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Deliverable 12.1

THE MEASUREMENT OF SKILLS NEEDS, SKILLS TRANSFERABILITY AND SKILLS IMBALANCES WITH DATA FROM INTERNATIONAL SURVEYS, WEB SOURCES AND WEB-BASED SURVEYS

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Abstract

This document examines the measurement of the concepts of skills needs, skills transferability and skills imbalances using international employer and employee surveys and new data sources from the Internet. First, it provides a conceptual clarification regarding these skills-related concepts based on definitions used in the literature, and how these concepts are mobilised as well as the main empirical results obtained. Second, it presents the different types of international data sources used in the literature to measure the aforementioned concepts. Third, it discusses the measurement of the above concepts using three types of Internet-based data sources: job portals, social networking websites and nonprobability Internet-based surveys. These have an incredible potential as data sources for the analysis of skills-related issues, but are not or rarely used for that purpose and their mobilisation raises several methodological issues.

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List of abbreviations

ALL*: Adult Literacy and Lifeskills*
Cedefop*: European Center for the Development of Vocational Training*
CHEERS: *European graduate survey*
DOT: *Dictionary of Occupational Titles*
EBS: *European Business Survey*
ECHPS: *European Community Household Panel Survey*
ECS: *European Company Survey*
ESCO: *European Skills/Competences, Qualifications and Occupations*
ESJ: *European Skills and Jobs survey*
ESS: *European Social Survey*
ESWT: *Establishment Survey on Working Time and Work-Life Balance*
EU-LFS: *European Union Labour Force Survey*
EU-SILC: *European Union - Statistics on Income and Living Conditions*
GDP: *Gross Domestic Product*
GVC: *Global Value Chains*
HEGESCO: *Higher Education as GEnerator of Strategic COmpetences*
IALS: *International Adult Literacy Survey*
ICT: *Information and Communication Technology*
ILO: *International Labour Organisation*
IRT: *Item Response Theory*
ISCO: *International Standard Classification of Occupations*
JRA: *Job Requirement Approach*
KSA: *knowledge, skills and abilities*
MTSS: *ManPower Talent Shortage Survey*
NEPS: *National Educational Panel Study*
O*NET: *Occupational information NETwork*
OECD: *Organisation for Economic Co-operation and Development*
OSHC: *Occupation-Specific Human Capital*
PIAAC: *Programme for the International Assessment of Adults competencies*
REFLEX: *Research into Employment and professional FLEXibility*
SAA: *Skills Assessment and Anticipation*
SCED: *International Standard Classification of Education*
SOC: *Standard Occupational Classification*
STEM: *Science, Technology, Engineering and Mathematics*
STEP: Skills Towards Employability and Productivity

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1. Introduction

In the last decades, economies all around the world - especially in developed countries - have been experiencing continuous transformations due to several factors that are usually called the mega-trends. These are technological innovation, changes in the global division of labour with Global Value Chains (GVC), changes in work organisation, demographic changes and changes in consumption models. These rapid and substantial changes affect the demand for skills in all economies. At the same time, the supply of skills has also changed due to a number of elements, such as the expansion of compulsory and higher education, improvements in the quality of education, increases in female labour force participation, migratory flows and changes in retirement behaviours (OECD, 2017). This dynamism of both - skill demand and supply - has led to severe and persisting skill imbalances. It makes the task of matching skills in the labour market harder than ever before (Hartog, 2000).

To avoid skills imbalances and achieve a better matching between skills demand and supply, skill needs have to be assessed and anticipated continuously to adapt the supply (OECD, 2016). This adjustment may consist of redistributing the workforce across occupations or countries, which raises the question of the transferability of skills across occupations and countries, i.e. to what extent the skills mobilised in a given occupation can be applied in others and to what extent skills owned by workers that move abroad can be applied in the country of destination. Moreover, such a solution is dependent on the workforce being able if needed to transfer their skills from one occupation or country to another, which requires a continuous development and adaptation of the skills of this workforce (employability).

A persistent misalignment between the demand for skills and the supply of skills can have drastic consequences on individuals, firms and economies. For individuals, skill imbalances are associated with poor labour market outcomes such as lower job satisfaction and wage losses (Montt, 2015). For firms, skills imbalances are linked to weaker economic performance with a lower level of productivity and an increased on-the-job search and turnover (OECD, 2012). Overall, skills imbalances lower the aggregate demand of an economy with a reduced output level and a high level of structural unemployment (Sattinger, 2014; OECD, 2012; Adalet, McGowan & Andrews, 2015).

In response to these skills imbalances, many countries and international institutions are more than ever committed to matching the supply to the demand for skills (ILO, 2014; OECD, 2013; Cedefop, 2015a). However, to deal with what is often described by employers as the *skill problem*, it is necessary to know the extent of these imbalances (Cappelli, 2015). In fact, if we are not able to measure the extent of mismatches, it would be difficult to know whether the policies implemented to solve the *skill problem* are actually working. To measure skill imbalances, we need information on both the demand and supply of skills.

Usually, each country has its own source of information on skills, which may come from different national sources. Such information is mobilised to perform a Skills Assessment and Anticipation (SAA) exercise to help designing their national education and training policies (OECD, 2016). However, to perform an international comparison or to have an international perspective on skill imbalances, the main source of information is the data derived from international employer or employee surveys.

Parallel to the above-mentioned data sources, recent years have witnessed an unprecedented development of internet-based data sources for labour market analysis (Autor et al. 2003; Askitas & Zimmermann, 2009, 2015 ; Faberman & Kudlyak, 2016). In many countries, matching between demand and supply of skills is increasingly done using the internet, especially white-collar occupations. Using different types of internet platforms, employers advertise the skills they are searching and employees and people searching for work advertise their skills. In addition to the international large-scale assessment surveys, the use of so-called volunteer (non-probability) internet-based surveys, such as the WageIndicator, has increased for the analysis of a range of skills-related issues (Fabo & Tijdens, 2014). The question however remains, in how far such alternative data sources may constitute an alternative and/or complement to the traditional ones. Against this background, the purpose of this document is to examine the benefit of Internet-based data sources, from Internet jobs portals, non-probability Internet-based surveys and social networking websites, to the analysis of skills-related concepts, in comparison to international employer or employee survey specifically designed for that purpose.

The document proceeds as follows. Section II provides definitions and usage in the literature of concepts on skills needs, skills transferability and skill imbalances. Section III makes a distinction between the different types of international surveys used in this literature. Section IV presents two different types of data from the internet and discuss how they can be used to measure the above concepts. The last section concludes and discusses several avenues of research on skills using internet-based data sources as an alternative to data from international employer or employee surveys.

2. Skills needs, skills transferability and skills imbalances

This section provides conceptual clarifications regarding skills needs, skills transferability and skills imbalances in the literature. It first discusses the concept of skills needs, followed by the concept of skills transferability and finalised with skills imbalances,[1] which encompass several other concepts.

2.1 Skills needs

The labour demand in an economy is a reflection of employer behaviour whereby employers create new jobs or replace leaving workers. A job can be defined according to the International Labour Organisation (ILO, 2012, page 11) as a list of tasks and duties meant to be executed by one person. In order for this person to be deemed competent, he/she must possess the knowledge, skills and abilities among other personal attributes that are needed to adequately perform these tasks and duties. Thus, skills needs in an economy are the skills required to perform those tasks and duties in current or future job openings (expansion or replacement demands for labour).

However, in an economy, there are thousands of different jobs titles. An occupation regroups jobs that are similar based on the nature of their tasks and duties. Therefore, the jobs in an occupation presumably require the same set of skills. This is the reason behind the use of occupation as the level of analysis in many studies on issues related to skills, notably in the analysis of skill imbalances.

The identification of these skills needs is usually based on Skills Assessment and Anticipation (SAA) exercises - which are regularly conducted by nearly every developed economy around the world (OECD, 2016). A correct assessment and anticipation of skills needs can help avoid severe skill imbalances. In fact, when skills needs go unmet, there are skills shortages (as well as many other types of skills imbalances). The latter refer to a situation where, due to a lack of an adequately skilled workforce, employers are having difficulties recruiting employees with the skills they need in the accessible labour market despite offering appropriate wages and working conditions (Quintini, 2011).

The concept of skills shortages is implicitly dependent on the concept of skill needs, thus raising the same conceptual and empirical difficulties (Shah & Burke, 2005). OECD (2017) defines skills needs as the skills (in shortages) employed in the occupations that are in shortages of labour and use it in its indicator of skill needs.[2] However, as we will see later, skill shortage is a form of skill imbalance.

These SAA exercises consist of forecasting employment growth by sector, occupation and skills level. The demand for skills is then confronted with the supply of skills in the labour market for eventual adjustment in education and training policies to improve matching in the labour market. A limitation in many of these exercises is the use of qualification as a proxy for skills. This is usually due to a lack of detailed individual skills data. These two concepts are in fact very different, especially in cases where the classification level of qualifications is not detailed enough (Quintini, 2011a; b). The expected demand in each occupation is partitioned into demand for qualifications with a granularity that varies from one country to another depending on the availability of data sources on skills. The information regarding skills requirements at the occupational level can also be found in occupational and job titles dictionaries, such as the occupational information network (O*NET) in the US or the European Skills/Competences, Qualifications and Occupations

1 To avoid confusion, we will use the term *skills imbalances* instead of *skills mismatches*. Indeed, skills imbalances incompass skills mismatches (over- or underskilling), but also other imbalances like skills shortages.

2 See the appendix for a presentation of the construction of the OCDE's indicator of skill needs

(ESCO). These occupational databases provide the skills requirements (level required and intensity of use) of each occupation in their occupational classification system.

Information on skills needs can also be found by looking at the skills employers are searching among potential recruits in the labour market. This is possible using vacancy surveys, online vacancies from job portals as well as other online supports diffusing job offers. A direct assessment of skill needs can also be obtained by asking employers in an employer survey. Given that employers are the creators of these needs, they are best suited to assess them and therefore are a privileged source of information on skills needs. However, the questions in these employer surveys usually focus more on hiring difficulties than on skills needs. In addition, employers' job requirements in terms of skills may be higher than what is required to actually perform the job advertised (Sasser Modesto et al., 2019; Deming and Kahn, 2018).

Given the evolution of technology, organisations and demography, among other factors, the supply of and demand for skills are very dynamic (OECD, 2017). As a result, the skill requirements of many occupations change continuously. In addition, some occupations tend to disappear while others are created. This situation has led to the distinction between current and future skill needs as well as to question about the reliability of information on skills requirements provided by occupational dictionaries. Indeed, it is very difficult to update them regularly given the costs of such an operation. SAA exercises usually consider these changes by allowing the matrix of transition from sectoral and occupational demand and from the latter to the demand for qualifications or skills to vary over time (Argouarc'h, 2015).

Another way of looking into skills needs is first to identify occupations that are in shortage of adequately skilled labour, like in the *OECD's Skill for Jobs Indicators* (OECD, 2017) or by confronting demand and supply of skills in labour market forecasts. Then identify the skills required or needed in these occupation by using occupational dictionary databases such as O*NET or ESCO. The rationale behind this approach is that the impossibility for employers to find adequately skilled recruits to fill a job in the accessible labour market in a given occupation (shortage) would mean that the skills required to work in the occupation are in shortage and are needed. Likewise, when skills are in surplus in a given occupation, prospective workers in that occupation may transfer to another occupation, provided skills can be transferred across them.

2.2 Skills transferability

Skills transferability usually refers to the possibility to transfer skills acquired in a given occupation to another occupation. However, this transferability may also be across sectors or countries. Shaw has first introduced the notion of skills transferability in the literature as occupation- or employer-specific skills transferability (Shaw, 1984). In fact, the task-based approach of occupations implicitly assumes the transferability of skills across employers or occupations that are close, thus questioning the longstanding view that only generic or basic skills are transferable. Indeed in this approach an occupation groups jobs according the similarities in the tasks performed and skills used. In the context of the SAAs, many countries, such as Germany for example, use occupational mobility matrices to account for occupational changes during labour market matching or for the projection of replacement demands. In fact, people trained in a given occupation may work or search for work in another one, depending on the transferability of skills between occupations. These matrices of occupational switches provide proportions or rates of transitions between occupations and may evolve over time as the economy evolves and affects the matching process in the labour market.

When first utilised in Shaw (1984), skill transferability was a determinant of the variation of wages when workers switched occupations. The methodology was designed to cope with the lack of data on skills. Studies that are more recent benefit from the existence of richer data on skills (Ormiston, 2014). They focus specifically on the role played by skill transferability across occupations in labour markets adjustments to structural changes. Studying the transferability of skills enables to analyse the possibility of the reallocation of workers across occupations, or, in other words, the extent to which skill surpluses in some occupations can compensate for skills shortages in other ones.

An analysis of the transferability of skills across occupations is usually conducted using two or three different approaches (Nawakitphaitoon & Ormiston, 2016). They all provide a measure of commonalities between occupations, which corresponds to a matrix of occupational transitions or a transferability matrix.[3] The elements of this matrix vary between zero and one, and represent the distances between occupations. This distance is interpreted as the proportion of skills transferable from one occupation to another. The size of such a matrix depends on the degree of detail of occupations. However, these methods of measurement differ in the inputs used to compute the distances between occupations.

Shaw (1984) has developed the so-called market approach. It is based on the analysis of occupational mobility. It provides a measure of the distance between occupations using transition probabilities. This approach considers that a higher rate of transition between two distinct occupations corresponds to a higher level of transferability between them. The resulting occupational transition matrix is symmetrical, i.e. the transferability from a given occupation A to occupation B is equal to the transferability from B to A. Each element of the matrix provides the rate of transferability between two distinct occupations.

