Levels and specificity of skills in Europe: alternative approach towards measurement

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1. Introduction

“Skills” is central concept in a number of theoretical debates. Vast human capital literature seeks to explain the effects of the level and types of skills (specific v.s. general/transferable) on incidence of training, productivity and wages (Becker, 1964, Acemoglu & Pischke, 1999, Leuven, 2005). Labour economics focuses on transferability of skills in explaining labour market adjustment after exogenous shocks (Poletaev & Robinson, 2008, Lamo, Messina & Wasmer, 2011). Varieties of Capitalism approach (Hall & Soskice, 2001, Hancke, Rhodes & Thatcher, 2007) relies on the distinction between specific and general skills in explaining institutional complementarities that shape different strategies of firms in liberal and coordinated market economies. Asset Theory of Social Policy Preferences argues that specificity of skills of the labour force has an effect on voters’ preferences for the level of social protection (Iversen & Soskice, 2001, Iversen, 2005). Lastly, economic sociology has focused on the effects of technological change and proliferation of new work organisation methods on up-skilling and de-skilling of the labour force (Gallie, 1991, Heisig, 2009).

Despite the role of skills in a broad range of theories, there is a lack of adequate instruments for theoretically grounded empirical measurements. The most widely used indicators focus on educational attainment. The level of skills is typically measured by years of schooling and types of skills are represented by educational pathways: vocational training is supposed to provide specific skills and graduates of tertiary education are assumed to possess general widely transferable skills. The numerous critics (see for e.g. Borghans, Green & Mayhew, 2001) of such approach argued that the same quantities of education do not directly imply acquisition of the same quantities or qualities of skills, this neglects depreciation of “unexploited” skills and acquisition of skills beyond school.

To counter these drawbacks, more recent approaches to measuring level of skills focused on student performance in international tests (Hanushek & Kimko, 2000), earnings differentials (Mason, O'Leary & Vecchi, 2012) and years spent in employment (Portela, 2001). Specificity of skills has been assessed by comparing tenures, differences in wages after switching jobs (Sullivan, 2008) and structure of employment by occupational groups (Iversen & Soskice, 2001). The more sophisticated approaches (for examples the ones following the skill weights approach; see: Lazear, 2003) used extensive national data sets (Gathmann & Schönberg, 2006, Poletaev & Robinson, 2008, Neffke & Henning, 2012). Such aggregate indicators, however, suffer from at least one of the following drawbacks: they capture individuals’ potential rather than actual use of skills, include range of variables that are only indirectly related to skills (e.g. tenure) or rely on data that is not conductive to cross national comparisons.

This paper seeks to propose and test an alternative methodology for measurement level and specificity of skills. The ambition is to develop an index measuring what skills are actually used, which stands in contrast to previously discussed proxies that mostly capture potential rather than actual use of skills. Theoretical framework assumes that skills used at workplace represent the skills an individual has. This is captured by analysis of how tasks are performed. Complexity of procedures for acquiring and working with information (degree of uncertainty), extent to which workers can change or redefine these procedures (worker autonomy) and opportunities for continuous skill-building – these dimensions are used for measuring level of skills. Accordingly, skills could range from application of limited number of simple “if, then” algorithms (low skills increasingly replaced by technology) in structured environments to reflexive work that involves complex decision making in highly uncertain environments and transformation of working environments (high skills). The specificity of skills is measured on two dimensions: transferability of skills and specificity of work. If an employee cannot be easily replaced by an outsider, then such work domains require highly specific skills. Similarly, if an employee has very limited number of outside options, then her/his skills are not transferrable.

To facilitate cross-national comparisons empirical measurement of the level of skills in the EU-27 countries relies on the European Working Conditions Survey (European Foundation for the Improvement of Living and Working Conditions, 2010). The specificity of skills is captured by the data from European Social Survey (2010). Longitudinal nature and cross-national comparability are the main advantages of these data sets. Use of survey data is motivated by the fact that workers are best situated to provide information on how they perform the tasks at work.

The paper is divided in four parts. The next part provides a brief overview of literature and discusses conceptual approach adopted in this paper for measuring skills. The third part discusses data and operationalization of dimensions of skills. The fourth part provides the results and discusses their implications. The last part concludes by discussing strengths and weaknesses of the proposed approach and lays out agenda for further research.

2. What do we mean by skills?

Mason, O'Leary & Vecchi (2012) among others argue that “[a]s an intangible asset, human capital is notoriously difficult to measure” (p. 352). The difficulties are further amplified by extensive use of proxies without explicit discussion on what should be measured, i.e. what are skills and their properties? As a result skills have been equated with qualifications, occupations, tenure etc. Hence, before discussing the proposed approach in section 2.2, this part outlines key terms and provides a short overview of previous attempts to measure skills (section 2.1).

At the most abstract level ‘skills’ denote intrinsic quality of performance of a task or a job. Initial definitions of “skills” focused on quality and quantity of motor output (Pear, 1927). As the jobs became more complex, cognitive dimensions (such as problem solving or decision making) were introduced alongside the manual (Welford, 1976, Fuchs, 1962). Further research on the process of learning suggested that these are not simply two different dimensions of skilled performance: development of even the most basic motor skills depends on prior knowledge and cognitive abilities to understand the results (Winterton, Delamare - Le Deist & Stringfellow, 2005). Hence, this paper follows Mumford, Peterson & Childs (1999) and defines skills as procedures for acquiring and working with information. The benefit of such definition is that it moves beyond a priori divides between manual vs. cognitive tasks, blue vs. white collar occupations, etc. Instead, what matters in defining and measuring skills is how a task is performed, i.e. what procedures for acquiring and working with information are used.

‘Skills’ are sometimes confused with other two terms – ‘qualifications’ and ‘competence’. The former refers to a formally recognised outcome of education or training and is linked with requirements to progress in further education or enter a profession (Tessaring, 2004, p. 235). It encompasses a formal recognition that the knowledge and abilities of a person meet some standards. Typical examples include high school diploma or license to practice law. ‘Competence’ refers to ‘motives, traits, self-concepts, attitudes or values, content knowledge, or cognitive or behavioural skills – any individual characteristic <…> that can be shown to differentiate significantly between superior and average performers’ (Spencer & Spencer, 1993, p. 4). Accordingly, the term ‘competence’ is broader than ‘skills’ as it also includes behavioural and psycho-social characteristics (Jucevičienė, 2007). Popularity of the term in management, educational science and psychology literature is clearly motivated by the ambition to explain and predict different levels of performance of workers and enterprises. However, it is also a rather “fuzzy” concept (van der Klink & Boon, 2003): alongside vast academic discussion on the contents of ‘competence’, ‘competency’ and ‘competencies’, the meaning of the term is deeply embedded within social, political and cultural contexts (Delamare - Le Deist & Winterton, 2005).

2.1. Measuring skills: different objects and incompatible scales

Previous discussion on measurement of skills has predominantly focused on the use of proxies. It largely ignored the questions related to nature of skills: is it a characteristic of an individual or do levels and types of skills depend on the interaction between individual and the context of work (tasks, technologies, etc.)? The answer has profound implications to the measurement strategy.

