26	2.03	1.24
Finland	1.45	0.82	1.97	1.24	1.97	1.22
Germany	1.67	0.82	2.09	1.20	2.10	1.17
Ireland	1.52	0.84	2.51	1.50	2.77	1.44
Netherlands	1.45	0.81	1.80	1.13	1.83	1.09
Poland	1.70	0.77	2.74	1.69	2.78	1.69
Slovak Republic	1.50	0.89	2.45	1.63	2.56	1.61
Sweden	1.33	0.81	1.77	1.16	1.77	1.13
United Kingdom	1.54	0.89	2.18	1.33	2.17	1.30
United States	1.58	0.83	2.17	1.23	2.40	1.17
Total	1.53	0.84	2.17	1.34	2.23	1.31

Ratio of total skills of **employed workers** and total job requirements (minima and maxima).

Pooling all the countries together, the stock of workers' ICT skills substantially exceeds the stock of minimum requirements for the existing jobs by over 50%. In other words, there seems to be enough skills overall in the economy to satisfy the minimum requirements of all active jobs. This result obviously does not mean that reshuffling workers could completely eliminate mismatch because the stock of skills is not perfectly separable, as some workers are endowed with lots of kills and others with little and the first cannot share their endowment with the others. Nevertheless, the magnitude of the excess stock of skills is suggestive that shortages may not be particularly relevant for active jobs. Obviously, this analysis does not consider shortages leading to potential jobs not being opened or vacancies remaining unfilled. These types of shortages might still be very important.

Table 5 also compares the stock of workers' skills to the stock of maximum rather than minimum requirements and, in this case, there does seem to be a shortage, although one may not necessarily expect all jobs to be filled with workers having the maximum required skill level. Pooling all countries together, the stock of skills of the current workers appears to be short of the stock of maximum requirements by about 15%. Table 5 also shows that the supply of skills in ICT is somewhat lower than in literacy and numeracy compared to the active demand of such skills.

The analysis in Table 5 does not take into account the unused skill potential of the unemployed and the inactive, so Table 6 further extends the analysis by re-computing all the denominators of the ratios of Table 5 as the sum of the skills of all respondents to the PIAAC survey (i.e. the employed, the unemployed as well as the inactive).

Now, the stock of skills massively exceeds both the stock of minimum and maximum requirements and also the wedge between ICT and literacy/numeracy seems to vanish, probably due to the stronger ICT skill of the many young unemployed and inactive.

***Table 6*: Skills stocks relative to job requirements – all adults**

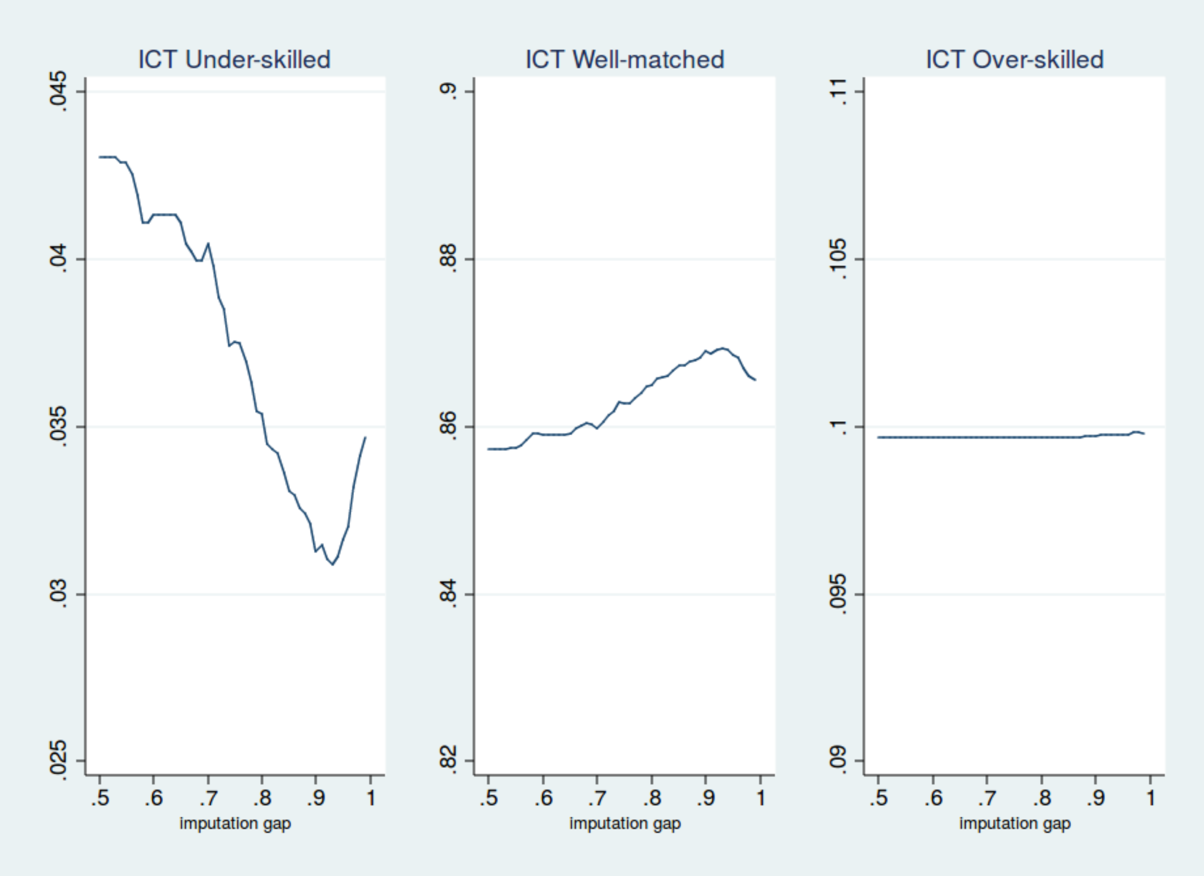
	ICT		Literacy		Numeracy	
	min	max	min	max	min	max
Austria	2.16	1.19	2.08	1.24	2.32	1.22
Belgium	2.15	1.27	2.09	1.32	2.07	1.29
Czech Republic	2.81	1.50	2.47	1.59	2.49	1.54
Denmark	2.12	1.16	1.97	1.21	1.97	1.17
Estonia	2.26	1.19	2.02	1.26	2.03	1.24
Finland	2.14	1.22	1.97	1.24	1.97	1.22
Germany	2.30	1.14	2.09	1.20	2.10	1.17
Ireland	2.63	1.45	2.51	1.50	2.77	1.44
Netherlands	1.95	1.09	1.80	1.13	1.83	1.09
Poland	3.05	1.39	2.74	1.69	2.78	1.69
Slovak Republic	2.62	1.55	2.45	1.63	2.56	1.61
Sweden	1.88	1.14	1.77	1.16	1.77	1.13
United Kingdom	2.27	1.32	2.18	1.33	2.17	1.30
United States	2.29	1.19	2.17	1.23	2.40	1.17
Total	2.33	1.27	2.17	1.34	2.23	1.31