In the second *skill-based approach*, developed by Ormiston (2014), the level of transferability from occupation A to occupation B is not the same as the transferability from occupation B to occupation A. This approach analyses commonalities of occupations across standardised knowledge, skills and abilities using O*NET. It estimates occupational distance based on the proportion of knowledge, skills and abilities utilised in a given occupation that can be applied in another one.[4] The degree of transferability between two given occupation increase with this proportion.

The *task-based approach* developed by Gathman and Schönberg (2010) is very similar to the skill-based approach. It analyses commonality of occupations through tasks performed by workers from those occupations. The task-based measure of occupational distance uses proportions of workers performing similar tasks across occupations. The higher, this proportion, the higher the degree of transferability between occupations and the chance to observe a transition between these occupations.

Occupational-skills transferability can also be measured subjectively, with employees giving a self-assessment of the transferability of the skills used in their current occupation to other occupations. The notion of perceived skill transferability is first mentioned in the study by Angle and Perry (1983) when analysing the determinants of organisational commitment by asking 'how useful is your knowledge and ability in your present job to other organisations?' with answers given on a four-point scale ranging from 'not at all useful' to 'quite useful'. This method, unlike the previous objective ones, is however subject to individual subjective biases and do not allow for comparative analyses across countries.

To conclude, all measurements of skills transferability show that skills are not completely transferable. In fact, the transferability measures are always greater than zero, but lower than one. This means that the worker that is the object of an occupational switch, within or across occupations, may lack some of the skills required in the new occupation and, as a result, may experience skill imbalances.

Transferability of skills across countries and economic sectors is also examined in the literature (European Commission, 2011). In particular, skills transferability across countries is usually tackled in the case of the transferability of immigrants' qualifications. In fact, immigrants' qualifications, acquired abroad are usually not recognised in the labour market of the countries of destination. This subject is closely related to the impossibility to completely transfer skills mentioned above and it has raised attention in the literature, especially but not uniquely in the US (Duleep & Regets, 1997; Chriswick & Miller, 2009; Visintin et al., 2015; McGuinness & Byrne, 2015). These studies focus on qualification mismatches among immigrants and the determinants of immigrants' lower earnings, vis-à-vis their peers with the same levels of qualifications. These two-issues identified in the literature about labour market outcomes for immigrants to the US point to imperfect transferability of skills across borders which often result in an overqualification[5] of foreign-born workers. Zooming in on the European labour market, Damas de Matos and Liebig (2014) estimate that the overqualification rate of foreign-born workers is on average 12% higher than for native-born workers. Similarly, Aleksynkah and Tritah (2013) estimate that across Europe, 22% of immigrants face overqualification,

3 See the appendix for a more detailed presentation of the three methods considered.

4 The approach used by the OECD to analyse commonalities between occupations is also a skill-based. In fact, for each country and for each occupation (4-digit ISCO), in addition of the skills in shortage and the skills in surplus, OECD calculates distances between occupations taking into account the skills one possesses and those additional ones needed to be operational in another occupation.

5 Defined as a situation where a worker's educational qualifications are higher than those required by their job (see next section for detailed discussion)

compared to only 13% of native-born workers. However, qualification mismatches that affect skills transferability across borders can entail also underqualification[6] of foreign-born workers. Chiswick and Miller (2009) find that 16% of migrant workers in the US are underqualified and argue that such workers could compensate for the limited level of education or transferability of qualifications with higher ability and motivation to learn. In Europe, underqualification seems however more common for natives than for foreign workers, as reported by Tijdens and van Klaveren (2012).

Reviewing existing studies on skills transferability across countries, Baiocco et al. (2020) remark that although overqualification of foreign-born workers is a common pattern across countries, there is significant heterogeneity in overqualification rates depending on the destination and origin country (Damas de Matos, 2014; Damas de Matos & Liebig, 2014). The rates and levels of underqualification, too, depends on these factors (Tijdens & van Klaveren, 2012). For example, Visintin et al. (2015) find that differences in the rate of overqualification between native and non-native workers are not only related to the country of residence but also to the combination of country of origin and destination. For example, workers from EU15[7] countries that move to another EU15 country or a non-EU European country (i.e. Russia) have only a slightly higher incidence of overqualification in comparison to their native counterparts. By contrast, workers from other EU countries,[8] have higher overqualification rates than natives in all the countries of destination (including EU15), but in Northern-American and Oceanian countries.

As argued in Baiocco et al. (2020), this points to the fact that institutional arrangements and cultural proximity play a role in the process of skills transferability. Damas de Matos and Liebig (2014) also highlight the role of language in limiting skills transferability. In their study, 21% of immigrants report a lack of knowledge of the local language as their main difficulty in finding a job, regardless their level of education. Indeed, the literature shows that in most countries, overqualification of foreign-born workers decreases over the time they spend in the country of destination, as language skills, country-specific work experience and general knowledge about the country increase (Damas de Matos, 2014). This indicates that overqualification of foreign-born workers may be temporary and linked to cultural barriers, which *de facto* limit skills transferability across borders, at least in the short term.

The transferability of skills across borders remains a challenge even when qualifications are recognised across borders, as it is more often the case for mobile workers within the EU.[9] The multifaceted nature of skills questions the extent to which skills can be fully recognised and transferred across borders (Damas de Matos, 2014), or whether qualifications are good-enough predictors of skills to this aim (Quintini, 2011a; 2011b), as already pointed out in previous sections. This unveils a methodological gap in measuring skills transferability across countries, because skills transferability is commonly measured in the literature by qualifications, as a proxy for skills. For example, several studies on skills mismatches of migrants in the European labour market rely on data from the EU-LFS (Eichhorst et al., 2011), which however allow to measure skills only in terms of qualifications, as explained in the next section.

Qualifications are likely to reflect competencies such as information processing and subject-specific skills (OECD, 2013). However, they miss out information about additional skills developed outside formal learning, for example on the job (Fialho et al., 2019), or about socio-emotional, non-cognitive skills[10] (Kautz et al., 2014). As pointed out in previous sections, detailed data on skills at the individual level are scant. However, advances have been made by the OECD Programme for the International Assessment of Adult Competencies (PIAAC), which allows for measuring skill levels in literacy, numeracy and problem solving in

6 Defined as a situation where a worker's educational qualifications are lower than those required by their job (see next section for detailed discussion).

7 Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

8 Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia.

9 The EU has adopted several initiatives to promote labour mobility within the EU Single Market (Baiocco et al., 2020), including those to ensure recognition of qualifications, such as the Directive on the recognition of professional qualifications (Directive 2005/36/EC) and the European Qualification Framework (Recommendation 2008/C 111/01).

10 Kautz et al. (2014: 13) define non-cognitive skills as 'personal attributes not thought to be measured by Intelligence Quotient (IQ) tests or achievement tests. These attributes go by many names in the literature, including soft skills, personality traits, non-cognitive abilities, character skills, and socioemotional skills. […] "Skills" suggests that these attributes can be learned'.

adults.[11] This is useful to assess the extent to which skills are transferable and actually transferred across countries, but also in general to have a better knowledge of skills levels in the labour market, as mentioned in the next section. In their reviews, Baiocco et al. (2020) refer to the he analysis of PIAAC results (OECD, 2013), which effectively show how qualifications are predictors of skills only to a limited extent, in particular when making comparisons across countries. Educational attainment is positively correlated to skills proficiency, but the level of skills proficiency varies markedly within levels of educational attainment, both within and across countries. Importantly, holding the level of education constant, the average level of skills proficiency is different from one country to another (OECD, 2013). This demonstrates that qualifications are not particularly accurate when measuring and evaluating workers' skills across countries. To overcome the limitations of using qualifications as proxy for skills in general and in studies on cross-border skills transferability, PIAAC data can also be used to measure skills mismatches beyond qualification mismatches. While, in line with the literature referred to above, foreign-born workers are more likely to be overqualified than their native counterparts, they are less likely to be overskilled or differences are insignificant. As noted for qualifications, however, language barriers influence these results, since the survey is conducted in the language of the host country (OECD, 2013). Yet, to pinpoint another methodological gap in measuring skills transferability across countries, there are currently no measurements to disentangle the effect of language, which is itself an important component of an individual skills set, on skills transferability.

2.3 Skill imbalances

Limited skills transferability can be a source of skills imbalances. However, skill imbalances affect the labour market beyond what concerns foreign-born workers. They reflect a whole range of phenomena (Capelli, 2015; McGuinness & Pouliakas, 2017) and can be measured at the employee, the employer or the occupation level (see Table 1).

At the employee level, a skill imbalance refers to the extent to which levels of skills or education relate to the requirements of the current job (McGuinness & Pouliakas, 2017). In the literature the concept of mismatch aims at capturing the imbalance with a distinction between *vertical* and *horizontal mismatch*. *Vertical mismatch* refers to situations where the levels of education (or qualification) or skills do not match. The literature speaks of *overqualification/education* and *underqualification/education* in the first case*, overskilling* and *underskilling* in the second one. It enables to determine whether there is a surplus/deficit of skills. *Skills underutilisation*, is sometimes used to designate a skill surplus, which may have detrimental effects on individuals' labour market outcomes, firms' performance and the economy as a whole. *Horizontal mismatch* refers to a mismatch between the employee's field of study and the field of study required in the occupation. It evaluates the extent to which people trained to work in a specific occupation unexpectedly work in a different one. This also includes people in general education with a literary degree who work in science, technology, engineering and mathematics (STEM) occupations.

At the employer or the firm level, skill imbalances refer to the degree to which the education and skills of job applicants and holders meet the requirements of the hiring firm. The three following concepts of skills imbalances are usually analysed in the literature at the employer level: *skill gaps*, *skill shortages* and *skill obsolescence*. *Skill gaps* are evoked when workers in a firm (or occupation) lack or do not possess the competencies or skills that are necessary to adequately perform the tasks and duties of their current jobs. *Skill gaps* are similar to underskilling at the employee level. *Skill shortages* designate situations where employers are having difficulties to fill vacancies due to a lack of suitably qualified candidates in the pool of potential recruits. It does not concern unfilled or hard-to-fill vacancies due to a lack of adequate wages and working conditions (Shah and Burke, 2005). *Skill obsolescence* describes a situation where employers do no longer require some of the skills that they used to need due to technical progress or changes in market conditions, among others.

11 The PIAAC provides an assessment also of non-cognitive, behavioural skills; although the assessment is task-based, PIAAC Pilot Study on Non-cognitive Skills was carried out in 2017 to test the measurement properties of non-cognitive skills. Moreover, the OECD is conducting seminal research on non-cognitive, socio-emotional skills through its Study on Social and Emotional Skills, to assess how educational systems can support their development.

Both, *skill gaps* and *skill obsolescence* can also be analysed at the employee level, in which case skill gaps correspond just to underskilling. In what follows, we present each of these measures of skill imbalances.

Table 1. Skill imbalances: definition, measurement and data used

Skill imbalances, employee level			
	Individual concepts of mismatch relate to the degree to which workers in firms possess skill or education levels that are above, below or poorly connected to those required within their current job		
Skill obsolescence	**Definition**	**Measurement**	**International Data**
	Skills of workers are obsolete, i.e. no longer required by the employer due to technical progress or changes in market conditions	Subjective questioning of workers	ESJS
Vertical mismatch of skills			
Education or qualification mismatch			
Overeducation or overqualification **Undereducation or underqualification**	The education level of the worker is higher than the educational requirement of the current job The current education of the worker do not meet the level required by the job	Subjective, empirical (realised matches), job evaluation	ESJS; PIAAC; EU-LFS; ECHPS; CHEERS; STEP; ESS; REFLEX; HEGESCO
Skill mismatch			
Overskilling or skill underutilisation **Underskilling or skill deficit**	The skill level of the worker is higher than the current job requires The current skill level of the worker do not meet the level demanded by the job	Self-reported (subjective) vs direct measures of skill mismatch (Job requirements or realised matches)	PIAAC; ESJS; ALL; IALS; REFLEX; STEP
Horizontal mismatch			
Field-of-study mismatch	The workers is employed in a job that is not relevant to the skills and knowledge accumulated in the field of study of formal education	Subjective vs independent	EU-LFS; REFLEX; CHEERS; HEGESCO
Skill imbalances, employer or occupation level			
	The degree to which the education and skills of job applicants or holders meet the requirements of the hiring firm		
Skill gaps	**Definition**	**Measurement**	**International Data**
(=underskilling)	Workers in a firm or occupation do not possess the adequate competencies to successfully discharge their current role (lack the skills necessary to perform job tasks)	Subjective	ESJS; EBS; ECS; Manpower Talent shortage survey
Skill shortages			
	Employers are having difficulties to fill vacancies due to a lack of suitably qualified candidates (unfilled or hard-to-fill vacancies that have arisen as a consequence of a lack of qualified candidates for posts)	Subjective vs indirect	EBS; ECS; Manpower Talent shortage survey; EU-LFS; EU-SILC; O*NET
Skill transferability			
(Occupation-specific) Across occupations and countries	The extent to which skills acquired in one occupation (country) can be used in another occupation (country). Usually measured as the percentage of skills used in an occupation (country) that would serve in another occupation (country).	Compare occupations in terms of skills required, tasks performed or incidence of occupational switches	PIAAC; O*Net; International data on occupational mobility

* ESJS - European Skills and Jobs Survey; PIAAC - Programme for the International Assessment of Adults competencies; EU-LFS - European Union Labour Force Survey; ECHPS - European Community Household Panel Survey ;CHEERS - European graduate survey - Higher Education and Graduate Employment in Europe; STEP - Skills Toward Employment and Productivity; ESS - European Social Survey; REFLEX - Research into Employment and professional FLEXibility- International survey higher education graduates; HEGESCO - Higher Education as GEnerator of Strategic COmpetences; ALL - Adult Literacy and Lifeskills; IALS - International Adult Literacy Survey; EBS - European Business Survey ; ECS - European Company Survey; MTSS - Manpower Talent Shortage Survey; EU-SILC- European Union Statistics on Income and Living Conditions; O*NET - Occupational Information Network

2.3.1 Qualification- or education-level mismatch

Education or qualification mismatch has been for a very long time the sole focus of studies on skill imbalances. This situation results from the lack of a consensus on the definition of skills, but more importantly from the lack of appropriate data on skills. In this regard, many have settled on using qualification as a proxy for skills. Moreover, data on qualification levels are available in almost all household surveys and therefore allow international comparisons. A qualification mismatch refers to a situation where the level of education of an employee does not match the level required to perform the tasks and duties of his/her job adequately (Quintini, 2011a; McGuinness & Pouliakas, 2017). An employee is said to be mismatched in terms of qualification if he/she, either does not have the qualification required (*underqualified*) or have a level of qualification higher than the level needed (*overqualified*). However, it is necessary to distinguish this notion from that of skill mismatch, as a qualified employee can still be skill-mismatched (Quintini, 2011b; Allen & Van Der Velden, 2001).