2.1.1 Level of skills

The early human capital literature (Mincer 1958, Becker 1964) argued that education and training leads to accumulation of skills that constitute intangible human capital 'owned' by an individual. It is based on implicit assumption that skills constitute objective characteristic of an individual (similarly to hair colour). This implies that individuals with 'higher level of skill' are likely to demonstrate superior performance in all occupations, sectors, etc. Since skills cannot be observed directly, levels of qualifications (or years of schooling) are widely used as external reference system for measuring levels of skills.

Other proxies developed within the same set of assumptions sought to address two criticisms related to equating qualifications with skills. First, the same quantities of education do not necessarily result in the same quality or quantity of skills. Hence, Hanushek & Kimko (2000) proposed that student performance in international tests could be used for comparative analysis to grasp qualitative differences in level of skills. A similar approach would include analysis of standardised adult literacy, numeracy and problem solving tests (OECD, 2012).

Second, equation between skills and obtained qualifications assumes that skills of an individual are static, i.e. they do not develop or depreciate after graduation. Two addition proxies have been developed (Mason, O'Leary & Vecchi, 2012, Portela, 2001) to address this problem: years spent in employment and earnings differentials. Years in employment are assumed to measure on the job training, while wage differentials indicate variation in productivity, which depends on the level of skills unaccounted for by formal education. These, however, are very strong assumptions that ignore differences in incidence of training, quality of jobs and other factors affecting productivity (e.g. technology) and wages (e.g. the effects of labour market institutions).

'Individuals' reports of job requirements' approach provides a conceptually different strategy by measuring skills in relation to actual on-the-job performance. The main idea is that skills cannot be conceptualised and measured without reference to work domain (tasks, technology, etc.). Accordingly, it is assumed that the skills most frequently and intensively used in a workplace roughly represent the skills that a worker has (Felstead, Gallie, Green & Zhou 2007). This approach relies on surveys of employees that investigate the contents of a job. With some variations this is adopted by the O*NET and UK Skills Survey. It has a number of advantages as it studies skills within performance domains, accounts for skills gained through formal or informal (e.g. on the job) training and allows for depreciation of unused skills. However, the most serious limitation refers to the low level of cross-national comparability as questionnaires and specific indices are developed nationally.

2.1.2. Specificity of skills

Becker (1964) paved the way for analysis of types of skills by distinguishing between specific and general skills. The latter is understood as skills that are of use for many employers, whereas specific skills are valuable only in current job. The subsequent discussions focused on a question: what makes some skills specific or general? The literature provides at least three distinct answers.

The first strand – in line with human capital theory – argues that a person has a combination of general and specific skills and the mix depends on the type of education and experience in the labour market. Specific skills are obtained in vocational education and training and further developed during long tenures within a firm, occupation or industry (Estavez-Abe, Iversen & Soskice 2001, Culpepper, 2007, Thelen, 2007). The German vocational training system with the system of apprenticeships and long tenures within the same industry is said to represent industry-specific skills formation systems. Japan is considered as an ideal type of firm-specific skills formation system due to long tenures and frequent reallocation of workers to different positions within the same firm. General skills are obtained during academically based education and further developed during frequent job changes. The US represents a prime example of such skills formation system.

The second view builds on skills weights approach (Lazear, 2003) and holds that all skills in principle are general, but unique mixes of general skills make them specific (Gathmann & Schönberg, 2006, Poletaev & Robinson, 2008, Neffke & Henning, 2012). If similar tasks are shared by many occupations, then the labour force in these occupations is assumed to have general skills. Conversely, if an occupation involves a number of unique tasks, then it is said to require specific skills. Accordingly, skill-specificity of occupations could be measured by assessing the distances or overlaps in combinations of tasks and associated skills.

Similarly the third strand of literature (Iversen & Soskice, 2001, Iversen, 2005) argues that occupations differ in terms of tasks and associated skills. Some occupations require considerable further training beyond formal education to carry out occupation-specific tasks, while others rely on more general set of skills. The larger proportion of workforce is employed in narrowly defined occupations, the higher the skill specificity.

The above discussion implicitly assumes different sources of skills specificity. The first approach considers that skills represent individual characteristics and therefore educational and employment histories are the main sources of specificity. This is largely in line with Becker's conception of transferable skills. On the other hand, the skills weights approach and Iversen et al. refer to the differences in types of tasks (or performance domains) as the key source of specificity. Note that this view is not necessarily compatible with Becker's definition. Workers in narrowly defined occupations could possess skills that are of value to a large number of firms, if the industry employing such workers is sufficiently large. Hence transferability of skills (ease of switching employers) and specificity of work (ease of replacing employees) do not necessarily coincide.

2.2. The proposed conceptual framework for measuring skills

The proposed approach rests on a distinction between potential to act and actually realised skills. The former is typically captured by past experience, obtained education and training. This, however, does not signify skills of an individual *per se*, since potential may or may not be utilised. It depends on tasks, technology, work organisation practices (Levin 1987) and other factors related to performance domain. If potential to act remains unrealised, the observed level of skills (i.e. quality of performance of task or a job) is low. Conversely, individual using complex procedures for acquiring and working with information should be considered as highly skilled, irrespective of previous experience or type of education obtained.

Hence, skills are treated as an outcome of interaction between individuals' potential to act (education, training, past experience) and work domains (tasks, technology used, working environments and organisation of work). Accordingly, skills can be observed at a workplace by analysing how individual is performing the tasks. Skills are also dynamic: they develop or depreciate throughout working life. In this respect employment domains could be viewed as important as formal education in building (or destroying) skills.

This has several implications for the measurement strategy. First, analysis should focus on how a task is performed rather than attempt at cataloguing different tasks according to level or types of skills required (for e.g. by using International Standard Classification of Occupations (ISCO-88)). Focus on 'how' rather than 'what' provides a more direct and sensitive measure of skills, since it encompasses interactions between work requirements (captured by ISCO-88), conditions within individual work domains (technologies, work organisation practices, etc.) and qualities of individuals (previous education, training and experience).

This leads to the second issue: since educational, occupational and other classifications are not accurate enough in conveying information on skills, then the measurement strategy should rely on self-reports as individuals are the best informed about how they perform the tasks. There are multiple benefits of such strategy. For example, it provides data at individual level that could be linked to a number of other relevant variables (income, occupation, tenure, etc.). On the other hand, self-reports could be regarded as subjective and lead to high measurement errors. To minimise this risk, the measurement should focus on information regarding behaviour rather than capabilities or individual qualities (Felstead et. al. 2007).