Ratio of total skills of the best **employed, unemployed and inactive individuals** and total job requirements (minima and maxima).

7. Robustness

In this section we present two types of robustness checks. First, in Figure 12 we investigate the effect on our main results of the arbitrary value of 0.8 that we used to discount the imputed values of the ICT scores for the non-respondents. Our imputation procedure uses predicted ICT skills estimated from the regressions described in Section 5 (augmented by the normal random term) but, in order to account for the intuition that the non-respondents most likely have worse skills than observationally similar respondents, we further discount such predictions by multiplying them by 0.8. In other words, we impute the missing values with 80% of the predicted values. We call this value the *imputation gap* and we acknowledge that the choice of 80% is clearly arbitrary. Hence, in Figure 12 we replicated the imputation by varying it from 0.5 to 1.

***Figure 12*: ICT mismatch and the imputation gap**



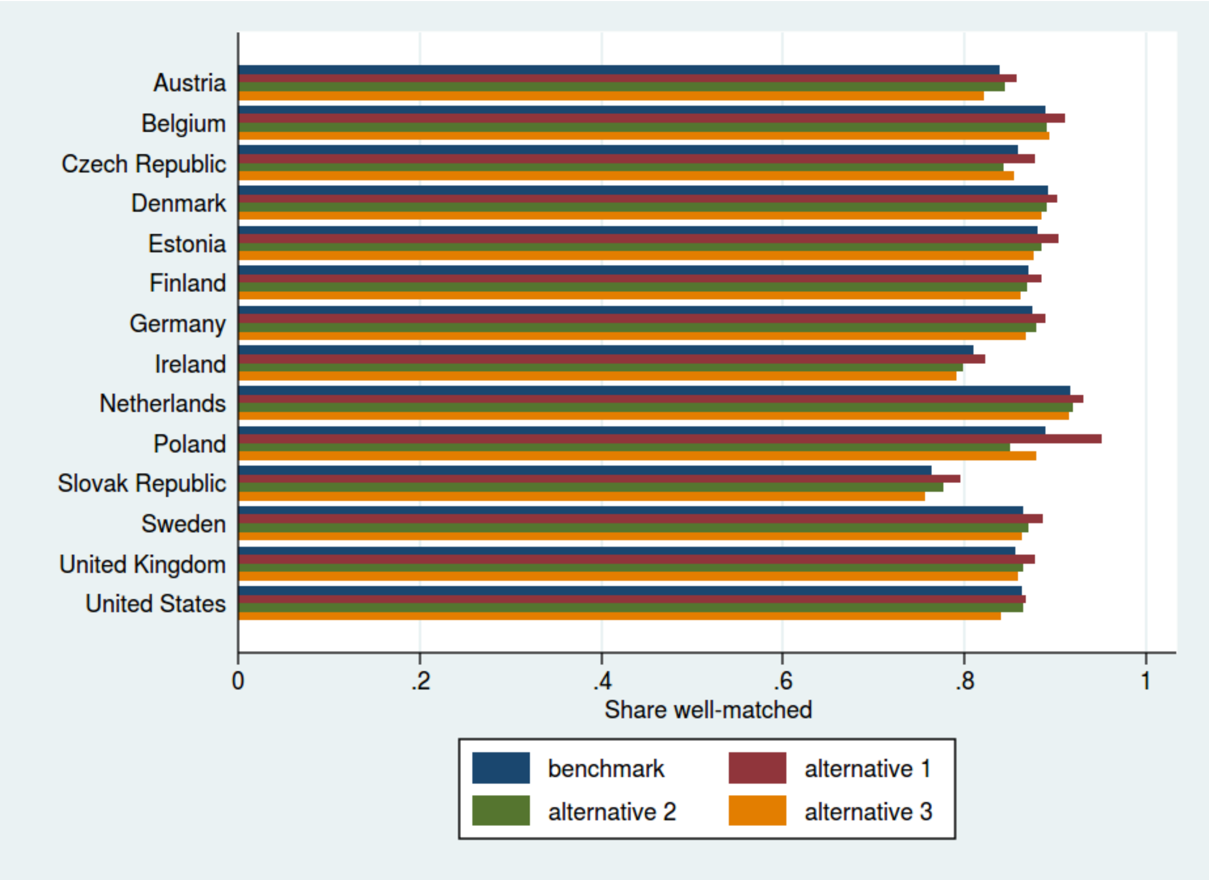
Results indicate that this particular feature of the imputation procedure is rather irrelevant for the main results of our analysis. When we let the imputation gap range from .5 up to 1, under-skilling only varies between around 3% and 4%, over-skilling is almost entirely unaffected and the incidence of the well-matched varies within the narrow interval of .86 and .87.