Measuring qualification mismatch requires knowing the qualification requirements of jobs and comparing them with the levels of qualification of employees to determine whether there is *overqualification/ underqualification*. Three approaches are used in the literature to measure education mismatch depending on how qualification requirements are determined: *subjective, empirical* and through *job evaluation* (Leuven & Oosterbeek, 2011). Table 2 shows a description of each of these approaches as well as their respective advantages and limitations.

The *subjective approach* determines qualification requirements of jobs by directly asking workers to assess the level of education required to do or get a job in their occupations. This self-assessed level of education is then compared to employees' highest level of education attained to determine whether they are matched (level of education equal to that required), *overeducated/overqualified* (level of education above that required) or *undereducated/underqualified* (level of education below that required). Furthermore, instead of comparing the highest level of education to the self-assessed level of education required, workers can directly assess whether they are matched by comparing their level of education to the qualification level required. This method of measurement of qualification mismatch has the advantage of being easily applicable in survey data. However, it has a number of shortcomings. It is subject to potential subjective biases and cannot be retrospectively applied to existing data. Moreover, this method makes the comparison of results across surveys difficult as the implementation of the mismatch question may differ, with different formulations giving very different results (Leuven & Oosterbeek, 2011).

The *empirical approach*, also known as the realised matches method, estimates the qualification/educational requirement of an occupation by assessing the mean or the modal level of education within a given occupation and workers with a level of education below (above) are underqualified/*undereducated* (overqualified/ *overeducated*). This method is easily implementable using any micro-data with information on both educational attainment and occupations, such as data from labour force surveys. It therefore allows more easily international comparisons. However, given that *underqualified* workers might compensate their lack of qualification with their work experience; this method tends to reflect historical entry requirements. Furthermore, due to *sample size constraints*, the mean or modal education level is usually derived from broad occupational categories. This makes the approximation of skills by qualifications less valid in comparison to using a more detailed occupational grouping closer to individual job titles (Verhaest & Omey, 2010).

Table 2. Qualification or education level mismatch

	Subjective method	Empirical method	Job evaluation method
Qualification mismatch (Overeducation or Overqualification and Undereducation or Underqualification)	**Educational requirement of occupation are obtained from workers self-assessment of the level of education required to do or to get a job in their occupation**, and then compared to the highest level of education actually acquired by the worker in order to determine if they are matched (have a level of education equal to that required), overeducated (have a level of education above that required) or undereducated (have a level of education below that required). Or direct question asks individuals to assess their education as a whole in relation to the qualification needed.	Estimates the **educational requirement of an occupation by assessing the mean or modal level of education within a given** occupation, deeming workers with acquired education above (below) the average level as overeducated (undereducated)	**Assessments of professional job analysts** who are tasked with measuring the **educational requirements of occupations** for the purpose of constructing occupational dictionaries (such as DOT or O*NET in the United States or SOC in the United Kingdom)
Advantages	Relatively easy to apply in survey data	Can be easily applied to any existing microdata sets containing information on both educational attainment and occupation, such as national labour force surveys, thereby facilitating cross-country comparisons	Perceived to be more accurate
Disadvantages	- Potential of subjective bias; - Cannot be retrospectively applied to existing data - No uniform approach to the implementation of the overeducation question within data sets	- Does not contain any information of the actual skill requirements of the job - Due to sample size constraints the mode education level is typically derived for broad occupational groups (e.g. health professionals) and not at a level that is close to an individual job title (e.g. nurse) - Tends to reflect historical entry requirements, rather than current ones	- Very expensive to carry out - Risk of obsolescence if not updated as occupational requirements change - Involve some level of subjectivity

The *job evaluation or objective approach* is usually performed by professional job analysts who define the educational requirements of each occupation used in the construction of occupational dictionaries, such as the dictionary of occupational titles (DOT) or O*NET in the US and the standard occupational classification (SOC) in the UK. It is considered as more reliable, but very expensive to carry out. However, it also involves some degree of subjectivity and the resulting data can become rapidly outdated if not updated regularly, given the continuous changes in occupational skill requirements (Verhaest & Omey, 2010).

Table 3. Empirical literature on qualification mismatch: some main results

Qualification mismatch	Some empirical results
Overeducation: 98 papers published, with 4 review articles and 94 empirical analyses. Method used: 48 subjective , 38 empirical and 23 job evaluation	- Incidence of overeducation in 73 papers, covering 39 countries; - 296 estimates of the incidence of overeducation (149 subjectives (avg. 21.5%), 103 empirical (avg. 25.9%) and 44 job evaluation (avg. 25.5%)) - High rate of overeducation for countries such as Ireland, Spain, Greece and Italy and low rate in Czech Republic, Norway, Switzerland and Finland; - Most studied country is Belgium - Sizable differences may appear within countries, depending on the measurement approach used - Little correlation between the measures - Within a single measurement approach, estimates may vary - Variations also exist in the exact approach used for the empirical measurement of overeducation or focus on different segments of the population or number of occupational categories used - Consistent evidence of a wage penalty for overeducated individuals, relative to individuals with the same education in matched employment (23 papers and 74 estimates of the overeducation wage penalty (avg. 13.6% less than matched individuals with similar levels of education)) - Overeducation wage penalty has been found across the wage distribution - Overeducation wage penalty for females is typically greater than that for males - Wage premium of overeducated relative to matched individuals in the same occupation - Estimates of the overeducation pay penalty may suffer from omitted variable bias - Upward bias in ordinary least squares (OLS) estimates is offset by downward bias due to measurement error - OLS estimates are similar to, or greater than, panel estimates which control for unobserved heterogeneity - Mixed effect of overeducation on job satisfaction - Overeducation is more prevalent among graduates of social sciences, services and humanities, in workplaces that rely heavily on shift and part-time workers and areas where commuting to other labour markets is difficult - Literature on the persistence of overeducation is mixed - Similar pay penalty for both old and young workers - Personal characteristics such as extraversion and conscientiousness are shown to reduce the probability of experiencing persistent overeducation - Overeducation is associated with higher gross domestic product (GDP) growth
Undereducation: 30 papers published (Studied in conjunction with overeducation)	- Incidence of undereducation is reported in 21 papers with a total of 79 estimates covering 35 countries - 52 subjective, 23 empirical and 4 job-evaluation estimates of undereducation - Average incidences of undereducation for the three measures are as follows: 10.7% (subjective), 26.2% (empirical) and 15.8% (job evaluation) - Empirical findings on undereducation are mixed: undereducation wage premium relative to workers with the same education in a matched job and (vs statistically significant) - Undereducation is associated with higher subjective well-being vs no relation to job satisfaction - While overeducated individuals are more likely to suffer from depression, undereducated individuals are similar to matched individuals - Negative association between undereducation and firm productivity - Undereducation is more prevalent among females

As stated earlier, any microdata providing information on both, education and occupation, can be used to implement at least the empirical method. Therefore, in the literature, besides national surveys, there are a number of international data sources that can be used to measure the incidence of qualification mismatch, among these are:[12] EU-LFS, EU-SILC, ECHPS, CHEERS, STEP, ESS, REFLEX, HEGESCO, PIAAC, ESJ.

The empirical literature makes use of all three approaches with these different data sources (see Table 3). Making an inventory of all published work on educational mismatch, McGuinness and Pouliakas (2017) find that the subjective method is the most used method and that there are many disparities in the results across

12 ESJS - European Skills and Jobs Survey; PIAAC - Programme for the International Assessment of Adults competencies; EU-LFS - European Union Labour Force Survey; ECHPS - European Community Household Panel Survey ; CHEERS - European graduate survey - Higher Education and Graduate Employment in Europe; STEP - Skills Toward Employment and Productivity; ESS - European Social Survey; REFLEX - Research into Employment and professional FLEXibility- International survey higher education graduates; HEGESCO - Higher Education as GEnerator of Strategic COmpetences; EU-SILC- European Union Statistics on Income and Living Conditions.

surveys and depending on the method of measurement (Barone & Ortiz, 2011; European Commission, 2015). In fact, using the same survey, very different results can be found depending on the method. Also, using the same method of measurement, we can end up with very different proportions of mismatched workers. There is also a disproportion in the type of qualification mismatch measured, as the literature seems to focus more on measuring the incidence of overeducation and investigate mostly its effects on individuals (wages and job satisfaction). Indeed, there is a strong evidence of a wage penalty of overqualified individuals, compared to those with the same level of education in matched employment, but also of a wage premium in comparison to matched individuals in the same occupation. However, these effects of overeducation on wages may differ across different segments of the population. The literature also investigates determinants of overeducation as well as its effects on job satisfaction and GDP.[13] The empirical literature on under-education addresses the same issues, in addition to the effect of undereducation on firm productivity, with very mixed results.

Vertical educational mismatch is, however, to be distinguished from horizontal educational mismatch, which occurs when the worker has the required level of qualification, but the work is not related or is poorly related to its field-of-study. In fact, the vertical educational mismatch concerns the level of education, whereas horizontal or field-of-study mismatch is regarding the field of study.

2.3.2 Horizontal or field of study mismatch

A field-of-study mismatch refers to a situation where the field of education of an employee does not match his/her occupation. It happens when workers are employed in a job that is not relevant to the skills and knowledge accumulated in formal education (see Table 4). This type of mismatch is usually measured using two different approaches. The first approach is subjective and therefore based on the subjective assessment of workers of the extent to which their current job is related to the field of study of their highest qualification (Allen & de Weert, 2007; Robst, 2007; 2008; Verhaest et al., 2017). The second approach is an independent measure comparing field of study variables with occupation codes (Béduwé & Giret, 2011; Domadenik et al., 2013; Levels et al., 2014; Sellami et al., 2017).

Measurement of field-of-study mismatch is in general done using higher education graduate surveys such as CHEERS, REFLEX and HEGESCO, or labour force surveys such as EU-LFS. A number of papers in the literature – though sparser in comparison to the vertical mismatch literature - are produced using these surveys to measure field-of-study mismatch, either solely or in conjunction with vertical mismatch and use both the above methods of measurement (see Table 5). These studies have covered a number of countries and produced at least half a hundred estimates of field-of-study mismatches using both the subjective and independent approach. However, the empirical literature is poor in comparison to vertical mismatch.[14] The subjects addressed are mainly looking at/addressing the consequences of field-of-study mismatch, such as its effects on wages and job satisfaction. In this regard, there is evidence of a wage penalty for horizontally mismatched workers, especially among those late in careers and among those that suffer a vertical mismatch as well. Horizontal mismatch has also been linked to lower job satisfaction. There are some studies on the causes of horizontal mismatch, notably regarding the demographics of mismatched workforce. For instance, horizontal mismatch is preponderant among graduates from arts, humanities and social sciences, in comparison to graduates from vocational training.

13 For more information on the empirical literature on the causes and consequences of vertical educational mismatch on individuals, firms and macroeconomic indicators: McGuinness and Bennett, 2007; McGuinness, 2008; Robst, 2008; Budria and Moro-Egido, 2009; Mavromaras *et al.*, 2012; Sanchez-Sanchez and McGuinness, 2015; Lindley, 2009; Chiswick and Miller, 2010; Lenton, 2012; Levels *et al.*, 2014; Verhaest and Omey, 2006, 2012; Peir´o *et al.*, 2010; Diem, 2015; Piper, 2015; Congregado *et al.*, 2016 ; Green and Zhu, 2010; Sloane, 2014 ; McGuinness and Sloane, 2011; McGuinness and Byrne, 2015; Verhaest and Verhofstadt, 2016; Ortiz and Kucel, 2008; Belfield, 2010 ; Ramos and Sanroma, 2011; McGowan *et al.*, 2015; Verhaest *et al.*, 2015 ; Clark *et al.*, 2014; Ramos *et al.*, 2012; Kampelmann and Rycx, 2012; Di Pietro and Urwin, 2006; Salinas-Jiménez *et al.*, 2016 ; Peir´o *et al.*, 2010 ; Bracke *et al.*, 2013 ; Jauhiainen, 2011; Rubb, 2014.

14 For more information on the consequences and determinants of horizontal mismatch, see Robst, 2007a, 2007b, 2008; Robst and VanGilder, 2016; Nordin *et al.*, 2010; Bender and Roche, 2013; Bender and Heywood, 2011; Zhu, 2014; Béduwé and Giret, 2011; Montt, 2015; Bender and Heywood, 2009; Verhaest *et al.*, 2015; Robert, 2014; Levels *et al.*, 2014; McGuinness *et al.*, 2016.

2.3.3 Skill mismatch

Skill mismatch is also part of the category of vertical mismatch and refers to a situation where the skills of an employee do not match the skills required to perform his/her job adequately. It may correspond to two situations (see Table 1). A skill-mismatched employee may be either underskilled or overskilled. Underskilling designates a situation where the worker's skill level is lower than the level required by the current job. Overskilling refers to the situation when the level of skill of the worker is higher than the level demanded by the job. This case points to an underutilisation *of skills* (McGuinness & Pouliakas, 2017).