2.2.1. Dimensions of levels of skills

Since skills are defined as procedures for acquiring and working with information, the level of skills includes three dimensions: complexity of procedures (degree of uncertainty), capacities to change or redefine them (level of autonomy) and opportunities to learn (continuous skill-building). The first dimension focuses on degree of uncertainty as the main criteria for distinguishing simple and complex modes of operation. Simple, repetitive tasks in stable environment require application of straightforward "if, then" algorithms. As all possible outcomes of action could be easily predefined, this requires masterful execution of task, but is not related with Bravermanian (Braverman 1974) conception. Such skills are increasingly replaced by technology. On the other end of scale, solving unforeseen problems and performing complex tasks in the face of high uncertainty require advanced adaptive algorithms for obtaining and working with information. This requires tacit and explicit knowledge from a number of fields as well as past experience in predicting the outcomes of a range of actions in fuzzy environments. Hence, higher level of uncertainty should reveal higher level of skill.

The second dimension focuses on the extent to which workers engage in changing their employment domains. Accordingly, the main criteria refer to the level of autonomy. Absence or low levels of autonomy are related with work under direct supervision in a structured environment. Lack of engagement at operational (changing own methods, sequence of tasks) or organisational (changing work organisation and processes within larger units) does not allow putting ones work within broader context. On the other hand, high level of autonomy refers to the skills needed to manage and transform working environments, develop and apply innovations. High discretion also signals holistic view of production and management processes.

The third dimension refers to continuous skill-building. Workers whose job includes assessment of own work and continuous learning of new things are expected to have developed meta-competences. They involve capacities to assess own strengths and weaknesses in applying skills and engage in self-directed learning. The absence of self-assessment and learning imply lack of incentives and opportunities to advance skills.

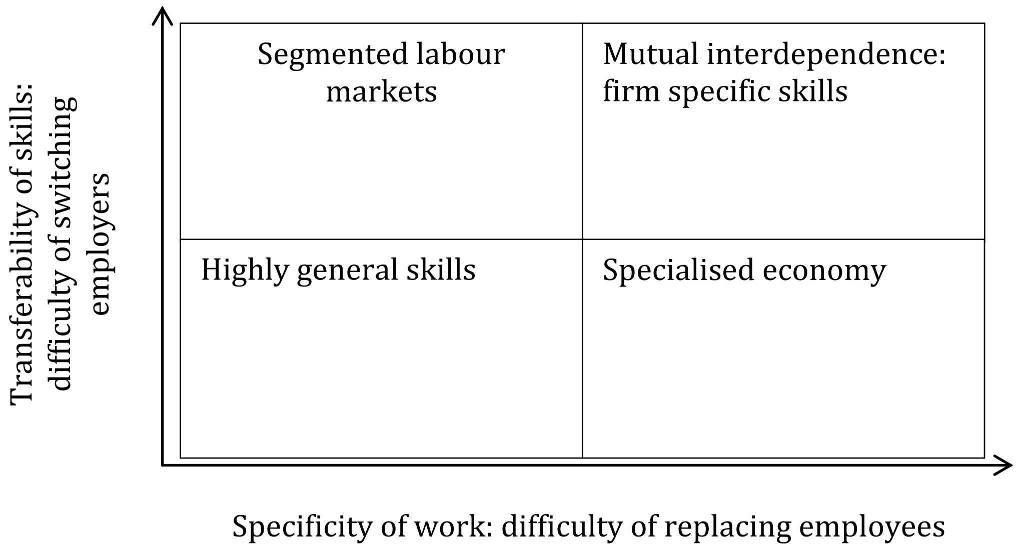
2.2.2. Specificity of skills

Specificity of skills is measured on two dimensions: ease of replacing employees (specificity of work) and ease of switching employers (transferability of skills). The first dimension is based on the following intuition: if performance of specific tasks requires skills that are unique and outsiders would require considerable further training, then such work is highly specific. Alternatively, if any current employee could be easily replaced by an outsider, then such work is highly general. On the demand side, the source of specificity of such skills stems from production technology, work organisation practices, etc. On the supply side, the level of abundance of these skills is related to: a) the match between the content of initial education and training and job-requirements as well as b) the types of skills developed in other firms.

The dimension on transferability of skills (in line with Becker's definition) focuses on the extent to which skills could be transferred across performance domains (firms, occupations or sectors of economy). It is captured by the number of outside options for an employee. In order to go beyond occupation- or industry-specific discussion, let's assume that within (national/regional) labour markets there are segments of work domains that involve different tasks, technologies, etc. Accordingly, the level of transferability of skills depends on the size of these segments and distances (in terms of skills required) between them. This implies that the level of transferability of the same skills could differ depending on national or regional economic contexts.

The two dimensions do not necessarily correlate. If workers can easily transfer their skills between firms and the latter can easily replace employees (south-western corner of Figure 1), then such skills are highly general. This is an 'ideal case' of a 'perfect labour market', where each employee and each firm are equivalent. An 'ideal case' of mutual interdependence is portrayed in the north-eastern corner of Figure 1. Here neither employers, nor employees have any outside options. Hence, mutual cooperation is essential, but easily enforced. The remaining two cases pose interesting puzzles. The south-eastern corner portrays an 'ideal case' of highly specialised economy. The tasks, technologies and work organisation practices require specific skills that are not abundant in the labour market. However, since work domains in a number of firms require the same skills (for e.g. due to large clusters or integrated production chains), employees enjoy quite a few outside options. At the other side of the spectrum (north-western corner) the reverse holds true: work domains require skills that are abundant, but due to 'shallow labour markets' (small size of labour market segments or large distances between them), employees do not have many outside options.

Figure 1. Dimensions of skill specificity



Source: own compilation.

3. Measurement of concepts

3.1. Level of skills

Measurement of the level of skills in the EU-27 countries is based on the results of European Working Conditions Survey (European Foundation for the Improvement of Living and Working Conditions, 2010). It was carried out in 2010 and includes a number of questions on what the respondents do in work. The survey covers 27 EU Member States, EU candidate countries and potential candidates.

The questions that were used to operationalize the three dimensions (uncertainty, autonomy and continuous skill-building) are described in Table 2. The level of uncertainty is measured by assessing, whether work includes solving unforeseen problems and complex tasks. The answers to the questions under the same dimensions should correlate as they measure the same empirical category. As could be expected the relationship between these characteristics of work is statistically significant, but strength of association is moderate (Cramer's V value equals 0.287). Theoretically, the index could also include the extent to which a person performs non-monotonous tasks. However it was excluded, because it is not statistically significantly related with 'solving unforeseen problems' and very weakly related with 'complex tasks'. Variable Uncertainty was constructed so as to differentiate between work practices at the extremes.

The level of autonomy is measured at operational and organisational levels. If a person can choose or change the order of own tasks, methods and speed of work[1], then she has high level of operational autonomy, i.e. can have influence on her own work. Organisational autonomy refers to the extent to which individuals are involved in changing work domains of larger

[1] The relationships between these aspects of operational autonomy are all statistically significant and moderately strong. Cramer's V values are: a) 0.609 for ability to choose order of tasks and methods of work; b) 0.520 for order of tasks and speed or rate of work; c) 0.551 for methods of work and speed or rate of work.

units and can have influence on the work conditions of others. As organisational autonomy is related with more complex tasks, it is given larger weight when constructing aggregate Autonomy index. As expected the correlation between the two components of Autonomy index is statistically significant, but moderate (Kendall's tau b equals 0.275).