***Table 7*: ICT mismatch under different imputation methods**

	Method 1			Method 2			Method 3		
	Under	Well	Over	Under	Well	Over	Under	Well	Over
Austria	0.008	0.858	0.134	0.021	0.845	0.134	0.028	0.837	0.135
Belgium	0.020	0.911	0.068	0.042	0.890	0.068	0.035	0.897	0.068
Czech Republic	0.000	0.877	0.123	0.035	0.842	0.123	0.023	0.854	0.123
Denmark	0.022	0.902	0.076	0.034	0.890	0.076	0.040	0.885	0.076
Estonia	0.000	0.904	0.096	0.019	0.885	0.096	0.023	0.880	0.097
Finland	0.012	0.885	0.103	0.029	0.868	0.103	0.037	0.860	0.103
Germany	0.000	0.889	0.111	0.010	0.879	0.111	0.020	0.869	0.111
Ireland	0.019	0.823	0.158	0.044	0.798	0.158	0.055	0.787	0.158
Netherlands	0.014	0.931	0.055	0.026	0.919	0.055	0.031	0.915	0.055
Poland	0.000	0.951	0.049	0.095	0.850	0.055	0.093	0.858	0.049
Slovak Republic	0.012	0.795	0.193	0.030	0.776	0.194	0.029	0.776	0.195
Sweden	0.040	0.886	0.074	0.056	0.870	0.074	0.054	0.872	0.074
United Kingdom	0.007	0.878	0.115	0.021	0.864	0.115	0.032	0.853	0.115
United States	0.033	0.867	0.100	0.036	0.864	0.100	0.056	0.842	0.102
Total	0.021	0.879	0.100	0.034	0.866	0.100	0.047	0.852	0.101

The second robustness check concerns the very nature of the imputation exercise. Table 7 replicates the main results on the distribution of ICT skill mismatch reported in Table 1 under three different alternative imputation methods. Method 1 simply imputes missing values with 80% of the minimum observed ICT skill scores in each country. Method 2 imputes missing values with the 5th percentile of the distribution of the observed ICT skill scores within cells defined by country, age (3 categories), gender and education (3 categories). Method 3 imputes the missing values with one randomly selected value drawn from the bottom quarter of the distribution of ICT skill scores within cells defined by the same observable used for method 2. Results indicate that these variations of the imputation method are rather unimportant for the overall final results. In order to further substantiate this point and to allow more direct comparison with the benchmark results, Figure 13 reports the share of ICT well-matched workers estimated using the benchmark imputation and each of the alternative methods.

***Figure 13*: ICT mismatch by imputation method**



8. Conclusions

This report extends the analysis of skill mismatch in OECD (2013) and Pellizzari and Fichen (2013) to the ICT domain. The main difficulty in this exercise is the imputation of the numerous missing values in the distribution of ICT skill scores. Our approach consists in proposing a reasonable and relatively standard statistical procedure for imputation and presenting robustness checks using alternative methodologies.

Results show that, on average, across the 13 European countries considered, plus the United States, ICT mismatch affects approximately 15-20% of the employed workers, with over-skilling being relatively more important than under-skilling.