Table 4. Measures of skills imbalances

	Self-reported or subjective measure	**Direct or objective measure**
Skill mismatch (Overskilling, underskilling)	Asking workers **to what extent their skills correspond to the tasks performed at work** (e.g., Allen & van der Velden, 2001; Green & McIntosh, 2007; Mavromaras, McGuinness & Fok, 2009; Mavromaras, McGuinness, O'Leary, Sloane & Fok, 2007); two separate questions	**Workers' skills are compared to skills required at their workplace**. Required skills can be measured using the Job Requirement Approach (JRA: Felstead, Gallie, Green & Zhou, 2007) or obtaining a general, occupation-specific skill level (e.g., Pellizzari & Fichen, 2013), similar to the 'Realised Matches' approach applied in education mismatch research (Hartog, 2000; Leuven & Oosterbeek, 2008)
	Subjective measure	**Independent measure**
Horizontal or field-of-study mismatch	A subjective question asking the **respondent to assess the degree to which their current job is related to the study field of their highest qualification** (Allen & de Weert, 2007; Robst, 2007a, 2008; Verhaest et al., 2017)	**Comparing a field of study variable with occupation codes** (Béduwé & Giret, 2011; Domadenik et al., 2013; Levels et al., 2014; Sellami et al., 2017)
	Subjective measure	
Skill gaps	Collecting **information from the employer on the perceived skill deficiencies of workers** **Questions directed at workers within firms** (akin to underskilling)	
	Subjective direct measure	**Indirect measure**
Skill shortages	A series of **questions** that begin by establishing the **existence of unfilled or hard-to-fill vacancies**, followed by a series of questions establishing the employer's views for the **reasons underlying any recruitment difficulties**	**Signals of occupational shortages**: - Volume measure (employment growth, unemployment rate, vacancy rates) - Price measure (hourly wage growth) - Work intensity measure (growth in hours worked, incidence of overtime) - Quality measure (incidence of under qualification and training) - **Weighted sum of these different indicators of occupational skill shortage**

Measuring skill mismatch raises issues for the most part due to the unavailability of objective individual data on skills. There is not a widely accepted measure of skill mismatch to date. There are different approaches, which find different shares of mismatched workers in the population, leading to different conclusions regarding the relationship between skill mismatch and labour market outcomes and consequently to different policy implications. Two different approaches (see Table 4) are used to measure skill mismatch, based on methods from educational mismatch measures: subjective, objective or a mix of both (Quintini, 2011; Perry et al., 2014).

The subjective method provides a measure of skill mismatch based on employees' self-reported skill mismatch. Workers are asked to assess the extent to which their skills level corresponds to the level required to execute tasks and duties in the workplace (Allen & Van der velden (2001); Green & McIntosh (2007); Mavromaras et al. (2007)). As always, subjective methods have the advantage of being easy to implement in a survey and obtain up-to-date information on skills but are prone to biases. The method is based on self-reported information by employees, which are potentially biased (Hartog, 2000). In reality, employees tend to overstate their skill requirements to upgrade position at work.

The objective measures of skill mismatch compare directly workers' skill level to the level required at work. The approaches, as for qualification mismatch, differ in terms of their measure of occupational skill requirement. Most studies use the Job Requirement Approach (JRA) (Felstead et al., 2007) based on a measure of the intensity of skill use in several domains of skill proficiency. Perry et al. (2014) provides a very detailed picture of the different methods used to measure skill mismatch with data from PIAAC (See Table 1 in Perry et al. (2014)). Occupational skill requirements are determined by applying the realised matches' method to either skill use intensity or to the levels of skill proficiency. The occupational skill requirements are then compared to individual levels of skill proficiency to classify them into well-matched, underskilled and overskilled, using decision criteria that are somewhat arbitrary (Pellizzari and Fichen, 2013; Perry et al., 2014).

Individual levels of skill proficiency are estimated using Item Response Theory (IRT) and thus lead to several plausible values[15] for each individual. Therefore, the question of which one to use is recurrently raised in the literature. Some use all plausible values (Perry et al., 2014), while others use only a specific one (Allen, Levels & van der Velden (2013); Quintini (2011)) or the average of all plausible values (Pellizzari & Fichen, 2013; OECD, 2013). This is a very important question; given that we may find different values for the incidence of mismatch depending on how these plausible values are taken into consideration.

Data on the skills possessed and used by workers are available in international large-scale assessment surveys such as IALS, ALL and now PIAAC, STEP or in national competency assessment such as NEPS in Germany. These types of data are scarce and only available for a limited number of countries and period. Cedefop has recently carried out a survey on Skills and Jobs (ESJ) in European countries, but unlike the surveys cited above, it does not assess the level of skill proficiency of surveyed individuals; all measures of skill mismatch are based on workers' self-assessment.

The subject of skills mismatches, as stated earlier, is on the agendas of many international institutions[16]. The OECD's skills for jobs indicators provide an indicator of two out of three types of mismatch: qualification and field-of-study. It also provides a measure of numeracy skill mismatch using the PIAAC survey (OECD, 2013), which does not include all EU 28 countries among its 33 participating countries (members or partners of the OECD). The Cedefop's skill panorama use the European Skills and Jobs (ESJ) survey and provides the following subjective measures of skill mismatch: underskilling at hiring, underskilling, skill underutilisation (overskilling), overqualified tertiary graduates, skill obsolescence and skill gap.

15 Plausible values (PVs) are multiple imputations drawn from an *a posteriori* distribution by combining the IRT scaling of the cognitive items with a latent regression model using information from the BQ (see PIAAC technical report for more information) in a population model. It is a in fact statistical means to replicate a probable score distribution that summarises how well each respondent answered a small subset of the assessment items; and, how well other respondents from a similar background performed on the rest of the assessment item pool. Each individual case in the PIAAC data set has a set of ten PVs for each proficiency domain (literacy, numeracy, problem solving in technology-rich environments), and all ten PVs must be used together to estimate proficiency.

16 See appendix for an overview of The OECD's *skills for job indicators* and The Cedefop's *skill panorama*.

Table 5. Some empirical results on skills imbalances

Skills imbalances	Some empirical Results
Overskilling or skill underutilisation 22 papers published, with 14 examining overskilling and overeducation together, and the remaining 8 focusing exclusively on overskilling	- Incidence of overskilling is reported in 14 papers, covering 30 countries - All estimates use the subjective method, and the average incidence is 27.5% Largely focused on Australia, which accounts for 10 of the 22 papers - Overskilled individuals earn less than those with equivalent levels of education who are in matched employment (11 papers, average overskilling wage penalty, based on 38 estimates, is 7.5%) - Overskilling wage penalty is found to be smaller than the overeducation wage penalty - Disabled workers are more likely to be overskilled and the wage penalty is particularly large - Being overskilled also increases an individual's probability of future unemployment and is associated with lower job satisfaction and lower workplace harmony - Overskilled workers are also more likely to want to quit their job and experience less skills development - Overskilling is more likely for those who have been overskilled in the past and for individuals with low levels of education - Female migrants have a higher likelihood of overskilling - Persistence of overskilling (80% using ESJS) - Overskilling and overeducation are found to be weakly correlated
Underskilling Only 3 papers published	- Underskilling has received little attention in the literature - Average incidence of underskilling across EU countries is 13.2% - Significantly lower than the incidence of overskilling; underskilling has no statistically significant effect on wages - Underskilled workers are more likely to be concentrated in high-skilled occupations
Horizontal or field-of-study mismatch 17 papers, of which 12 focus solely on horizontal mismatch and 5 on both horizontal and vertical mismatch	- Literature on horizontal mismatch is relatively sparse in comparison to that of vertical mismatch - Incidence of horizontal mismatch is reported in 12 papers out of the 17, covering 36 countries - Average incidence of horizontal mismatch, based on 52 estimates, is 25.4%;- Evidence of a wage penalty for horizontally mismatched individuals - Negative consequences are concentrated among those late in careers - No strong evidence of wage effects - Cost of horizontal mismatch on earnings is high only when combined with vertical mismatch - Horizontal mismatch has been linked to lower job satisfaction and higher turnover - Higher likelihood of horizontal mismatch among graduates of arts, humanities and social sciences - Lower incidence of horizontal mismatch among vocationally trained individuals
Skill shortages Only 12 papers published	- Literature on skill shortages is typically based on employer surveys such as the European Business Survey (EBS), the Manpower Talent Shortage Survey and the European Company Survey (ECS) - Difficulties in disentangling genuine skill shortages from other recruitment difficulties such as low wages or poor working conditions - Inconsistency in the estimates of the incidence of recruitment difficulties across the EU using EBS, ECS and MTSS - Relatively low incidence of skill shortages among employers - Incidence of skill shortages in high-tech firms is not significantly greater than other firms - Skill shortages have a negative impact on firm productivity - Ways to deal with skill shortages: improved utilisation of core workforce through longer hours and better pay, use of peripheral strategies such as temporary employment and outsourcing - Simple skill shortages, defined as skill shortages having one cause, are typically short-lived
Skill gaps Only 6 papers published	- Existing studies of skill gaps typically use data from employer surveys - Sectoral-level collective bargaining and a well-developed human resource function are important factors in correctly identifying skill gaps in firms - Skill gaps are found to be a key determinant of training expenditures and labour costs - Skill gaps delay the introduction of new products - Skill gaps are a barrier to the introduction of new work practices - Literature on firm-level skill gaps remains underdeveloped
Skill obsolescence Only 5 papers published	- Literature in this area tends to focus on the determinants of skill obsolescence - Workers in higher education levels are exposed to greater depreciation of human capital - Workers are more likely to suffer from skill obsolescence when learning and technical knowledge are key components of the job - Greater work complexity is associated with a greater degree of skill obsolescence

Besides qualification mismatch, skills mismatch remains the most analysed measure of skills imbalances. However, most of the studies are addressing *overskilling*. Table 5 reports the main results from the empirical literature on skills mismatch. The focus of these empirical studies is on the effect of skills mismatch on wages and job satisfaction as well as on its determinants. The results highlight a wage penalty related to overskilling as well as less satisfaction at work. Furthermore, immigrants, disabled persons and women are more concerned with *overskilling*.

2.3.4 Skill gaps

Another term used when analysing skill imbalances is the term '*skill gaps*' (see Table 1). It refers to a situation where, due to a failure of the education and training system, employees or prospective employees, though qualified or possessing the appropriate level of qualification, do not have all the skills required to adequately perform the tasks and duties related to their jobs (Cappelli, 2014; McGuinness & Pouliakas, 2017). This can be considered as a manifestation of skill mismatch at an aggregate level (firm, occupation, etc.). In other words, skill gap is just a measure of *underskilling* at an aggregate level. For instance, if employees or prospective employees in an occupation are generally underskilled, we can say that there is a skill gap in this occupation. Skill gaps are usually measured subjectively, using employer surveys such as EBS, ECS and MTSS. In addition, a recent survey by Cedefop provides measures of skill gaps in several skill domains, but this is based on individual self-reported data (see Table 4). This subjective measure of skill gaps consists of asking questions to employers regarding the extent of skill deficiencies of their workers. However, when these questions are directed to workers within firms, it is akin to *underskilling*[17].

As Table 5 shows, the empirical literature on skill gaps is very poor and uses data from employer surveys at the national level to study its consequences on firms' training policies, the introduction of new products and new work practices, as well as its determinants (McGuinness and Ortiz, 2016).

2.3.5 Skill shortages[18]

The last notion of skill imbalance that we present here is skill shortages (and skill surplus). While skill gaps refer to prospective employees lacking skills, skill shortages refer to a lack of suitably skilled persons (see Table 1). It corresponds to a situation where employers are having difficulties finding, in the accessible labour market and despite appropriate wage and working conditions, prospective employees with the set of skills required to perform a job adequately in a given occupation (Quintini, 2011; McGuinness & Pouliakas, 2017). At the opposite, a skill surplus designates a situation where the supply of appropriately skilled labour in an occupation is higher than the demand.

Skill shortages can be measured directly using data from employer surveys such as the ones cited above for skill gaps, or indirectly using data from labour force surveys (EU-LFS) in combination with occupational databases such as O*NET to go from occupational shortages to skill shortages (see Table 4). For example, the OECD's skills for jobs database combines data from EU-LFS and EU-SILC with occupational information from O*NET to provide for each EU 28 country and South Africa, and for each occupation, the skills that are in shortage and those that are in surplus.

The subjective measure of skill shortages is based on questions asking employers to determine whether there are unfilled or hard-to-fill vacancies. These questions are followed by other questions on employers' perspective regarding the causes of recruitment difficulties. The indirect measure uses indicators of occupational shortages based on:

- volume measures: employment growth, unemployment rate and vacancy rates;
- price measures: hourly wage growth;

17 Cedefop's skills panorama on the other hand provides different types of subjective measures of skill gaps using the ESJ survey on employees in the EU 28 such as job-specific or technical skill gap, foundation or basic skill gap, and transversal skill gap.

18 For more information on skill shortages, see Healy et al. (2012); Veneri (1999); Richardson (2009); Shah and Burke (2005); MAC (2008); OECD (2017).

- work intensity measures: growth in hours worked and the incidence of overtime;
- quality measures: incidences of underqualification and training.

Taken individually, each of these indicators provides a signal of a different dimension of a skill shortage. Therefore, to circumvent any potential shortcomings pertaining to employing only one of them, many measures of occupational shortages are composite indicators calculated as a weighted sum of part or all of these indicators (OECD, 2017).

The direct measure is a self-assessment of employers' hiring difficulties (see Table 4). Therefore, employers are asked questions regarding their hiring intentions and their hiring difficulties in an employer survey. Employer surveys provide a direct source of information on skill needs, but are subjective and suffer a low comparability, as they are usually inconsistent with one another. They also often neglect the other reasons for recruitment difficulties such as poor working conditions, wage or HR policies.