The third dimension seeks to measure, whether an individual is involved in continuous skill building. This includes two aspects: whether an individual has incentives to improve skills (it is assumed that such incentives are provided by self-assessment of the quality of own work) and actually realise the learning potential (i.e. whether work involves learning new things). As expected the two aspects are statistically significantly related (Cramer's V value equals 0.269). The variable Skill_Building is constructed so as to reflect collective necessity of both aspects.

Table 2. Level of skills: operationalization of dimensions.

Dimension	Questions in the questionnaire	Recoding and aggregation
Degree of uncertainty	Q49.C.Generally, does your main paid job involve ('yes' or 'no' answers): C. solving unforeseen problems on your own; E. complex tasks.	Rule of aggregation: 0, if all negative; 0.5, if one answer positive; 1 if all positive
Level of autonomy	Q50. Are you able to choose or change: A. your order of tasks; B. your methods of work; C. your speed or rate of work	Rule of aggregation: 0, if all negative; 0.5, if one or two positive; 1 if all positive; Weight in the level of autonomy index = 0.25
	Q51 For each of the following statements, please select the response which best describes your work situation: D. You are involved in improving the work organisation or work processes of your department or organisation.	1-always; 0.75- Most of the time; 0.5. Sometimes; 0.25-Rarely; 0-Never Weight in the level of autonomy index = 0.75
Continuous skill-building	Q49.C.Generally, does your main paid job involve ('yes' or 'no' answers): B. assessing yourself the quality of your own work; F. learning new things	Rule of aggregation: 0, if all negative; 0.5, if one positive; 1 if all positive

Source: own compilation based on questionnaire used by European Foundation for the Improvement of Living and Working Conditions, 2010.

Since the three dimensions should measure the same concept, they should be correlated. As expected their relationships are statistically significant (see Table 3). The strongest relationship was found between uncertainty and continuous skills building.

Table 3. Relationships between three dimensions measuring level of skills

		Autonomy	Uncertainty	Continuous skill-building
Autonomy	Kendall's tau_b	1.000	.248**	.269**
	N	37899	37280	37130
Uncertainty	Kendall's tau_b	.248**	1.000	.458**
	N	37280	42789	42013
Continuous skill-building	Kendall's tau_b	.269**	.458**	1.000
	N	37130	42013	42603

Note: ** Correlation is significant at the 0.01 level (2-tailed). Source: own computation based on data from European Foundation for the Improvement of Living and Working Conditions, 2010.

There is no theoretical reason to assume that any dimension should be given higher weight. Hence they were all weighted equally when constructing an aggregate index of Skill_Level. The key results by country and industry are discussed in section 4.1.

To test robustness of the aggregate measure, it is useful to assess, whether the constructed measure is related with the ones previously used. For instance, the level of skills should be related with the highest level of education obtained. As expected the two measures are statistically significantly correlated at the 0.01 level, but the strength of relationship is rather moderate (Spearman's rho 0.293). As discussed in section 2.2 obtained qualifications are clearly related with skills, but also a poor predictor of the level of skills, since highest level of education does not account for actual use of skills and ignores skill acquisition or depreciation after initial education.

The second test of robustness sought to assess, whether level of skills is related with occupational groups. ISCO-88 includes 9 occupational groups (armed forced excluded from analysis) that are arranged considering the level of skills required for each occupation. For example the first group includes legislators, senior officials and managers, while the ninth group includes elementary occupations. The level of skills is statistically significantly related with 1 digit ISCO-88 occupations and the strength of association is moderate (Spearman's rho -0.4). Since the relationship is significant and stronger than in the case of education, this provides empirical support to argue that the above constructed measure of the level of skills is not far off in measuring skills within work domains.

3.2. Specificity of skills

Measurement of specificity of skills is based on European Social Survey (2010) carried out in 2010-2011 in 21 EU Member State and Croatia, Israel, Russian Federation, Norway, Switzerland and Ukraine. The questionnaire focuses on value systems, but includes several relevant questions on jobs.

The questions used for operationalization of the two dimensions of skills specificity are described in Table 4. Ideally questions on similarities or differences of skills applied in a number of jobs should have been asked to capture transferability of skills. The current questionnaire, however, does not provide such opportunities. The measurement approach taken in this paper includes three steps. The first step is to assess whether employees have many outside options that could make use of the skills developed in current jobs (see G20 in Table 3). The main advantage of this question is that it directly focuses on transferability of currently used skills. The main drawback, however, is that it refers to perceptions. In order to tackle the latter problem, an artificial categorical variable OtherEmpl was created so as to separate ‘many’ outside options from the ‘some’, ‘one or two’ or ‘none’. This variable alone, however, does not convey full information on transferability of skills. If, individual does not have outside options that could make use of present skills, she: a) still could switch occupation/sector by abandoning some of the skills developed in present job or b) stay with current employer. Therefore, the second step seeks to assess actual performance in the labour market: a variable SameWork measures what proportion of years spent in employment individuals have been doing the same kind of work as currently. This is used as a proxy for occupational and/or sectoral mobility. Transferability variable is calculated at third step by multiplying OtherEmpl with SameWork. The overall logic is this: if individual has many outside options his/her skills are transferable. However, if the number of outside options is limited, then the level of transferability depends on the proportion of career devoted to particular kind of work. If the whole career was devoted to the same kind of work, then skills are not transferable. Conversely, if faced with limited number of other firms that could make use of current skills an individual decides to switch occupation or industry and abandon some of current skills, then his/her skills are more transferable than in the absence of switch.

One could argue that variable OtherEmpl actually measures labour market situation (for e.g. the respondent does not know other employers due to economic hardship) rather than transferability of skills. To assess this, OtherEmpl was correlated with answers to the question, whether respondents have been unemployed for more than 3 months during the past 5 years. The correlation is not statistically significant and association between these variables is close to zero (Cramer’s V value equals 0.012).

Table 4. Specificity of skills: operationalization of dimensions

Dimension	Questions in the questionnaire	Recoding and aggregation	Variables	
Non-transferability of skills: difficulty of switching employers	G.20 Do you know of any other employers who would have good use for what you have learnt in your present job?	0 if ‘Yes, many’; 1, if ‘yes some’, ‘yes, one or two’ and ‘no, none’.	OtherEmpl	Transferability= OtherEmpl x SameWork
	G14. Including all the jobs you have ever had, how many years in total have you been doing the kind of work* you currently do?	% of all years doing the type of work=(G14*100/G11)/100	SameWork	
	G11 In total, how many years have you been in paid work?			
Specificity of work: difficulty of replacing employees	G. 25 If somebody with the right education and qualifications replaced you in your job, how long would it take for them to learn to do the job	1, if one year or more; 0, if less than one year.	SpecWork	

	reasonably well?		

Notes: * the questionnaire links the kind of work with description of occupations that is recoded into ISCO-88. Source: own compilation based on questionnaire used by European Social Survey (2010).