Our methodology also allows comparing the stock of skills in the workforce with the stock of requirements among active jobs. On the basis of such comparison there do not seem to be major shortages of skills. However, it must be noted that our approach cannot detect shortages leading employers to not open jobs that they would have opened were the workforce more skilled nor shortages leading to vacancies remaining unfilled.

In this report we do not tackle the issue of statistical inference and we only provide point estimates. In order to construct standard errors of confidence intervals for the estimates reported here one would have to apply the procedure described in the appending of Pellizzari and Fichen (2013), an exercise that is left for future research.

References

Jim Allen and Rolf van der Velden (2001). Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, 53(3):434–452, 2001.

Thomas K. Bauer (2002). Educational mismatch and wages: a panel analysis. *Economics of Education Review*, 21(3):221–229, 2002.

Lee J. Cronbach (1951). Coefficient alpha and the interval structure of tests. *Psychometrika*, 16(3): 297–334, 1951.

Francis Green and Steven McIntosh (2007). Is there a genuine under-utilization of skills amongst the over-qualified? *Applied Economics*, 39(4):427–439, 2007.

Francis Green and Yu Zhu (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers*, 62(4):740–763, 2010.

B. F. Kiker, Maria C. Santos, and M. Mendes de Oliveira (1997). Over-education and Under-education: Evidence for Portugal. *Economics of Education Review*, 16(2):111–125, 1997.

Kostas Mavromaras, Seamus Mcguinness, and Yin King Fok (2009). Assessing the incidence and wage effects of overskilling in the Australian labour market. *The Economic Record*, 85(268): 60–72, 2009.

Seamus McGuinness and Mark Wooden. Over-skilling, job insecurity, and career mobility (2009). *Industrial Relations: A Journal of Economy and Society*, 48(2):265–286, 2009.

M. Mendes de Oliveira, M. C. Santos, and B. F. Kiker (2000). The role of human capital and technological change in over-education. *Economics of Education Review*, 19(2):199–206, 2000.

OECD (2013). First International Report on PIAAC - Volume I. OECD Publishing, 2013.

OECD (2015). Adults, Computers and Problem Solving: What's the Problem? OECD Publishing, 2015.

Michele Pellizzari and Anne Fichen (2013). A new measure of skills mismatch: Theory and evidence from the survey of adult skills (PIAAC). OECD Social, Employment and Migration Working Papers 153, OECD Publishing, 2013.

Richard R. Verdugo and Naomi Turner Verdugo (1989). The impact of surplus schooling on earnings: Some additional findings. *The Journal of Human Resources*, 24(4):pp. 629–643, 1989.

APPENDIX

Description of the PV-TRE benchmarks:

0-240 score points (Below level 1) : Tasks are based on well-defined problems involving the use of only one function within a generic interface to meet one explicit criterion without any categorical or inferential reasoning, or transforming of information. Few steps are required and no sub-goal has to be generated.

241 – 290 score points (Level 1)

At this level, tasks typically require the use of widely available and familiar technology applications, such as e-mail software or a web browser. There is little or no navigation required to access the information or commands required to solve the problem. The problem may be solved regardless of the respondent's awareness and use of specific tools and functions (e.g. a sort function). The tasks involve few steps and a minimal number of operators. At the cognitive level, the respondent can readily infer the goal from the task statement; problem resolution requires the respondent to apply explicit criteria; and there are few monitoring demands (e.g. the respondent does not have to check whether he or she has used the appropriate procedure or made progress towards the solution). Identifying content and operators can be done through simple match. Only simple forms of reasoning, such as assigning items to categories, are required; there is no need to contrast or integrate information.

291 – 340 score points (Level 2)

At this level, tasks typically require the use of both generic and more specific technology applications. For instance, the respondent may have to make use of a novel online form. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) can facilitate the resolution of the problem. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, though the criteria to be met are explicit. There are higher monitoring demands. Some unexpected outcomes or impasses may appear. The task may require evaluating the relevance of a set of items to discard distractors. Some integration and inferential reasoning may be needed.

341 – 500 score points (Level 3)

At this level, tasks typically require the use of both generic and more specific technology applications. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) is required to make progress towards the solution. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, and the criteria to be met may or may not be explicit. There are typically high monitoring demands. Unexpected outcomes and impasses are likely to occur. The task may require evaluating the relevance and reliability of information in order to discard distractors. Integration and inferential reasoning may be needed to a large extent.