As shown in Table 5, the literature on skills shortages generally uses employer surveys and often has difficulties disentangling skill shortages from other recruitment difficulties such as those due to poor wages and working conditions (Cedefop, 2015; European Commission, 2015). Moreover, there is an inconsistency in the estimates provided by the different employer surveys. Nevertheless, the studies show a low incidence of skill shortage regardless of the sector or occupation (Weaver & Osterman, 2017). The literature[19] is also underdeveloped and focuses on the causes and consequences of skill shortages as well as the potential solutions to it. Skill shortages are usually localised within high tech firms and have a negative impact on their productivity. In general, it is addressed using strategies such as an improved utilisation of core workforce through longer hours and better pay or temporary employment and outsourcing.

2.3.6 Skill obsolescence

Skill obsolescence is also considered as a measure of skill imbalances (see Table 1). It designates a situation where the skills of workers are obsolete (Van Loo *et al.*, 2001; De Grip & Van Loo, 2002; Allen & De Grip, 2007). In such cases, the employer no longer requires all or some of the skills possessed by the worker due to technical progress or changes in market conditions. Skill obsolescence is measured by directly questioning employees. Few international surveys provide information on skill obsolescence.[20]

The literature on skill obsolescence is very thin and focuses mainly on its determinants (see Table 5). It is found that workers with higher education level, whom learning and technical knowledge are central to the job, or with complex work are more likely to experience skill obsolescence.

19 See for example Bennett and McGuinness, 2009; Tang and Wang, 2005; Haskel and Martin, 2006; Forth and Mason, 2006; and Mason *et al.*, 1994; Healey et al., 2015; Frogner, 2002.

20 Cedefop's European skills and Jobs survey (ESJ) provides self-assessment of skill obsolescence.

3. Measurement using international surveys

To measure the concepts of skills needs, skills transferability and skills imbalances, there are a number of different data sources available. However, most of those are national surveys. Thus, to provide an international comparison, we need to combine several national data sources.

In this report, the focus is on surveys providing some measurement of the above-mentioned concepts and allowing for direct international comparisons. We may distinguish four categories of surveys: household surveys, higher education graduates surveys, employer surveys and mixed household and employer surveys (see Table 6). In this section, we provide a description of each type of survey as well as the concepts of skill imbalance they measure (see Table 7).

Table 6. Web links to most used international surveys on skill needs, skill transferability and skill imbalances

International Surveys	Websites
Household surveys	
Labour force surveys	
ECHPS - European Community Household Panel Survey	https://ec.europa.eu/eurostat/web/microdata/european-community-household-panel
EU-SILC- European Union Statistics on Income and Living Conditions	https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions
EU-LFS - European Union Labour Force Survey	https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey
Large scale assessment surveys	
IALS - International Adult Literacy Survey	https://nces.ed.gov/surveys/ials/
ALL - Adult Literacy and Lifeskills	https://nces.ed.gov/surveys/all/index.asp
PIAAC - Programme for the International Assessment of Adults competencies	http://www.oecd.org/skills/piaac/publicdataandanalysis/#d.en.408927
Skills mismatches survey	-
ESJS - European Skills and Jobs Survey	http://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey
Higher education graduates surveys	-
CHEERS - European graduate survey - Higher Education and Graduate Employment in Europe	http://www.qtafi.de/cheers-european-graduate-survey.html
REFLEX - REsearch into employment and professional FLExibility	http://www.reflexproject.org/
HEGESCO - Higher Education as GEnerator of Strategic COmpetences	http://www.hegesco.org/content/view/8/10/
Employer surveys	
EBS - European Business Survey by Grant Thornton	not found
ECS - European Company Survey	https://www.eurofound.europa.eu/surveys/european-company-surveys
MTSS - Manpower Talent Shortage Survey	https://go.manpowergroup.com/talent-shortage-2018#thereport
Household and employer surveys	
STEP - Skills Toward Employment and Productivity	http://microdata.worldbank.org/index.php/catalog/step
Online information on skills	-
Cedefop's skills panaroma	https://skillspanorama.cedefop.europa.eu/en/indicators-list
OECD's skills for jobs database	http://www.oecd.org/els/emp/skills-for-jobs-dataviz.htm
Occupations and jobs dictionaries	
O*NET - Occupational Information Network	https://www.onetonline.org/
ESCO - European Skills, Competences, Qualifications and Occupations	https://ec.europa.eu/esco/portal/home

Table 7. Subjective measures of skill imbalances in international surveys

Subjective measures of skill imbalances		
Survey	**Question(s)**	**Answer(s)**
Skill mismatch		
PIAAC	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? Do you feel that you need further training in order to cope well with your present duties?	1: yes, 2: no
ESJ	Overall, how would you best describe your skills in relation to what is required to do your job?	1: My skills are higher than required by my job; 2: My skills are matched to what is required by my job 3: Some of my skills are lower than what is required by my job and need to be further developed
CHEERS	If you take into consideration your current tasks altogether: To what extent do you use the knowledge and skills acquired in the course of study?	1: to a very high extent, ..., 5: not at all
REFLEX and HEGESCO	To what extent are your knowledge and skills utilised in your current work? To what extent does your current work demand more knowledge and skills than you can actually offer?	1: not at all, ..., 5: to a very high extent
ECHPS	Do you feel that you have skills or qualifications to do a more demanding job than the one you have now?	yes/no
Qualification or education level mismatch		
CHEERS	If you consider all dimensions of your employment and work: to what extent is your employment and work appropriate to your level of education?	1: completely appropriate, …, 5: not at all appropriate
REFLEX and HEGESCO	What type of education do you feel is most appropriate for this work?	PhD, other postgraduate qualification, Master, Bachelor and lower than higher education
Field of study mismatch		
PIAAC	If applying today, what would be the usual qualifications, if any that someone would need to get this type of job? Thinking about whether this qualification is necessary for doing your job satisfactorily, which of the following statements would be most true?	**ISCED** 1 This level is necessary 2 A lower level would be sufficient 3 A higher level would be needed
CHEERS	How would you characterise the relationship between your field of study and your area of work?	My field of study is the only possible/ by far the best field; some other fields could prepare for the area of work as well; another field would have been more useful; the field of study does not matter very much; higher education studies are not at all related to my area
REFLEX and HEGESCO	What field of study do you feel is most appropriate for this work?	exclusively own field, own or a related field, a completely different field, no particular field;
Skill Shortages		
ECS	Does the management encounter any of the following problems at this establishment currently: difficulties in finding employees with the required skills?	1: yes, 2:no
MTSS	Are you having difficulties filling jobs due to lack of available talent?	1: yes, 2:no
STEP	Did you encounter any of the following problems when trying to hire managers, professionals, ...? Applicants lacked required skills	yes/no
Skill obsolescence		
ESJ	Several of my skills will become outdated in the next five years	0: very unlikely, …., 10: very likely
Skill gap		
STEP	Is there a difference between what is required for this occupation type and the current level of this skill? 12 type of skills	yes/no

3.1 (International) Households surveys

Household surveys are conducted on the labour force in nearly every country in the world and they usually target all individuals aged over 15 (the age limit is usually 65). This type of survey considers all individuals, who are able to work regardless of their status in the labour market (employed, unemployed or inactive). We distinguish three types: labour force surveys, large-scale assessment surveys and skills mismatches surveys (see Table 8). All of them are international household surveys and have been used in the literature to get an international perspective of the issues related to the concepts of skills needs, skills transferability and skills imbalances.

Table 8. International household surveys

Household surveys	Period covered	Survey themes	Countries	Skill imbalances	Method
Labour force surveys					
ECHPS - European Community Household Panel Survey	1994-2001	Panel survey of households	AUT, BEL, DNK, FRA, DEU, GRC, IRL, ITA, LUX, NLD, PRT, ESP, SWE, UK	Skill mismatch, qualification mismatch and field of study mismatch,	Subjective and objective
EU-SILC- European Union Statistics on Income and Living Conditions	2004-2018	Income and living conditions	EU 28: AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, UK	Qualification and field of study mismatches	Objective or empirical
EU-LFS - European Union Labour Force Survey	2004-2018	Labour force survey	EU 28: AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, UK; EFTA: ISL, LIE, NOR, SWI	Qualification and field of study mismatches	Objective or empirical
Large scale assessment surveys					
IALS - International Adult Literacy Survey	1994, 1996, 1998	Prose literacy, document literacy and quantitative literacy; skill use at work and in general	1994: CAN, GER, IRL, NLD, POL, SWE, SWI, USA 1996: AUS, BEL, UK, NZL, NIRL 1998: CHL, CZE, DNK, FIN, HUN, ITA, NOR, SVN, SWI	Skill mismatch, qualification mismatch and field of study mismatch	Subjective and objective
ALL - Adult Literacy and Lifeskills	2003, 2006-08	Prose and document literacy, numeracy and problem solving; skill use at work and in general	2003: ITA, NOR, SWI, BMU, CAN, MEX, US 2006--08: HUN, NLD, AUT, NZL	Skill mismatch, qualification mismatch and field of study mismatch	Subjective and objective
PIAAC - Programme for the International Assessment of Adults competencies	2012, 2014, 2016	Proficiency level and use at work and everyday life of skills in Literacy, numeracy and problem solving in a technology-rich environment	2012: AUS, AUT, BEL, CAN, CYP, CZE, DNK, EST, FIN, FRA, DEU, IRL, ITA, JPN, KOR, NOR, NLD, POL, RUS, SVK, ESP, SWE, UK, US;2014:CHL, GRC, IDN, ISR, LTU, NZL, SGP, SVN, TUR; 2016: ECU, HUN, KAZ, MEX, PER	Skill mismatch, qualification mismatch and field of study mismatch	Subjective and objective
Skills mismatches survey					
ESJS - European Skills and Jobs Survey	2014	Self-assessment of skill imbalances	EU 28: AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, UK	skill mismatch, qualification mismatch and field of study mismatch, skill obsolescence, skill gaps	Subjective and objective

3.1.1 Labour force surveys

The first international studies on skills needs, skills transferability and skills imbalances did not have access to detailed information on skills. Therefore, most of them have used qualification as a proxy for skill and exploited international surveys such as the European Household Community Panel Survey (ECHPS) and afterwards the European Union Labour Force Survey (EU-LFS) or the European Union Statistics on

Income and Living Conditions (EU-SILC) (see Tables 6 and 8). These surveys, even though they do not have information on skills, do provide information on occupations at the four-digit level, as well as information on qualification levels and allow performing an occupation-level analysis of the different skill concepts. Moreover, the ECHPS allows tracking individuals over a certain number of years and provides a subjective evaluation of skill imbalance by employees as well (see Table 7).

International labour force surveys allow measuring only one type of skill imbalance: education or qualification mismatch. They are also mobilised in the measurement of skills needs as well as in measuring skills transferability adopting Shaw's (1984) market approach, which uses occupational switches probabilities to measure the degree of similarity between occupations. The use of labour force surveys to analyse skills-related issues generally results from the lack of international data on skills. However, skills and qualifications, even though they overlap, are different, as being qualified for a position does not necessarily mean that you have all the skills required (Quintini, 2011). To fill the gap some international large-scale assessment surveys have been developed with the objective to assess the skills of the adult population.

3.1.2 Large-scale assessment surveys

International large-scale assessment surveys are designed to measure the level of skill proficiency as well as the level of skill use at work and in everyday life of labour forces in several participating countries (see Tables 6 and 8). Cognitive assessment on several proficiency domains is carried out on paper and, recently, on computer. The first survey of this kind was the International Adult Literacy Survey (IALS), conducted between 1994 and 1998 in 22 countries in three different waves of data collection. It assesses adults' literacy in three literacy domains: prose literacy, document literacy and quantitative literacy.[21] The Adult Literacy and Lifelong Learning (ALL) follows the methodology adopted in the previous survey to allow comparability over time for countries that participated in both surveys. The survey was conducted between 2001 and 2008 in three waves of data collection and included 11 participating countries. The cognitive assessment in this survey measure proficiency in the following skill proficiency domains: Prose and document literacy, numeracy and problem solving.[22] The last survey is the Programme for the International Assessment of Adult Competencies (PIAAC). It has been carried out between 2012 and 2017 in three waves of data collection and regroups 38 participating countries. The cognitive assessment measures proficiency in literacy, numeracy and problem solving in a technology-rich environment.[23]

In addition to an objective assessment of skill mismatch, PIAAC allows measuring skill mismatch using two different yes/no questions: *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 *Do you feel that you need further training in order to cope well with your present duties?* This way of measuring skill mismatch may be problematic as pointed by Pery et al. (2014). For example, individuals that answer yes to the two questions are overskilled and underskilled at the same time, a result that is difficult to interpret.

All three surveys allow comparison across countries. Each of them has a background questionnaire providing information on personal and job characteristics and on the extent to which skills are used in and outside the workplace.

These surveys offer more information on skills, notably on information processing skills, in comparison with labour force surveys and they enable a more thorough analysis of skills-related concepts. They allow estimating several measures of skill imbalances, especially skill mismatch. Indeed, with these surveys, it is possible to go beyond qualification mismatch and compute a measure of skill mismatch in several domains of skill proficiency. However, given that such surveys are very costly, the number of observations is limited and usually there are not enough observations per country for an analysis at the occupation level (or at the sectoral level). Therefore, the utilisation of these surveys may be hindered by what is known as the sample size constraint. This may raise some difficulties when running an occupation-level analysis of concepts such as skills needs or skills transferability.

21 For the definition of these proficiency domains, go to: https://nces.ed.gov/surveys/ials/measure.asp.
22 For the definition of these proficiency domains, go to: https://nces.ed.gov/surveys/all/measure.asp.
23 For the definition of these proficiency domains, go to: http://www.oecd.org/skills/piaac/.