Specificity of work seeks to measure, how much additional training employees need in order to perform the tasks well. This is directly captured by question G25 (see Table 4) in the European Social Survey. The answer categories in questionnaires included different time intervals, but we are mostly interested in positions that take considerable period of training (and the differences between few weeks or few months could be quite subjective). Therefore an artificially categorical variable SpecWork was created to separate work that requires more and less than one year of additional training.

One could also be tempted to include additional questions: 'How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?' to measure transferability of skills and 'how difficult or easy would it be for your employer to replace you if you left?' to capture specificity of work. These questions, however, are excluded as they are purely subjective and do not explicitly refer to skills and therefore could capture other issues related to job mobility.

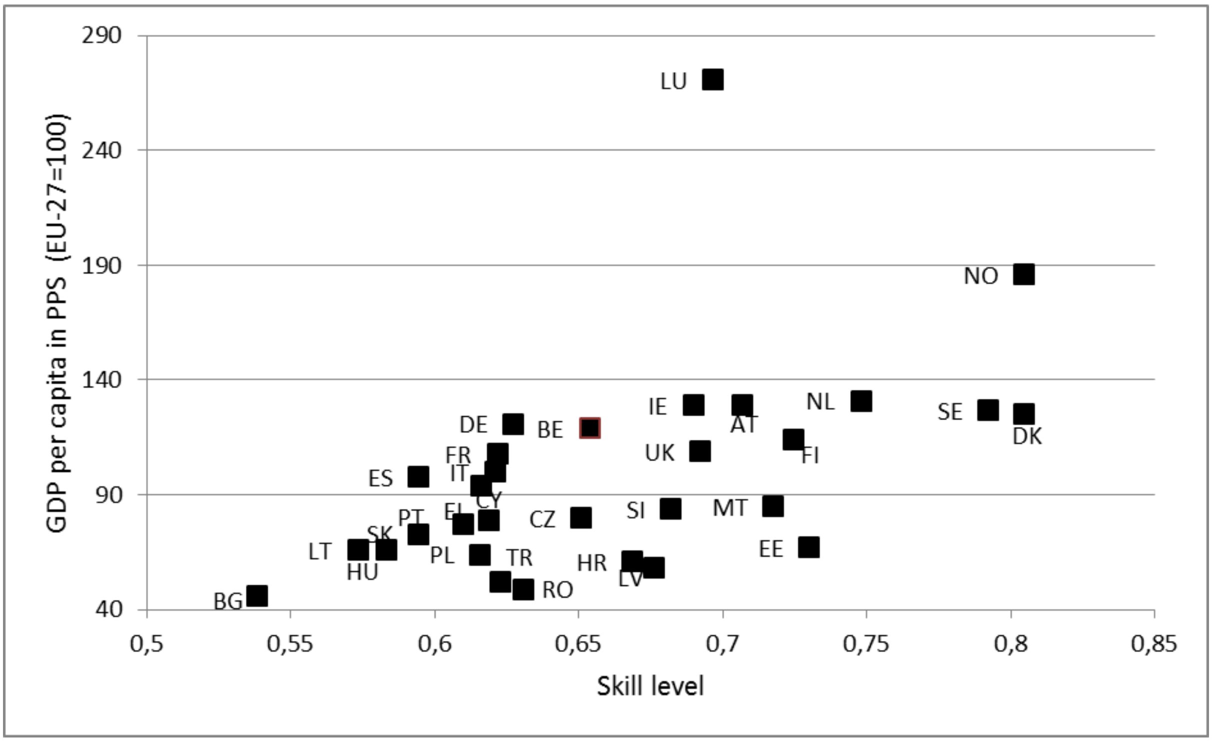
As argued above, there are no theoretical reasons, why the dimensions measuring transferability of skills and specificity of work should necessarily correlate. The test reveals that the relationship is statistically significant (at 0.01 level), but extremely weak (Kendall's tau_b equals -0.042). It is interesting to note that the literature discussed in section 2.2.2. assumed single dimensionality although the employed proxies captured both dimensions. This could explain inconsistency of empirical results in the literature.

4. Results and discussion

4.1. Level of skills

There are significant differences between European countries in the level of skills of labour force (see Table 5 in Annex A). The index of the level of skills obtains highest means in the Nordic countries (Norway, Denmark, Sweden, Estonia, Finland), the Netherlands, Malta and Austria (means over 0.7) and the lowest means in Bulgaria, Lithuania, Hungary, Spain and Slovakia (less than 0.6). As human capital literature would predict, the index measuring levels of skills is correlated with GDP per capita in PPS (see Figure 2). The Nordic countries in addition to highest skill levels also exhibit smallest standard deviations, which indicate relatively equal distributions of skills. The standard deviations are the highest in Bulgaria, Lithuania, Romania, Slovakia and the Mediterranean countries, which indicates significant within country differences in the levels of skills.

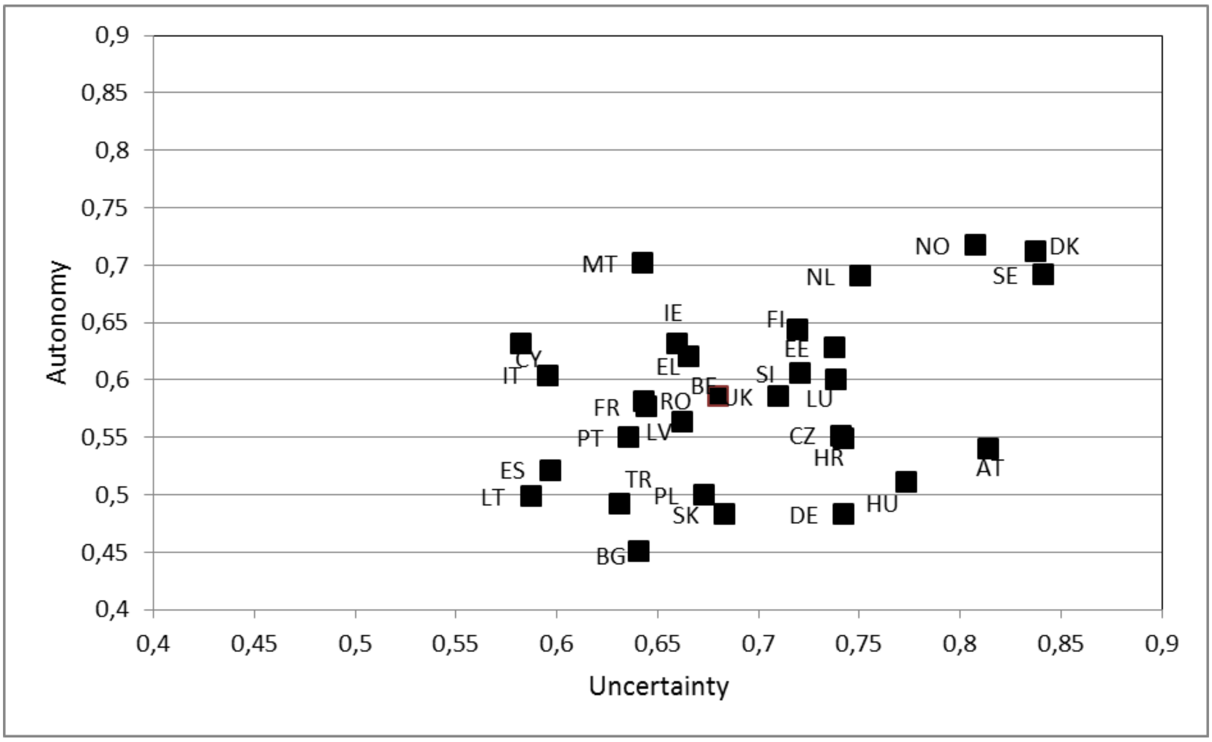
Figure 2. Level of skills and GDP per capita in PPS.