Tables

Table A1: Distribution of test scores

	Austria		Belgium		Czech Republic		Denmark	
	n	%	n	%	n	%	n	%
Below 241	475	13.52	763	18.75	726	17.26	1128	16.28
From 241 to Below 291	1585	42.14	1571	37.68	1775	38.44	2454	38.47
From 291 to Below 341	1545	38.43	1539	36.29	1745	35.46	2134	37.84
From 341 to Below 500	250	5.91	313	7.28	430	8.82	382	7.41
	Estonia		Finland		Germany		Ireland	
	n	%	n	%	n	%	n	%
Below 241	1057	19.57	591	13.54	716	17.79	760	18.65
From 241 to Below 291	2169	41.26	1591	35.43	1668	37.69	1791	43.77
From 291 to Below 341	1699	33.02	1850	40.78	1733	36.10	1346	32.91
From 341 to Below 500	309	6.14	472	10.25	423	8.42	195	4.67
	Netherlands		Norway		Poland		Slovak Republic	
	n	%	n	%	n	%	n	%
Below 241	634	14.41	533	13.59	1164	23.99	514	14.09
From 241 to Below 291	1739	37.61	1622	37.77	2296	37.77	1649	45.45
From 291 to Below 341	1815	39.58	1857	41.44	2026	30.58	1231	35.93
From 341 to Below 500	361	8.41	331	7.21	506	7.66	144	4.53

	Sweden		United Kingdom		EU Average
	n	%	n	%	%
Below 241	522	14.95	1421	18.05	16.75
From 241 to Below 291	1362	35.01	3087	40.43	39.21
From 291 to Below 341	1654	40.06	2421	34.77	36.66
From 341 to Below 500	425	9.98	393	6.74	7.39

Table A2: Do you think you have the computer skills you need to do your job well (respondents who answered "yes") according to highest level of educational achievement.

	Schooling/do you think you have computer skills needed to do the job well	n	yes (%)
Belgium	Less than high school	160	88,45
	High school	830	90,35
	Above high school	1381	90,93
Cyprus	Less than high school	48	80,08
	High school	467	88,99
	Above high school	1190	94,33
Czech Republic	Less than high school	130	92,92
	High school	1545	95,93
	Above high school	1003	96,81
Denmark	Less than high school	390	91,32
	High school	1577	89,18
	Above high school	2189	89,73
Estonia	Less than high school	164	87,39
	High school	1102	89,47
	Above high school	2022	88,98
Finland	Less than high school	229	83,03
	High school	1062	86,78
	Above high school	1801	88,47
France	Less than high school	265	85,04
	High school	1148	84,02
	Above high school	1477	89,52
Germany	Less than high school	183	92,94
	High school	1161	93,41
	Above high school	1565	95,08
Ireland	Less than high school	180	81,28
	High school	420	91,62
	Above high school	1970	93,52
Italy	Less than high school	160	85,2
	High school	921	92,85
	Above high school	558	94,48
Netherlands	Less than high school	575	92,88
	High school	1294	93,22
	Above high school	1279	94,8
Norway	Less than high school	224	82,37
	High school	1024	83,45
	Above high school	1707	83,24
Poland	Less than high school	96	97,02
	High school	1211	87,89
	Above high school	1689	93,58

Slovak Republic	Less than high school	23	100
	High school	1097	94,76
	Above high school	750	95,25
Spain	Less than high school	349	83,72
	High school	438	91,37
	Above high school	1165	92,76
Sweden	Less than high school	233	88,5
	High school	1108	90,52
	Above high school	1482	91,19
United Kingdom	Less than high school	166	84,59
	High school	1820	91,48
	Above high school	2417	93,34
EU average	Less than high school	.	88,04
	High school	.	90,31
	Above high school	.	92,12

Table A3: Highest level of schooling/Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?

country	Highest level of schooling	Skill use work - ICT - Computer - Lack of skills affect career	n	**%**
	Less than high school	Yes	20	**11,7**
		No	160	**88,3**
	High school	Yes	66	**7,36**
		No	850	**92,64**
	Above high school	Yes	63	**4,21**
Belgium		No	1446	**95,79**
	Less than high school	Yes	18	**22,32**
		No	45	**77,68**
	High school	Yes	78	**14,93**
		No	452	**85,07**
	Above high school	Yes	85	**6,43**
Cyprus		No	1173	**93,57**
	Less than high school	Yes	2	**3,25**
		No	131	**96,75**
	High school	Yes	82	**4,69**
		No	1536	**95,31**
	Above high school	Yes	37	**2,72**
Czech Republic		No	996	**97,28**
	Less than high school	Yes	18	**3,97**
		No	409	**96,03**
	High school	Yes	77	**4,93**
		No	1689	**95,07**
	Above high school	Yes	114	**4,97**
Denmark		No	2357	**95,03**

	Less than high school	Yes	14	**7,25**
		No	175	**92,75**
	High school	Yes	126	**10,51**
		No	1112	**89,49**
	Above high school	Yes	161	**7,43**
Estonia		No	2119	**92,57**
	Less than high school	Yes	8	**3,26**
		No	266	**96,74**
	High school	Yes	41	**3,5**
		No	1186	**96,5**
	Above high school	Yes	101	**5,03**
Finland		No	1940	**94,97**
	Less than high school	Yes	25	**8,42**
		No	284	**91,58**
	High school	Yes	111	**8,1**
		No	1254	**91,9**
	Above high school	Yes	105	**6,63**
France		No	1545	**93,37**
	Less than high school	Yes	9	**6,62**
		No	183	**93,38**
	High school	Yes	61	**5,15**
		No	1170	**94,85**
	Above high school	Yes	55	**3,1**
Germany		No	1593	**96,9**
	Less than high school	Yes	31	**15,54**
		No	187	**84,46**
	High school	Yes	39	**7,52**
		No	423	**92,48**
	Above high school	Yes	113	**5,35**
Ireland		No	2003	**94,65**
	Less than high school	Yes	21	**8,42**
		No	167	**91,58**
	High school	Yes	75	**7,21**
		No	923	**92,79**
	Above high school	Yes	42	**6,92**
Italy		No	546	**93,08**
	Less than high school	Yes	30	**5,26**
		No	587	**94,74**
	High school	Yes	49	**3,6**
		No	1341	**96,4**
	Above high school	Yes	42	**3,42**
Netherlands		No	1311	**96,58**