International large-scale assessment surveys are mostly used in the analysis of the different concepts of skill imbalances presented in Section II and measured at the employee or at the individual level, such as skill mismatch, qualification mismatch or field-of-study mismatch. They are rarely used to measure, for instance, the concepts of skill shortages or skill gaps. Such concepts are usually analysed using employer surveys or, when using employee surveys, the analysis is conducted at the occupational level.

3.1.3 Skills mismatches surveys[24]

In this category of surveys, we have only one survey carried out by Cedefop in 2014 in the EU-28. This survey, the European Skills and Jobs survey (ESJ), cannot be classified as a large-scale assessment survey as there is no objective assessment of individuals' skill levels. Individuals in the survey rate their own level of skill and provide a self-assessment of the extent to which they are mismatched in terms of qualification and skill (see Table 7). They are also asked to assess whether they lack some of the skills required (skill gaps) or whether some of their skills are no longer required by their current employer (skill obsolescence). Like the large-scale assessment surveys, this survey also faces a sample size constraint when analyses are conducted at the occupational or sectoral levels.

This survey provides a direct assessment of both skill mismatch and skill obsolescence.[25] Employees' direct assessment of skill mismatch is obtained through answers to the following question: *Overall, how would you best describe your skills in relation to what is required to do your job?* To this question, employees have to choose among these different answers: *1: My skills are higher than required by my job; 2: My skills are matched to what is required by my job; 3: Some of my skills are lower than what is required by my job and need to be further developed.* These answers allow determining whether the worker is skill-matched. The question regarding the self-assessment of skill obsolescence is as follows: *Several of my skills will become outdated in the next five years?* The answers provided are: *0: very unlikely ... 10: very likely.* Given the answers, some arbitrary choices are made regarding the score beyond which the individual is experiencing skill obsolescence. In Cedefop's skill panorama, when choosing the score *10: very likely,* 21% of workers in EU-28 experience skill obsolescence.

The Cedefop's skill panorama derives all its indicators of skill imbalances from the ESJ survey. Individuals' self-assessment of their skill levels is used to propose measures of the different concepts of skill imbalances[26] (see appendix). The results by McGuinness and Pouliakas (2017) also rely on this survey.

3.2 Higher education graduates' surveys

Unlike household surveys, higher education graduates' surveys are international surveys that focus on graduates from higher education institutions in several countries. The first survey is the European graduate survey, which is a survey on the link between higher education and graduate employment in Europe. It was carried out in 12 countries between 1998 and 2000. The second survey, REFLEX (REsearch into employment and professional FLEXibility), is on the employability of graduates from higher education institutions. It was carried out between 1999 and 2006 in 15 countries. The last survey, HEGESCO (Higher Education as GEnerator of Strategic Competences), is exactly the same as REFLEX but is carried out between 2002 and 2008 in five different countries than the ones covered in REFLEX (see Table 9).

24 As stated earlier, for clarity purposes, the concept of skill imbalances is preferred to that of skills mismatches. The title of this section makes an exception as the survey that we present is categorised as a skills mismatches survey.

25 Skill gaps in several skill domains and qualification can also be derived based on information provided by employees in the surveys, as shown the Cedefop's skills panorama presented in the appendix.

26 This panorama also provides measures of skill needs using Cedefop's skill forecasts. It provides previsions of future employment needs by occupation. See: https://skillspanorama.cedefop.europa.eu/en.

Table 9. International higher education graduates surveys

Higher education graduates surveys	Period covered	Survey themes	Countries	Skill imbalances	Method
CHEERS - European graduate survey - Higher Education and Graduate Employment in Europe	1998-2000	Links between study and employment	12: AUT, CZE, FIN, FRA, DEU, ITA, JPN, NLD, NOR, ESP, SWE, UK	Qualification and field of study mismatches	Subjective and objective
REFLEX - REsearch into employment and professional FLExibility - International survey higher education graduates	1999-2006	Employability of graduates	AUT, BEL, CZE, EST, FIN, FRA, DEU, ITA, JPN, NLD, NOR, POR, ESP, SWI, UK	Qualification and field of study mismatches	Subjective and objective
HEGESCO - Higher Education as GEnerator of Strategic COmpetences	2002-2008	Employability of graduates	LTU, POL, HUN, SVN, TUR	Qualification and field of study mismatches	Subjective and objective

These surveys allow measuring qualification and field-of-study mismatches as well as skill mismatch. Table 9 provides the questions asked in each survey regarding the different dimensions of skill imbalances. These questions are the same for REFFLEX and HEGESCO. Regarding qualification mismatch, these two surveys measure it by asking employees the following question: *What type of education do you feel is most appropriate for this work?* To which they respond as follows: *PhD, other postgraduate qualification, Master, Bachelor and lower than higher education*. While in CHEERS (European graduate survey), the question is formulated as follows: *If you consider all dimensions of your employment and work: to what extent is your employment and work appropriate to your level of education?* To which employees respond by choosing one of the following answers: *1: completely appropriate ... 5: not at all appropriate*. This survey provides a direct assessment of qualification mismatch, while in the two other surveys we have only a self-assessment of qualification requirements, which has to be compared to respondents" qualification levels.
All three surveys allow a direct measurement of horizontal mismatch. In CHEERS, the question, '*How would you characterise the relationship between your field of study and your area of work*?', enables to directly assess whether the worker is mismatched through the following answers: *My field of study is the only possible/ by far the best field; some other fields could prepare for the area of work as well; another field would have been more useful; the field of study does not matter very much; higher education studies are not at all related to my area.* In the two other surveys, the question, '*What field of study do you feel is most appropriate for this work?'* also allows determining the respondent's self-assessment of horizontal mismatch with the following answers: *exclusively own field, own or a related field, a completely different field, no particular field*.
However, the lexical differences in the formulation of these questions may be problematic, as when asked to the same workers they may lead to contradictory results. Therefore, in overall, the incidence of mismatches tends to differ from one survey to another.

3.3 Employer surveys

International employer surveys are usually used to provide a subjective assessment of the extent of some skills-related concepts such as skills shortages, skills gaps and skills needs. In the literature, the following three surveys are the most used ones: the European Business Survey (EBS), the ManPower Talent Shortage

Survey (MTSS) and the European Company Survey (ECS).[27] The ECS is older than the TSS. The former started in 2004 as the European Establishment Survey on Working Time and Work-Life Balance (ESWT) and was conducted every four years before being rebranded to the European Company survey from 2009 onwards. The ECS survey covers the following themes: work organisation, workplace innovation, HR practices, employee participation and social dialogue. The MTSS started in 2006 and is conducted annually ever since. It focuses mostly on employers hiring difficulties (see Table 10).

These international surveys on employers usually provide information on hiring difficulties through questions addressed directly to employers. As in the surveys above, the formulation of these questions differs from one survey to another, causing disparities in the measures of skills shortages found in the literature using these surveys. In fact, employers are asked to answer yes/no questions on hiring difficulties (see Table 10). In the ECS, the following yes/no question is asked to employers: *Does the management encounter any of the following problems at this establishment currently: difficulties in finding employees with the required skills?*[28] While in the MTSS employers are asked: *Are you having difficulties filling jobs due to lack of available talent?* As can be seen the formulation of these questions differs. However, in essence, they enable to identify employers' difficulties in filling jobs due to a lack of individuals endowed with the right set of skills. The disparities in the empirical literature regarding the incidence of skill shortage using these two surveys come necessarily from employers' subjective biases when assessing their hiring difficulties.

Table 10. International employer surveys

Employer surveys	Period covered	Survey themes	Countries	Skill imbalances	Method
EBS - European Business Survey	2002	Employers hiring difficulties - skill gaps, skill shortages	Europe	Skill shortage and skill gaps	Subjective
ECS - European Company Survey	Every four years since 2004 as the European Establishment Survey on Working Time and Work-Life Balance (ESWT) and since 2009 as ECS	Work organisation, workplace innovation, HR practices, employee participation and social dialogue	32 countries: EU 28: AUT, BEL, BGR, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, LVA, LTU, LUX, MLT, NLD, POL, PRT, ROU, SVK, SVN, ESP, SWE, UK; ISL, MKD, MNE and TUR	Skill shortage and skill gaps	Subjective
MTSS - Manpower Talent Shortage Survey	Annually since 2006	Employers hiring difficulties - skill gaps, skill shortages	43: JPN, PER, HK, BRE, ROM, GRC, IND, TWN, MEX, TUR, NZL, BUL, COL, HUN, CRC,PAN, DEU, GTM, AUS, POL, SWI, SGP, AUT, ISR, SWE, ARG, CAN, USA, ZAF, NOR, FRA, ITA, SVK, SVN, BEL, CHN, FIN, CZE, NLD, ESP, UK, IRL	Skill shortage and skill gaps	Subjective

3.4 Household-Employer Surveys

Unlike most of the surveys presented so far, which either provide information on individuals or on employers,[29] the World Bank survey on skills, called Skills Toward Employability and Productivity (STEP), provides

27 The European Business Survey (EBS) is also used in the literature. We focus on the two others because of data accessibility issues.

28 However, recently, Eurofound has collaborated with Cedefop and the OECD to include more questions on skills (skill mismatch and skill obsolescence). The 2019 survey asks directly managers to provide both numbers and percentages of their employees exactly matched, under-skilled and overskilled. Managers are also asked about how quickly the skills and knowledge needed from their employees change.

29 The European Company Survey is a dual voice survey, it complements the employer survey by questioning employee representatives.

information on both, individuals and employers, to better understand the interplay between skills, employability and productivity. The survey was carried out in four rounds between 2012 and 2017 in 17 low- and middle-income countries (see Table 11). The STEP household survey provides information on cognitive skills, with a direct reading assessment and a self-assessment of numeracy, literacy and writing. It also provides information on socio-emotional skills (personality traits, behaviour and preferences) and on job-relevant skills. The STEP employer survey provides information on some labour market challenges such as satisfaction with education, training, and levels of specific skills and job skill requirement, training and recruitment difficulties.

This survey can be used to analyse skills needs, skills transferability and skill imbalances. The combination of information on both employers and employees makes it unique among international data used to analyse skills-related issues. In fact, while some concepts of skill imbalances such as skill mismatch are analysed at the employee level, others such as skill shortage or skill gap are analysed at the employer level. Thus, using this survey, all the concepts defined in Section II can be measured. Moreover, the survey also enables to analyse the concepts of skills needs and skills transferability.

Table 11. International household-employer surveys

Household and employer surveys	Period covered	Survey themes	Countries	Skill imbalances	Method
STEP - Skills Toward Employment and Productivity	2012-2017	Household: reading proficiency; job-relevant skills level of respondents or skill use in their job Employer: cognitive skills, behaviour and personality traits, and job-relevant skills that are currently being used, as well as skills employers look for when hiring new workers Level of satisfaction with the education and skills training available in the labour force	ALB, ARM, AZE, BOL, BIH, COL, GEO, GHA, KEN, XKX, LAO, MKD, SRB, LKA, UKR, VNM, CHN	Skill mismatch, qualification mismatch and field of study mismatch, skill shortages, skill gaps	Subjective and objective

Skill shortage is measured by asking employers yes/no questions about hiring difficulties by occupation: *Did you encounter any of the following problems when trying to hire managers, professionals, Applicants lacked required skills.* This way of measuring skill shortage is different from what we have seen in other employer surveys (see Table 7). It provides information on occupations that are in shortage. This represents an advantage in comparison to MTSS and the ECS, in which we can only know whether an employer is experiencing skill shortages (hiring difficulties due to lack of appropriately skilled candidates for recruitment) and not in which occupation. Moreover, STEP enables to identify, in case of skill shortages, which skills are in shortage for each occupation through the question: What were the specific skills lacking from the applicants who applied for [name of the occupation]?

Skill gap is measured for 12 types of skills through the following yes/no question: *Is there a difference between what is required for this occupation type and the current level of this skill?* In general, many surveys enable to identify only employers experiencing skills gaps without any information given on which skills are missing.

The employee survey, as stated above, enables to measure empirically many of the different notions of skill imbalances studied at the employee level, such as qualification mismatch, field-of-study mismatch and skill mismatch. The survey has information on qualifications within occupations, which is needed for measuring qualification mismatch using the empirical method of the realised matches. It also performs a cognitive assessment of individuals' skill levels, which can be used to measure skill mismatch following the objective methods presented in the first section of this document.

STEP is an interesting source of information on skills for low- and middle-income countries, which usually lack these types of information. However, it does not include many countries and the questionnaire has some variations from one country to another. This constitutes a limitation to the utilisation of this international survey on skills.

4. Measurement using web-based surveys and social media data

In recent years, the utilisation of internet-based data sources in labour market analysis has increased (Autor et al., 2003; Lenaerts, et al. 2016). There are different types of internet (big) data sources that can be used for labour market analysis. Among these data sources are online job portals (job boards), labour platforms, and social media networks. Moreover, internet-based surveys are also emerging to collect data on the labour market, including regarding skills.

Job portals typically host vacancies and CVs, which both contain useful information about skills in demand and in offer. Moreover, online job portals may include wage comparisons, employer evaluations and career advice, which could provide additional, sometimes more qualitative in-nature, information to analyse skills trend in the labour market. **Labour platforms**, also called online market intermediaries or simply platforms, such as Mturk, oDesk and TaskRabbit enable individuals breaking down jobs into smaller units, then outsourcing these to platform workers around the world (Kilhoffer, 2020a). Information on both the tasks in demand and the workers available to perform them may be of interest to analyse skills demand and supply, in national labour market, but also across countries. Moreover, labour market information can come from **social media networks**, **social media** such as Facebook, LinkedIn, Twitter, etc. Each social media network has different types of information, but essentially, it can encompass personal data, including information on skills and education in some cases, advertisement data, metadata and much more (Kilhoffer, forthcoming).
Although the effects in the labour market are still not clearly assessed, in many countries, there is an observed trend towards matching skill demand and skill supply through the internet (Kuhn, 2014; Kuhn & Mansour, 2014). Employers advertise job openings and the skills they are looking for, while job seekers and prospective employees advertise their skills and qualifications on dedicated websites, being these job portals, labour platforms or social media.