Source: own computation on the basis of data from European Working Conditions Survey, 2010 and Eurostat. Note: GDP per capita in PPS refers to 2011.

The aggregate index conceals important cross-national differences. Figure 3 provides decomposition by the two least correlated elements (see table 3): level of autonomy and uncertainty. This suggests interesting historical and economic patterns. The work domains in the cluster of Nordic countries (upper right corner in Figure 3) are characterised by complex operational procedures and high worker autonomy in changing or redefining them. On the other hand, the work in German-Habsburg cluster (south eastern corner) involves highly sophisticated operational procedures, but relatively low worker autonomy. The tentative interpretations of these differences could include: historical-cultural traditions of organising work (collective decision making v.s. crisp separation of functions), the importance of manufacturing sectors (typically associated with lower worker autonomy) in German-Habsburg cluster and/or different institutional settings of national economies.

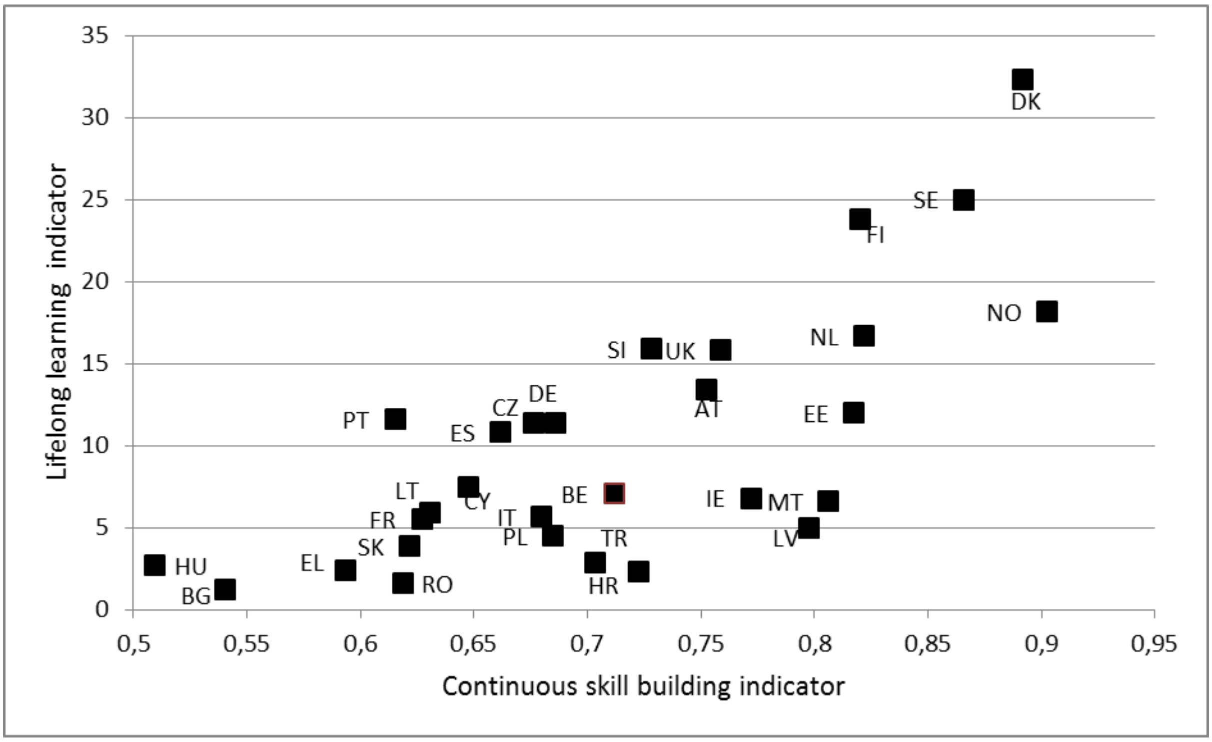
Figure 3. Uncertainty and Autonomy at work.



Source: own computation on the basis of data from European Working Conditions Survey, 2010.

Comparison between continuous skills building indicator and widely used measure of lifelong learning (measures % of persons aged 25 to 64 who stated that they received education or training in the four weeks preceding the survey) reveals that the two are strongly correlated (see Figure 4). It also points out to cross-national differences in learning practices. Comparison of, for e.g. Portugal and Latvia suggests that in the former learning more often takes place within structured formal or informal education and training (as measured by Lifelong learning index). The proportion of workers involved in such activities is considerably lower in Latvia, but here learning more often takes place on-the-job (as measured by Continuous skill building index).

Figure 4. Learning practices.



Source: own computation on the basis of data from European Working Conditions Survey, 2010.

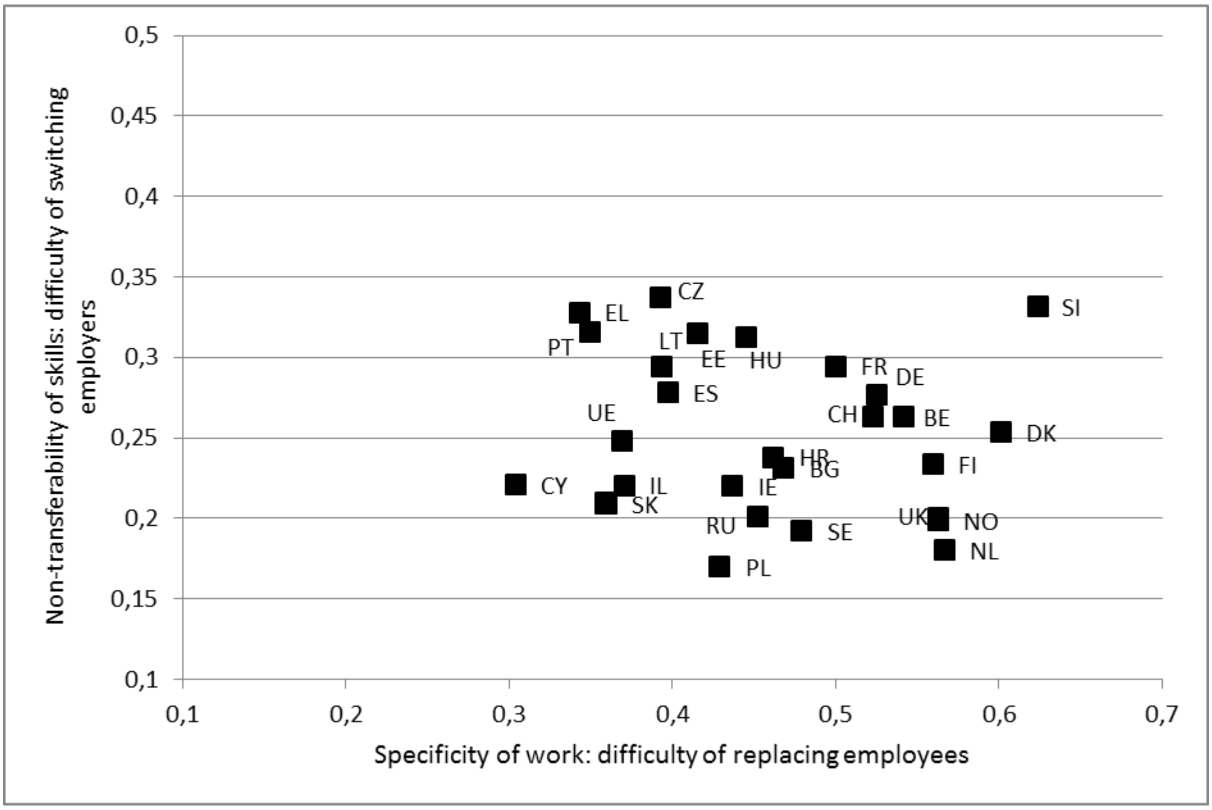
One of the benefits of the proposed measurement strategy is that it provides a number of other opportunities for assessment of the level of skills. Breakdowns by sector and occupation or comparison of highest level of education obtained and level of skills (this could be used for analysing skills mismatches), etc. are also possible.