	Less than high school	Yes	23	**9,55**
		No	244	**90,45**
	High school	Yes	76	**6,39**
		No	1141	**93,61**
	Above high school	Yes	86	**4,38**
Norway		No	1962	**95,62**
	Less than high school	Yes	9	**4,45**
		No	88	**95,55**
	High school	Yes	155	**10,13**
		No	1148	**89,87**
	Above high school	Yes	193	**10,24**
Poland		No	1577	**89,76**
	Less than high school	Yes	2	**9,98**
		No	20	**90,02**
	High school	Yes	78	**6,33**
		No	1081	**93,67**
	Above high school	Yes	42	**4,19**
Slovak Republic		No	742	**95,81**
	Less than high school	Yes	41	**9,93**
		No	371	**90,07**
	High school	Yes	36	**8,84**
		No	445	**91,16**
	Above high school	Yes	63	**5,13**
Spain		No	1189	**94,87**
	Less than high school	Yes	15	**6,33**
		No	243	**93,67**
	High school	Yes	50	**4,15**
		No	1170	**95,85**
	Above high school	Yes	57	**3,69**
Sweden		No	1565	**96,31**
	Less than high school	Yes	24	**12,61**
		No	172	**87,39**
	High school	Yes	131	**5,83**
		No	1849	**94,17**
	Above high school	Yes	138	**6,27**
United Kingdom		No	2452	**93,73**
	Less than high school	**Yes**	**.**	**8,76**
		No	**.**	**91,24**
	High school	**Yes**	**.**	**7,01**
		No	**.**	**92,99**
	Above high school	**Yes**	**.**	**5,3**
EU Average		**No**	**.**	**94,7**

Table A4: What level of computer use is needed to perform your job?

Country	Level of computer use at work	n	%	PVPSL (mean)	Std.Dev
Austria	Straightforward	896	35,07	**277,04**	36,54
	Moderate	1568	57,68	**293,33**	33,06
	Complex	202	7,24	**309,89**	36,85
Belgium	Straightforward	719	27,83	**267,37**	40,75
	Moderate	1555	61,94	**294,02**	38,51
	Complex	255	10,22	**303,67**	38,77
Czech Republic	Straightforward	792	29,6	**269,87**	40,05
	Moderate	1532	62,63	**297,89**	40,25
	Complex	178	7,77	**310,28**	40,98
Denmark	Straightforward	1223	29,05	**273,78**	41,61
	Moderate	2743	60,92	**293,5**	37,05
	Complex	435	10,03	**308,56**	36,79
Estonia	Straightforward	675	20,92	**266,32**	40,81
	Moderate	2300	71,69	**286,39**	39,85
	Complex	221	7,39	**309,86**	37,87
Finland	Straightforward	1059	33,52	**278,86**	41,61
	Moderate	1987	59,6	**299,54**	38,57
	Complex	229	6,88	**311,94**	37,98
Germany	Straightforward	999	34,32	**271,91**	42,16
	Moderate	1748	58,39	**297,03**	38,07
	Complex	215	7,29	**314,02**	37,69
Ireland	Straightforward	834	36,27	**269,84**	38,46
	Moderate	1387	56,1	**291,52**	36,01
	Complex	203	7,63	**299,82**	36,64
Netherlands	Straightforward	838	25,87	**277,19**	40,82
	Moderate	2146	65,83	**298,96**	35,8
	Complex	252	8,3	**310,15**	35,62
Norway	Straightforward	955	29,53	**278,53**	40,17
	Moderate	2157	63,35	**296,63**	35,58
	Complex	246	7,11	**308,94**	33,69
Poland	Straightforward	875	32,36	**268,7**	48,46
	Moderate	1398	58,56	**287,87**	44
	Complex	204	9,08	**302,28**	50,7
Slovak Republic	Straightforward	448	23,08	**272,45**	35,39
	Moderate	1105	65,85	**288,4**	35,89
	Complex	168	11,07	**305,75**	35,63
Sweden	Straightforward	1020	36,5	**278,26**	42,92
	Moderate	1747	56,8	**299,08**	39,17
	Complex	217	6,7	**318,2**	34,91