Data from (non)probability voluntary internet-based surveys, such as the WageIndicator (see WageIndicator.org) or Glassdoor (www.glassdoor.com), provide the participants with information on salary and working conditions in exchange of their participation to the survey. These new data sources are more and more used nowadays in labour market studies. They could constitute an alternative and/or a complement to international large-scale assessment surveys – among other surveys used to obtain information on skills - for the analysis of skills needs, skills transferability and skill imbalances (Kuhn & Skuterud, 2004; Askitas & Zimmermann, 2009; 2015; Tijdens & van Klaveren, 2012). However, even though these types of data sources are being abundantly used nowadays, few studies use them to measure concepts of skills needs, skills imbalances and skills transferability. This is mostly due to some methodological or technical difficulties related to the mobilisation of such data for analysis as well as their lack of comprehensive information on skills. Usually, data from the web are subject to coverage, self-selection and non-response biases and are therefore difficult to collect and mobilise for analysis. In fact, the exploitation of most online data sources requires the development of technologies on big data collection and analysis.

4.1 Job portals and online market intermediaries

Job portals provide different services to their users. Prominent examples like CareerBuilder, BurningGlass, Indeed or Monster typically allow employers to post job vacancies, while job seekers can build profiles with their CVs. In some cases, job portals also perform their own analysis from user data and additional sources, providing, wage comparisons, employer evaluations and career advice. From both data users post and data analysed by the job portals themselves, these websites have very relevant data for labour market analysis, especially on skills.

EU initiatives have also spawned job portals to facilitate market job matching within and across countries. For example, the website Europass Portofolio[30] collects and stores data on individuals' skills and qualifications in predefined formats and templates. As such, it provides a potential source of structured data. Moreover, the EURES job mobility portal provides a free service of matching companies' job vacancies with candidates' CVs online. As such, the EURES job mobility portal contains relevant information on the European and international labour market and specifically on skills transferability across countries. It represents a source of micro level data based on the content of job advertisements published for cross-border hiring, providing information on employers' demand for skills and competences during cross-border hiring. It is also an interesting source of data to investigate recruitment outcomes, the extent to which cross-border hiring leads to skills match or mismatch between the supply and demand sides of the labour market (Kureková et al., 2016). EURES has already been webscraped to identify skills demanded in some low- and medium-skilled occupations, and to understand employers' preferences in terms of cognitive and non-cognitive skills (Kurekova et al., 2016). The comparability of EURES data also offers significant advantages for comparative analyses, since the uploaded vacancies and CVs follow the ESCO classification and a variety of tags allow for more convenient structuring of data (Kurekova et al., 2016).

Online labour market intermediaries such as Mturk, oDesk, and TaskRabbit intermediate tasks requiring human intelligence, which are difficult or impossible to automate. These platforms for labour market matching are valuable sources of information for their users, but also constitute an important source of information for labour market analysis (Askitas and Zimmermann, 2009, 2015; Kuhn, 2014; Kuhn and Mansour, 2014). This information covers supply and demand of the labour market, and may allow analysis of their matching process. For example, Pavlick et. al (2014) studied language skills and how that corresponds to task acceptance for 'Turkers' who work on MTurk. Ellmer focused on the digital division of labour, exploring how MTurk facilitates de-skilling, or how Turkers perform tasks for which they are overqualified (2015). Hesse et al. (2020) used webscraping to compare 12 labour platforms. While they focused on the impact of trust-building mechanisms,[31] they demonstrated that webscraping is a usable method to gather data on skills from workers' profiles.

Most labour market research using online data sources are based on data extracted from job portals, and studies using data from online market intermediaries are rare. Still, both sources have served in the analysis of labour market matching, such as geographical mismatch and upskilling (Marinescu, 2015; Hershbein & Kahn, 2015) as well as individual behaviour in the labour market (Kudlyak et al., 2014; Faberman & Kudlyak, 2014). Skills have also been a focus of such research. For example, Hershbein and Kahn (2015) used data from BurningGlass to investigate one aspect of demand for upskilling - the tendency of employers to ask for more qualifications in areas with high unemployment rates.

However, accessing and using such data for labour market analysis can be problematic. Not all data of interest on job portals and online labour market intermediaries is publicly accessible, and webscraping is usually subject to technical, ethical and legal challenges (Kilhoffer, 2020b). Even if these barriers are overcome and data are gathered, technical difficulties persist.

30 https://europass.cedefop.europa.eu/

31 While beyond the scope of this paper, online platforms must implement different sorts of trust-building mechanisms (e.g. ID verification, ratings) to facilitate transactions between parties who do not know one another.

A prime example is representativeness, as job portals and online labour market intermediaries are imperfect representations of the greater labour market. Thus, these data are encumbered by coverage bias. Dealing with these obstacles to obtain non-biased statistics remain a very tedious exercise (Kurekova et al., 2015; Steinmetz, Tijdens, and de Pedraza 2009).

Additionally, data acquired from different websites and at different times may not be comparable (Japec et al., 2015). For example, data extracted from different job boards does not have the same structure (and may even be *unstructured*), and must be harmonised (cleaned, restructured, etc.). This process can be very complex, and the resulting data is not guaranteed to result in fruitful analyses. At processing skill, there are many recent projects aiming at extracting and analysing information from these platforms for labour market analyses. An example is the ESSnet Big Data project undertaken in EU-28 between 2016 and 2018.[32]

4.2 Web-based surveys on skills

Unlike standard statistical surveys where data collection is done via face-to-face interviews or telephone interviews, web-based surveys collect data online through the web. They have the particularity of being voluntary and, most often they are non-probability surveys, which constitute an important weakness of such data, i.e. their representativeness is unknown. However, these types of surveys, besides being flexible, fast, cheap and easy to set up, allow having real time information on the labour market and collecting a large number of observations.

Examples are the WageIndicator and the Glassdoor survey. In these surveys, participants from all around the world visiting these websites are invited to participate in the survey in exchange of information mainly on salary and working conditions.[33] These surveys are, to our knowledge, the only international web-based surveys providing information on labour market issues. Therefore, in what follows, we discuss how they can be used to measure skills needs, skills transferability and skill imbalances. Being employee level surveys, these surveys are therefore more appropriate for the measurement of skills-related concepts analysed at the employee level, such as vertical and horizontal mismatches. However, given the large number of participants they gather, they can also be used to perform an analysis at detailed occupational levels. Therefore, the concepts of skill gaps and skill shortages (skill need) can be measured using these two surveys, which also provide information for measurement of skills transferability.

Given the flexibility of online web surveys, modules regarding skills use or even a cognitive skill assessment can be added without any important cost (Fabo & Tijdens, 2014; Lenaerts et al., 2016). That is what has been done in Visintin et al. (2015) by implementing a task module to the WageIndicator survey for the Netherlands to analyse whether the variation in wages across individuals can be linked to the intensity of tasks implementation. Given the numerous advantages of this type of data sources, this type of experiment if reproduced in all countries would make them an incredible infrastructure for labour market research on skill-related issues.

Online web surveys have a shortcoming pertaining to their representativeness, as they are subject to limited or biased coverage, self-selection and non-response biases. As stated earlier, web surveys are often voluntary and provided to non-probability samples, and participants usually do not finish the questionnaire. Therefore, it is difficult to interpret estimates from these surveys through inferential statistics. That is the reason why most studies using web surveys are labelled exploratory studies: they may have valuable information but are not representative of the entire labour force. In the last decade, a number of studies are providing methodological instruments allowing inference using data from web surveys. The main approach in this literature consists of using a known representative sample of the population as a reference/control sample to the considered web survey to make it

32 https://webgate.ec.europa.eu/fpfis/mwikis/essnetbigdata/index.php/Main_Page.

33 In addition, they also provide employer evaluations and career advice.

representative. Several methods are used to construct weights such as post-stratification weighting or propensity score adjustment. However, these methods to address the representativeness of web surveys are under discussion regarding their efficacy in mirroring the reference sample (Vehovar & Manfreda, 1999; Steinmetz et al., 2009). Nevertheless, some of these surveys usually provide weighs to be used to obtain representative estimates.

Unlike standard international surveys, voluntary web-based surveys usually do not face sample size constraints, but are subject to coverage, self-selection and non-response biases. However, standard statistical surveys, more often than voluntary web-based surveys, face sample size constraints, which make it harder to conduct an analysis at the occupational level. It seems then that one of the major advantages of voluntary web-based surveys is the main disadvantage of standard international surveys while their drawbacks are rarely found in the latter. Therefore, it would be interesting to know whether combining both types of surveys provides better measures of all the aforementioned concepts. For example, this combination could consist of using international large-scale assessment surveys as reference surveys to be able to perform a more detailed analysis at the occupational level.

Online web surveys, as stated earlier, are not the only data source from the Internet that have the potential to analyse labour market issues. In fact, a number of studies are now starting to exploit data from social networking websites. These platforms have large users bases and contain information from both employers and employees, as well as information on other organisations.

4.3 Social media data on skills

Social networking websites, such as LinkedIn, Facebook or Twitter potentially constitute an important online data source on the labour market (Lenaerts et al., 2016). These types of platforms count among their large base of users, employers who post their vacancies, and employees and prospective employees posting their CVs. With this information, these platfoms can provide information on what skills employers are looking for, and on what skills and qualifications employees or prospective employees possess. Both job seekers and employers can benefit from this matching process (Mang, 2012; Fabo, 2017). These sources of data are abundantly researched, but rarely for labour market analysis (Kilhoffer, forthcoming). Yet, some examples exist. For instance, Barslund and Busse (2016) use data from LinkedIn, in particular, to analyse a specific segment of the labour market and labour mobility in this segment – i.e. that of IT professionals and their mobility trends.

Social networking websites, unlike job boards and other types of websites[34] publishing job offers, are not exclusively made for job matching. With the exception of sites like LinkedIn or Xing, most social networks are used to facilitate communication, primarily between individuals, but also organisations. The information provided by users on these websites may include vacancies, CVs, job histories, and network information – e.g. groups that individuals belong to, and connections between people and pages (followers, likes, friends) (Carnevale et al., 2014; Tufecki, 2014). Advertisement data, especially job vacancy ads, are also worth consideration to investigate the labour market and in particular, skills demand. The matching element of job ads is especially interesting, given that social networks target ads to certain groups specified by the ad poster, though this information is mostly unavailable to the public. Still, sources like Facebook's Ad Library[35] may be a good source of job vacancy data in the future, especially if its current technical limitations are addressed (Kilhoffer, forthcoming).

Social media networks certainly contain a wealth of data and are constantly being fed with more information by users. This has the advantage of higher granularity and timeliness compared to traditional sources. However, acquiring data from social media has become substantially more difficult in recent years, especially due to concerns about how social networks store and allow access to personal data. In some cases, webscraping or API calls can still retrieve these big data methodologies for

34 The ESSnet Big data project within the European Statistical System use webscrapingscrapping to collect data from websites in Europe posting job offers. For each of these job offers, information on skills are also collected and structured for analysis.

35 See https://www.facebook.com/help/259468828226154.

analysis. However, most data are simply inaccessible to all but analysts working for the social media network. For example, Bastos and Walker write that it has become virtually impossible to conduct large-scale research using Facebook data (2018). It is therefore important to be realistic about which data can be acquired.

Furthermore, these data are not always suitable for measuring skills needs, skills transferability and skill imbalances. Among others, one substantial challenge is that of representativeness, which is a very general problem in big data (Tufekci, 2014). Social media users are not representative of the general population, and social media networks have different (and constantly evolving) biases towards different demographics, such as age groups and gender. Social media networks like LinkedIn are biased towards higher-earning and higher-skilled professions (Carnevale et al., 2014). People and organisations may also post incomplete or misleading data, although interestingly, researchers have found that people are more honest about their job histories on LinkedIn compared to traditional resumes (Guillory & Hancock, 2012). Owing to these difficulties, few studies utilising data from social networks assess skills needs, skills transferability and skill imbalances.

In short, the primary advantages of social media data on skills are timeliness and granularity, but these are countered by problems of representativeness and accessibility. Each social media network is used by different people and organisations, and contains different data. This means that social media networks must be carefully considered before using their data to research skills.

5. Conclusions

The aim of this document is to provide a report on the measurement of skills needs, skills transferability and skill imbalances using data from international employee and employer surveys in comparison to when using new types of data sources from the internet, such as data from job boards, social media and internet-based surveys. This exercise was done to understand whether online data sources could constitute an alternative and/or a complement to these international statistical survey data.

It starts by providing a conceptual clarification of the concepts related to skills needs, skills transferability and skill imbalances. Then, for all these skills-related concepts, we provide, in addition to definitions, their measurement using international data, subjects investigated, and the main results found in the literature.

The third section presents all international surveys that are used in the literature to analyse the concepts of skills needs, skills transferability and skill imbalances. We make a distinction based on whether they are household surveys, employer surveys (or both) or higher education graduates' surveys. We then discuss how they have been (or could be) mobilised to measure the concepts of skills needs, skills transferability and skill imbalances.

The fourth section presents new data sources from the Internet, more specifically, data from job portal, nonprobability internet-based surveys and social networking websites. We present these types of data sources and how they could be used to address issues related to the measurement of the concepts of skills needs, skills transferability and skill imbalances. These surveys are not in particular used to measure these concepts. Most studies concern other areas of the labour market than skill-related issues. Moreover, social networking websites are more used as a subject of research than a source of data for labour market analysis. These platforms have very large base of users. In fact, nearly every individual connected to the Internet use them very extensively and in return provide access to their personal information online. The usage, especially by individuals, of these social media has reached such a proportion that it has become a concern for many and attracts researchers from many disciplines in social science (sociology, psychology, economics, etc.). Therefore, there is an extensive literature on the usage of social media by individuals. Unlike job portals, the usage of social networking websites as a data source is very new but both are being hindered by methodological challenges associated with the collection and mobilisation of such data for analysis. However, these data sources contain many of the information requested for the measurement of skills needs, skills transferability and skill imbalances.