4.2. Specificity of skills

The overall results by country are provided in Table 6 in Annex A. They suggest that one should not draw far reaching conclusions in terms of cross-country differences due to relatively small N (particularly for Cyprus, Croatia, Lithuania, Portugal, Slovenia, Ukraine). Furthermore, differences in country means are small, while within country variation (as captured by standard deviation) is very high. This would suggest that measurement strategy should be improved (potentially by introducing controls and changing formulation of questions) and/or theoretical explanations based on national skills formation systems (leading to either general or specific skills) fail to account for huge within country diversity.

To discuss the potential of methodological approach, Figure 5 below provides country means according to two dimensions: transferability of skills and specificity of work. With some notable exceptions, specificity of work seems to be lower in Mediterranean and post-socialist countries in comparison to Western and Northern European countries. Slovenia seems to be closest to the ideal type of firm-specific skills, while Cyprus could exemplify the system of general skills (although small N for Cyprus cautions against firm conclusions). Portugal, Greece, the Czech Republic, Lithuania and Estonia form an unexpected cluster of segmented labour markets: work domains require skills that are abundant, but due to small size of labour market segments and/or large distances between them, employees do not have many outside options. Norway, UK and the Netherlands seem to represent specialised economies, which rely on skills that are not abundant in the labour market, but due to large number of firms requiring the same skills, an average employee enjoys quite a few outside options. As a result the power of employees vis-à-vis employers is considerably higher in specialised economies in comparison to countries characterised by segmented labour markets.

Figure 5. Specificity of skills



Source: own computation on the basis of data from European Social Survey, 2010.

The differences emphasised in Varieties of Capitalism literature between Germany (assumed to be a prime example of specific skills formation system) and the UK (general skills) seem to hold in terms of transferability of skills, but not specificity of work. The differences in means, however, are not as large so as to refer to ideal types of skills formation systems. In these respects means for Norway and the Netherlands are quite similar to the UK, while the level of specificity of skills in France, Switzerland and Belgium is similar to Germany.

Overall, the approach adopted in this paper provides an opportunity for reinterpretation of literature that used types of qualifications as proxy for skills specificity. It seems that economic specialisation and labour market segmentation are at least as important as type of education in explaining transferability of skills. For instance, foreign language proficiency and IT literacy are commonly assumed to represent transferrable skills, but their actual transferability will largely depend on the level of demand in the local labour market. Similarly, skills associated with deep-sea fishery could be highly transferable in Norway, but not necessarily in Austria. Hence, instead of relying on assumptions based on *a priori* transferrable and non-transferable skills or typologies of training systems, further research should shift focus towards on actual developments in the labour market.

5. Conclusions and discussion

This paper sought to develop and test a methodology that could provide an alternative to commonly used proxies for measuring skills. The proposed approach views skills as deeply embedded rather than context independent characteristics of individuals. It seeks to capture interrelationships between individual qualities (education and training, prior experience, etc.) and performance domain (tasks, work organisation, technology, etc.). This has several benefits. First, measurements of how tasks are performed should provide more accurate and sensitive account of levels and specificity of skills in comparison to proxies (e.g. qualifications) that assume potential to carry our work. Such an approach has high potential to contribute to academic discussions on the links between level of skills and economic growth, types of skills and investment in training. Second, the proposed approach accounts for different dimensions of skills. This opens numerous opportunities for comparative analysis of these dimensions and their relationships with education and training, work organisation and other practices. Third, while use of widely available survey data has its drawbacks, it also present a range of opportunities for analysis, for e.g. by linking skills with regions, occupations, sectors, health at work and other characteristics of employment domains and individuals.

On the other hand, the proposed methodology also faces several challenges. First, further elaboration of framework for measuring levels of skills would be welcome. The key challenge is to provide a set of criteria that would be relevant for all employment domains. Qualitative insights from cases studies could be employed for further development of common criteria. Second, while use of widely available survey data has numerous benefits, self-reports could be regarded as subjective. Hence, the questions (particularly the ones used for measurement of specificity of skills) should be rephrased so as to focus on accounts of behaviour rather than subjective knowledge or opinions. Third, there is a low number of observations per country for measuring specificity of skills on the basis of results of European social survey (2010). The main reason is that the survey includes respondents irrespective of their status in the labour market. Hence the number of respondents that were employed and answered relevant questions is small.

The analysis suggests several implications for further academic debate. First, proxies related to educational attainment do not adequately grasp, how the human potential is actually used within work domains. While the correlation between the index proposed in this paper and educational attainment is significant, it is not very strong. This suggests the need for careful reconsideration of assumptions behind the widely used proxies for skills. Second, previous literature used proxies for skills specificity that refer to both: transferability of skills and specificity of work. This paper argues that conceptually these dimensions are different and should not necessarily correlate. In fact, data used from European social survey (2010) suggests that the correlation is close to zero. Third, the cross-national variation in indices measuring specificity of skills is rather low, while within country standard deviations are high. This poses a question, whether distinctions between general and specific skills formation systems are empirically grounded.

The main implication for policy makers is that increased funding and participation in education and training is not sufficient to improve the levels of skills of workforce. The quality of employment domains is as much important. Furthermore, actual transferability of skills (and adaptation to technological, economic and other shocks) is strongly related with (vertical, horizontal and geographical) labour market segmentation. This should be a primary target for tackling the so called ‘skills mismatch’ problem.

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ANNEX A.