United Kingdom	Straightforward	1476	30,97	**270,91**	39,82
	Moderate	2710	60,29	**296,84**	36,72
	Complex	352	8,73	**313,66**	34,69
EU Average	Straightforward	.	30,35	**272,93**	40,68
	Moderate	.	61,4	**294,36**	37,75
	Complex	.	8,25	**309,07**	37,77

Table A5: Categorised index of ICT skills at work according to PVPSL

Country	Index of use of ICT skills at work, categorised WLE	N of Cases	Sum of SPFWT0	Sum of SPFWT0 (s.e.)	%	% (s.e.)	**PVPSL (Mean)**	PVPSL (s.e.)	Std. Dev
Austria	All zero response	153	172612	15403,06	6,17	0,54	**272,59**	3,52	38,57
	Lowest to 20%	465	510741	25551,98	18,25	0,83	**276,29**	2,18	36,34
	More than 20% to 40%	509	544166	23667,86	19,44	0,78	**282,28**	1,99	33,82
	More than 40% to 60%	561	567904	24009,04	20,29	0,82	**292,28**	1,83	34,19
	More than 60% to 80%	557	572102	23115,64	20,44	0,82	**297,21**	2	33,99
	More than 80%	420	431305	21418,16	15,41	0,76	**302,77**	2,26	32,28
Belgium	All zero response	149	115540	8552,84	5,62	0,41	**260,84**	3,55	40,91
	Lowest to 20%	341	268541	13874,18	13,05	0,67	**264,89**	3,03	42,94
	More than 20% to 40%	485	395150	16504,38	19,21	0,75	**275,78**	2,26	38,72
	More than 40% to 60%	564	463500	18219,07	22,53	0,83	**291,83**	1,85	36,31
	More than 60% to 80%	567	467210	16533,76	22,71	0,77	**302,09**	1,97	37,09
	More than 80%	424	347378	14684,17	16,88	0,67	**302,23**	2,46	38,11
Czech Republic	All zero response	154	177202	21315,85	5,74	0,68	**262,8**	5,46	39,6
	Lowest to 20%	389	409730	31058,84	13,26	0,95	**277,37**	4,4	44,93
	More than 20% to 40%	444	517667	36848,75	16,76	1,15	**281,44**	3,4	40,54
	More than 40% to 60%	475	664106	31863,63	21,5	1,09	**293,42**	2,99	41,71
	More than 60% to 80%	550	719883	53054,45	23,3	1,48	**297,79**	2,94	40,04
	More than 80%	491	600964	44204,42	19,45	1,4	**303,78**	2,97	39,22
Denmark	All zero response	188	108165	8266,4	4,93	0,37	**274,64**	3,62	41,95
	Lowest to 20%	690	361457	13682,03	16,48	0,61	**275,86**	1,96	42,79
	More than 20% to 40%	898	451227	14169,65	20,58	0,63	**281,45**	1,76	39,39
	More than 40% to 60%	887	428621	13898,81	19,55	0,63	**290,18**	1,93	38,67
	More than 60% to 80%	807	380882	13235,86	17,37	0,58	**298,3**	1,76	36,4
	More than 80%	931	462643	14949,54	21,1	0,65	**302,58**	1,71	34,94
Estonia	All zero response	153	18817	1601,46	4,89	0,41	**264,9**	3,18	35,75
	Lowest to 20%	455	55081	2408,75	14,31	0,58	**267,11**	2,27	42,49
	More than 20% to 40%	545	64420	2682,84	16,73	0,65	**274,8**	2,28	42,19
	More than 40% to 60%	606	71142	2986,85	18,48	0,74	**283,28**	1,97	39,34
	More than 60% to 80%	636	77692	2545,65	20,18	0,62	**290,5**	2,42	39,14
	More than 80%	802	97880	2881,89	25,42	0,66	**298,24**	1,93	37,9