Unfortunately, this type of data source raises other issues. In addition to methodological issues related to the collection of such data, we would have to face the same limitations as in online voluntary web surveys, once the data is made available and structured with comprehensive information on skills. The measures obtained for these concepts from such data sources would suffer from self-selection, coverage and non-response biases. However, this problem might disappear with the expansion of internet coverage and the development of new methodologies to deal with it. These issues remain the same when dealing with the representativeness of data from nonprobability internet-based surveys.

Regarding the mobilisation of data from internet-based surveys to measure the concepts of skills needs, skills transferability and skill imbalances, most studies using them address issues concerning wage and working conditions. In fact, these surveys provide little information on skills. Usually, surveys that are used to analyse skills-related issues, like the large-scale assessment surveys, provide information on skill use intensity and assessments of cognitive skills. They also provide a self-assessment of skill levels and skill imbalances. These web surveys do not provide such information. Taking for example the WageIndicator survey, the only measure of skill imbalances one can obtain from it is qualification mismatch, using both empirical and subjective approaches. The few studies on skill mismatch, using the international version of these data, use this definition of skill imbalances. In addition, web surveys are conducted on individuals not on firms, while some of the skills-related concepts are analysed using employer surveys, providing information from employers. Therefore, they can only be used to analyse skill imbalances at the employee level. However, they offer the possibility to conduct an analysis at occupational or sectoral levels, given the usually considerable size of samples.

Our analysis here of the usability of nonprobability internet-based surveys to measure skills needs, skills transferability and skill imbalances mostly focuses on the WageIndicator web survey. However, our conclusions are that these surveys are rarely used for the measurement of skills needs, skills transferability and skill imbalances. This situation results mostly from the fact that these surveys have no or little information on skills, which is understandable given that their focus is on salary and working conditions. The rare studies found on skills are on qualification mismatch. However, if these surveys were to be amended to include modules on skills, they could soon constitute a real alternative to data from international employee surveys. And their issues of representativeness, for which there are solutions around, are bound to disappear in the near future.

To sum up, data from the Internet, even though they are not currently much used for the measurement of skills needs, skills transferability and skills imbalances, can represent an invaluable infrastructure of research on skill-related subjects if some changes were to be made to make available comprehensive information on skills.

The collection and mobilisation for analysis of data on skill-related issues from Internet data sources raise many technical and methodological issues that need to be addressed to be able to exploit their numerous advantages in comparison to standard statistical employer and employee surveys. However, we do not necessarily have to oppose these two types of data sources. Standard statistical surveys could be used in combination with Internet data sources to circumvent the many methodological challenges raised by the latter. They for example could serve as reference sample when trying to go around the representativeness issues posed by the mobilisation of online data sources.

The utilisation of web data for analysis raises so many questions, and therefore gives rise to many interesting opportunities for further research. These research questions already mobilise researchers from all around the world and solving them can open an all new era for social science, with continuously updated data allowing real-time analyses and answers on nearly every issues. However, for the time being, even though they have many advantages over traditional data sources, new types of data sources from the Internet cannot be considered as an alternative or a complement to the former. Internet data sources do not offer the types of detailed information on skills that can we can have with traditional data sources. Moreover, they pose methodological and technical issues that are still to be resolved.

6. Appendix

6.1 Online information on skills needs, skills transferability and skills mismatches

Here we present information on indicators of skills imbalances given in the OECD skills for jobs database and the Cedefop's skills panorama. These two platforms provide information on skill imbalances for a number of OECD members or partners. The data visualisation tools enable to visualise the data on skill imbalances and perform comparisons across countries and jobs and personal characteristics.

6.1.1 OECD's Skills for job indicators

The OECD skill needs indicator is constructed in two steps (OECD, 2017). It combines information on skill shortages provided by several indicators to determine whether an occupation is in shortage before using occupational dictionaries to identify skills that are in shortages and those that are in surpluses.

Step 1: Compute wage, employment and talent pressure indicators and combine them in a final occupational shortage index

Occupational shortage index

$$OS_{c,i,t} = w\left(\Delta W_{c,i,t} - \Delta \overline{W}_{c,t}\right) + 0.5w\left(\Delta E_{c,i,t} - \Delta \overline{E}_{c,t}\right) + w\left(\Delta H_{c,i,t} - \Delta \overline{H}_{c,t}\right) + w\left(\Delta U_{c,i,t} - \Delta \overline{U}_{c,t}\right) + w\left(\Delta Q_{c,i,t} - \Delta \overline{Q}_{c,t}\right)$$

$\Delta W_{c,i,t}$, $\Delta E_{c,i,t}$, $\Delta H_{c,i,t}$, $\Delta Q_{c,i,t}$ are yearly changes in the estimated long run trends of wages, employment, hours worked and underqualification in country *c* and 2-digit occupation *i* and year *t*. $U_{c,i,t}$ is the inverse of the unemployment rate

$OS_{c,i,t}$>0 shortage in occupation i in country c in year t

$OS_{c,i,t}$<0 surplus in occupation i in country c in year t

Step 2: Interaction with occupational skill, knowledge and ability requirements from O*NET to obtain an (objective) skill shortage indicator

Skill, knowledge and ability intensity of each occupation are obtained by normalising (using min-max scaling) the product of the importance and level of each skill, knowledge and ability domains given in O*NET. The final skill shortage indicator multiplies different skill dimensions for each occupation by the extent of the occupational shortage in step 1.

Intuition: Strong shortages in certain occupations that require certain skills more intensively will point to a shortage in those skills when aggregating the information at the country level in the final skill shortage indicator.

6.1.2 Cedefop's skills panorama

Cedefop's skills panorama provides information on several concepts of skill imbalances in following web link: https://skillspanorama.cedefop.europa.eu/en/indicators-list. The corresponding indicators of skills imbalances are constructed using the European Skills and Jobs Survey (ESJ) as follows:

- ✓ **Qualification mismatch**
  - o **Overqualified tertiary graduates**

This indicator shows the share of young (aged 25-34), tertiary education (ISCED 5 or 6) graduates employed in jobs not included in categories of managers (ISCO 1), professionals (ISCO 2), or technicians and associate professionals (ISCO 3).

- ✓ **Skill mismatch**
  - o **Overskilling or skills underutilisation**
    This indicator shows the percentage of adult employees who report that they have higher skills that required to perform their current job (overskilled workers).
  - o **Underskilling**
    This indicator shows the percentage of adult employees who report that their skills are lower than required to perform their current job.
  - o **Underskilling at hiring**
    This indicator shows the percentage of adult employees who report that their skills were lower than what was required by their job at the time of hiring.
- ✓ **Skill gaps**
  - o **Foundation skills gaps**
    The percentage of adult EU-28 employees whose foundation or basic skills (literacy, numeracy, ICT, foreign languages) are ranked lower/are barely matched to the level needed to do their job. Respondents in Cedefop's European skills and jobs survey were asked to score, on a 0-10 scale, their literacy, numeracy, ICT and foreign language skills compared to what is required for doing their job, where 0 means their level of skill is a lot lower than required and 10 means their level of skill is a lot higher than required. Scores below 7 (the lowest quartile) were used to calculate literacy, numeracy and ICT skills gaps. Scores below 5 (the lowest quartile) were used to calculate foreign language skills gaps.
  - o **Job-specific skills gaps**
    The percentage of adult employees whose job-specific/technical skills are ranked lower/are barely matched to the level needed to do their job. It is based on results of Cedefop's European skills and jobs survey. Respondents were asked to score, on a 0-10 scale, their technical skills compared to what is required for doing their job, where 0 means their level of skill is a lot lower than required and 10 means their level of skill is a lot higher than required. Scores below 7 (the lowest quartile) were used to calculate the extent of technical skill gaps.
  - o **Transversal skills gaps**
    The percentage of adult employees whose transversal skills - communication skills, customer handling skills, learning skills, planning and organisation skills, problem solving skills and team-working skills - are ranked lower/are barely matched to the level needed to do their job. It is based on results of Cedefop's European skills and jobs survey. Respondents were asked to score, on a 0-10 scale, what is the level of their transversal skills compared to what is required for doing their job, where zero means their level of skill is a lot lower than required and ten means their level of skill is a lot higher than required. Score below seven (the lowest quartile) were used to calculate transversal skill gaps
- ✓ **Skills obsolescence**
  This indicator shows the percentage of adult employees who believe it is likely or very likely, that several of their skills will become outdated in the next five years. Following this measure, almost one out of two (46%) EU workers feel their skills will become outdated. However, this would drop to one in five (21%) when only those feeling this is very likely to happen are considered.

6.2 Measurement of skills transferability

6.2.1 Skill transferability: market approach *(Shaw, 1984)*

Skills transferred from occupation i to occupation j

$$t_{ij} = \frac{OSHC_i \cap OSHC_j}{OSHC_i}$$

Numerator: amount of overlapping occupational skills required across both occupations.
Denominator: amount of occupational skills required in the former occupation i.
Occupation-Specific Human Capital (OSHC) transferability through observed cross-occupational switching rates (using retrospective questions in census): probability of occupational change increases with higher transferability of skills across vocations but is likely to pick up other determinants of mobility not related to human capital.
Distance between occupation i and occupation j

$$D_{ij} = \sum_{k=1}^{J} |P_{ik} - P_{jk}| = (P_{ij} + P_{ji}) - (P_{ii} + P_{jj}) + \sum_{k=1}^{J} |P_{ik} - P_{jk}|$$

P_{ik}: Probability of an occupational switch between occupation i and occupation k
P_{ii} and P_{jj} are the probabilities of moving across more detailed occupation within aggregate occupation i and j.
J: set of occupations
Scaled measure:

$$d_{ij} = 1 - \left(\frac{D_{ij}}{2}\right)$$

Direction of occupational movement does not matter: d_{ij} is a symmetric matrix (d_{ij}=d_{ji})

6.2.2 Skill transferability: skill approach (*see Ormiston (2014)*)

Estimate the proportion of knowledge, skills and abilities (KSA) utilised in occupation i that can also be applied in occupation j. Use O*NET data to examine commonality of occupations across 120 standardised knowledge, skills and abilities dimensions.
Transferability of skills from occupation i to occupation j

$$t_{ij} = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum_{m=1}^{M} \min(\delta_{im}, \delta_{jm})}{\sum_{m=1}^{M} \delta_{im}}$$

Numerator: amount of shared points between occupation i and occupation j summed across M skill components
Denominator: total number of points employed in occupation i summed across M components
N: three KSA categories; M: number of component within each category (33 knowledge, 35 skills, 52 abilities); δ_{im}: occupational skill intensity – multiplication of the level of proficiency needed (0-7) and the importance of each component to the occupation (1-5)

6.2.3 Skill transferability: task-based approach *(see Gathman and Schönberg, 2010)*

A task-based measure of occupational comparability considers that two distinct occupations have similar skill requirements if they put similar weights on tasks, i.e. individuals perform the same set of tasks. The maximum distance is obtained when the two occupations perform independent sets of tasks.

Transferability between occupation i and occupation j is given as follows.

$$D_{ij} = \frac{1}{M}\sum_{m=1}^{M}\left|\frac{q_{im}}{q_i} - \frac{q_{jm}}{q_j}\right|$$

q_{im}/q_i: fraction of workers in occupation i who perform task m.

Skill content or skill profile of occupation i ((based on tasks performed by workers from occupation i) is characterised by a vector$q_i = (q_{i1}, \dots, q_{iM})$, where q_{im} denotes the fraction of workers in occupation i performing task m. The distance between occupation i and occupation j is the angular separation of vectors q_i and q_j

$$D_{ij} = 1 - AngSep_{ij} = \frac{\sum_{m=1}^{M}(q_{im}q_{jm})}{\sqrt{(\sum_{m=1}^{M} q_{im}^2)(\sum_{m=1}^{M} q_{jm}^2)}}$$

Angular separation or uncentered correlation is extensively used in the literature on innovation to measure the proximity of technologies between firms. It is the cosine angle between their positions in vector space. The measure varies between zero and one. It is equal to zero for occupations that use identical skill sets and unity if two occupations use completely different skills sets. The measure will be closer to zero when two occupations overlap more in their skill requirements.

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InGRID-2
Integrating Research Infrastructure for European expertise on Inclusive Growth from data to policy

Referring to the increasingly challenging EU2020-ambitions of Inclusive Growth, the objectives of the InGRID-2 project are to advance the integration and innovation of distributed social sciences research infrastructures (RI) on 'poverty, living conditions and social policies' as well as on 'working conditions, vulnerability and labour policies'. InGRID-2 will extend transnational on-site and virtual access, organise mutual learning and discussions of innovations, and improve data services and facilities of comparative research. The focus areas are (a) integrated and harmonised data, (b) links between policy and practice, and (c) indicator-building tools.
Lead users are social scientist involved in comparative research to provide new evidence for European policy innovations. Key science actors and their stakeholders are coupled in the consortium to provide expert services to users of comparative research infrastructures by investing in collaborative efforts to better integrate microdata, identify new ways of collecting data, establish and improve harmonised classification tools, extend available policy databases, optimise statistical quality, and set-up micro-simulation environments and indicator-building tools as important means of valorisation. Helping scientists to enhance their expertise from data to policy is the advanced mission of InGRID-2. A new research portal will be the gateway to this European science infrastructure.

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More detailed information is available on the website: www.inclusivegrowth.eu

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InGRID-2

Integrating Research Infrastructure for European expertise on Inclusive Growth from data to policy Contract N° 730998

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