Table 5. Cross-country variation in level of skills

Country	Uncertainty Mean (std. dev.) (N)	Autonomy Mean (std. dev.) (N)	Skill building Mean (std. dev.) (N)	Level of skills Mean (std. dev.) (N)
Austria	.8141 (.31709) (963)	.5402 (.33179) (881)	.7527 (.34402) (942)	.7068 (.25163) (819)
Belgium	.6798 (.35281) (3955)	.5858 (.30696) (3606)	.7116 (.36808) (3930)	.6537 (.26490) (3547)
Bulgaria	.6409 (.37861) (972)	.4515 (.35085) (856)	.5402 (.39356) (969)	.5383 (.30520) (806)
Croatia	.7423 (.34591) (1077)	.5497 (.31583) (928)	.7225 (.34652) (1065)	.6687 (.26099) (897)
Cyprus	.5821 (.37477) (981)	.6314 (.32480) (950)	.6478 (.36629) (988)	.6162 (.27134) (929)
Czech Republic	.7411 (.34860) (958)	.5518 (.31435) (856)	.6764 (.36055) (855)	.6509 (.25528) (812)
Denmark	.8373 (.28037) (1057)	.7116 (.25623) (935)	.8916 (.22902) (1056)	.8045 (.18631) (916)
Estonia	.7378 (.33745) (963)	.6280 (.32591) (875)	.8175 (.30341) (970)	.7300 (.24886) (837)
Finland	.7196 (.34997) (1020)	.6438 (.25970) (986)	.8199 (.28330) (1019)	.7245 (.21253) (976)
France	.6442 (.36754) (3021)	.5773 (.33032) (2648)	.6271 (.38987) (2979)	.6218 (.27576) (2581)
Germany	.7424 (.34143) (2108)	.4836 (.29599) (1841)	.6858 (.35732) (2094)	.6274 (.25680) (1797)
Greece	.6652 (.36190) (1026)	.6204 (.34233) (901)	.5934 (.37319) (1023)	.6188 (.28581) (888)
Hungary	.7730 (.32965) (998)	.5113 (.34029) (898)	.5095 (.35449) (997)	.5830 (.25902) (887)
Ireland	.6599 (.38059) (991)	.6322 (.32734) (835)	.7720 (.33944) (989)	.6899 (.27263) (823)
Italy	.5956 (.36983) (1459)	.6044 (.31737) (1291)	.6799 (.37132) (1434)	.6210 (.27637) (1234)
Latvia	.6621 (.37966) (975)	.5634 (.32823) (939)	.7975 (.29307) (978)	.6760 (.25152) (896)
Lithuania	.5870 (.38164) (931)	.4991 (.32936) (846)	.6305 (.37031) (935)	.5733 (.29235) (759)
Luxembourg	.7386 (.34267) (983)	.6008 (.31921) (902)	.7425 (.35502) (969)	.6966 (.25575) (847)
Malta	.6424 (.32965) (987)	.7016 (.34029) (910)	.8059 (.35449) (984)	.7174 (.25902) (887)
Netherlands	.7507 (.29633) (1011)	.6911 (.28352) (940)	.8219 (.28337) (1005)	.7479 (.21878) (925)
Norway	.8074 (.28678)	.7178 (.24002)	.9023 (.21535)	.8045 (.17099)

	(1067)	(990)	(1065)	(963)
Poland	.6728 (.34957) (1464)	.5000 (.31194) (1227)	.6848 (.36975) (1461)	.6157 (.26916) (1190)
Portugal	.6358 (.35926) (994)	.5501 (.35916) (821)	.6152 (.39580) (994)	.6099 (.27545) (814)
Romania	.6433 (.38313) (984)	.5821 (.34080) (847)	.6188 (.40274) (985)	.6309 (.28564) (816)
Slovakia	.6834 (.38314) (954)	.4833 (.29478) (854)	.6217 (.39222) (957)	.5945 (.27962) (808)
Slovenia	.7207 (.34217) (1373)	.6064 (.30893) (1325)	.7283 (.34668) (1369)	.6820 (.24369) (1283)
Spain	.5969 (.34260) (991)	.5217 (.35984) (888)	.6618 (.37423) (986)	.5944 (.27592) (867)
Sweden	.8412 (.25262) (992)	.6920 (.26977) (941)	.8656 (.25090) (982)	.7922 (.17488) (917)
Turkey	.6312 (.37553) (2047)	.4920 (.32546) (1485)	.7033 (.38164) (2041)	.6226 (.26063) (1453)
UK	.7101 (.36080) (1561)	.5861 (.33874) (1413)	.7588 (.34869) (1557)	.6922 (.26587) (1393)

Note: std. dev refers to standard deviations; N refers to number of observations. Source: own computation on the basis of data from European Working Conditions Survey, 2010.

Table 6. Cross-country variation in level of skills

Country	Non-transferability of skills Mean (std. dev.) (N)	Specificity of work Mean (std. dev.) (N)
Belgium	.2632 (.31895) (508)	.5417 (.49861) (707)
Bulgaria	.2311 (.27916) (464)	.4684 (.49935) (711)
Croatia	.2381 (.31173) (274)	.4619(.49910) (446)
Cyprus	.2207(.28666) (245)	.3038 (.56050) (372)
Czech Republic	.3376 (.30141) (527)	.3926(.48859) (917)
Denmark	.2539 (.31869) (636)	.6014(.48995) (715)
Estonia	.3147 (.29405) (534)	.4153(.49311) (732)
Finland	.2340 (.31926) (618)	.5600 (.49673) (725)
France	.2946 (.30191) (596)	.5000 (.5033) (766)
Germany	.2765 (.30610) (939)	.5252(.49956) (1270)
Greece	.3280 (.32390) (360)	.3432 (.47515) (641)
Hungary	.3122 (.29403) (401)	.4453 (.49740) (622)
Ireland	.2203 (.27551) (505)	.4370 (.49635) (730)
Israel	.2206 (.27996) (555)	.3706 (.48327) (761)
Lithuania	.2944 (.29287) (316)	.3936 (.48904) (503)
Netherlands	.1801 (.27889) (635)	.5668 (.49584) (771)
Norway	.1984 (.28493) (713)	.5627 (.49635) (837)
Poland	.1700 (.26343) (470)	.4292(.49535) (650)
Portugal	.3161 (.33341) (338)	.3497 (.47738) (469)
Russian Federation	.2012(.26829) (795)	.4520 (.49792) (1115)

Slovakia	.2091 (.26341) (485)	.3596 (.48024) (648)
Slovenia	.3318 (.33090) (290)	.6238 (.48490 (521)
Spain	.2785 (.31182) (511)	.3973(.48971) (662)
Sweden	.1925 (.28118) (631)	.4794 (.49993) (703)
Ukraine	.2870 (.28456) (310)	.3691 (.48297) (596)
UK	.2003 (.27936) (800)	.5632 (.49624) (973)
Switzerland	.2632 (.30371) (551)	.5229 (49983) (698)

Source: own computation on the basis of data from European Social Survey, 2010. Note: std. dev refers to standard deviations; N refers to number of observations