Finland	All zero response	119	79267	7710,96	3,88	0,37	**279,67**	4,24	43,05
	Lowest to 20%	602	387679	15108,39	18,99	0,67	**280,94**	1,82	42,37
	More than 20% to 40%	825	520207	16936,14	25,48	0,77	**285,34**	1,81	39,66
	More than 40% to 60%	696	430503	13657,22	21,09	0,68	**298,57**	1,56	39,35
	More than 60% to 80%	598	358711	15009,03	17,57	0,75	**307,16**	1,92	37,18
	More than 80%	437	264912	13636,61	12,98	0,65	**304,96**	2,23	38,23
Germany	All zero response	200	1999897	139851,6	7,15	0,49	**261,9**	4,03	42,36
	Lowest to 20%	506	4752362	216326,7	16,99	0,71	**274,48**	2,51	42,11
	More than 20% to 40%	563	5408911	236650,9	19,33	0,79	**283,86**	2,53	41,15
	More than 40% to 60%	668	5982887	198056,7	21,39	0,68	**295,74**	2,24	41,93
	More than 60% to 80%	644	6117183	241156,5	21,87	0,79	**300,7**	1,99	35,03
	More than 80%	382	3714260	208158,8	13,28	0,73	**304,38**	2,65	36,44
Ireland	All zero response	113	66032	7135,54	5,84	0,61	**275,45**	5,53	41,56
	Lowest to 20%	379	188125	11652,57	16,64	0,99	**266,73**	2,32	39,34
	More than 20% to 40%	436	197672	11862,88	17,48	0,97	**273,98**	2,22	35,66
	More than 40% to 60%	418	197490	9955,04	17,47	0,76	**286,89**	2,49	35,37
	More than 60% to 80%	468	201543	9831,59	17,82	0,86	**294,34**	2,33	36,36
	More than 80%	611	279875	13621,77	24,75	1,15	**296,39**	2,07	36,17
Netherlands	All zero response	136	293172	28236,9	4,32	0,41	**271,61**	3,78	42,69
	Lowest to 20%	459	959083	41869,62	14,13	0,6	**280,73**	2,63	42,38
	More than 20% to 40%	571	1206028	49540,53	17,76	0,68	**284,42**	1,98	38,35
	More than 40% to 60%	711	1473690	51460,78	21,7	0,75	**297,5**	1,79	36,35
	More than 60% to 80%	789	1641773	55006,34	24,18	0,8	**303,63**	1,48	34,95
	More than 80%	571	1215951	50866,99	17,91	0,75	**303,58**	1,81	34,24
Norway	All zero response	106	70142	7141,71	3,34	0,33	**279,92**	4,61	42,13
	Lowest to 20%	585	385027	14180,38	18,32	0,61	**275,71**	1,92	42,08
	More than 20% to 40%	724	454906	14914,53	21,64	0,68	**285,39**	1,42	36,23
	More than 40% to 60%	748	456823	14316,85	21,74	0,69	**295,26**	1,47	35,07
	More than 60% to 80%	639	392081	14562,22	18,66	0,68	**302,15**	1,54	34,53
	More than 80%	556	342706	11703,86	16,31	0,55	**306,59**	1,56	32,28

Poland	All zero response	172	353685	43334,16	4,99	0,61	**254,52**	7,16	49,85
	Lowest to 20%	550	1245195	76590,46	17,57	1	**271,85**	3,6	47,35
	More than 20% to 40%	435	1274286	86600,23	17,98	1,13	**278,36**	3,49	47,77
	More than 40% to 60%	439	1316247	97334,9	18,57	1,21	**281,75**	3,5	44,15
	More than 60% to 80%	450	1559106	85534,58	22	1,19	**291,33**	3,26	45,24
	More than 80%	433	1338107	83204,81	18,88	1,1	**296,59**	3,16	44,91
Slovak Republic	All zero response	100	63198	6876	4,94	0,53	**276,29**	4,59	35,22
	Lowest to 20%	288	201879	13661,62	15,78	1,02	**274,67**	2,64	36,98
	More than 20% to 40%	308	214367	12599,79	16,76	0,92	**280,66**	2,62	36,95
	More than 40% to 60%	336	257994	16522,07	20,17	1,15	**286,11**	2,62	35,35
	More than 60% to 80%	333	261115	16095,17	20,41	1,11	**292,39**	2,81	37,34
	More than 80%	357	280836	14783,82	21,95	1,1	**297,17**	2,06	34,31
Sweden	All zero response	153	216580	20198,15	5,65	0,52	**274,07**	4,48	43,33
	Lowest to 20%	578	810328	30393,45	21,12	0,72	**278,66**	2,14	41,7
	More than 20% to 40%	705	905397	31196,12	23,6	0,77	**281,95**	1,81	41,99
	More than 40% to 60%	614	750339	29905,77	19,56	0,73	**300,15**	1,8	38,79
	More than 60% to 80%	512	630539	27925,36	16,44	0,76	**308,96**	1,94	36,48
	More than 80%	422	523179	26017,52	13,64	0,65	**310,94**	1,97	35,98
United Kingdom	All zero response	232	1045480	98248,91	5,55	0,51	**261,52**	4,5	41,78
	Lowest to 20%	684	2809468	129937,2	14,91	0,67	**269,65**	2,64	38,39
	More than 20% to 40%	783	3084616	134946,9	16,37	0,7	**280,16**	2,15	36,83
	More than 40% to 60%	854	3488598	153838,9	18,51	0,79	**291,85**	2,06	38,04
	More than 60% to 80%	1006	4072610	158534,5	21,61	0,81	**302,66**	2,04	36,48
	More than 80%	984	4347693	168780,2	23,07	0,83	**304,67**	1,89	35,84
EU Average	All zero response	.	.	.	5,21	0,13	**269,34**	1,22	41,34
	Lowest to 20%	.	.	.	16,41	0,21	**273,92**	0,71	41,58
	More than 20% to 40%	.	.	.	19,22	0,22	**280,71**	0,62	39,23
	More than 40% to 60%	.	.	.	20,18	0,23	**291,77**	0,59	38,19
	More than 60% to 80%	.	.	.	20,32	0,24	**299,23**	0,6	37,16
	More than 80%	.	.	.	18,64	0,23	**302,49**	0,6	36,49

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