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Working paper

WHAT ARE THE NEW OCCUPATIONS AND THE NEW SKILLS? AND HOW ARE THEY MEASURED?

State of the Art Report

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Abstract

This State of the Art Report aims to provide an overview of the academic and the policy debate on the emergence of new occupations and skills in the 21th century. Although the discussion on new jobs and skills is not new to the literature or the public debate, the issue still receives a lot of attention because of the socio-ecological transition that many countries in Europe are facing and the labour market implications that it brings along. Due to technological progress, globalisation and demographic and climate changes, new occupations are arising while other occupations disappear. At the same time, new jobs require new skills or combinations thereof, which need to be developed through formal education, on-the-job training or in another way. In order to better understand the labour market implications of such a transition, the report first thoroughly explores the concepts of occupations and skills and then continues with an analysis of the academic and policy view on these concepts. Commonly, the concepts of occupations, jobs, tasks and skills are studied simultaneously. From both the academic and policy work, it is clear that new occupations and skills are not entirely new phenomena, but the implications do appear to change over time. The academic and policy literature also appear to draw a lot on each other, in the sense that many concepts, definitions, methods and databases are shared. The remainder of the report is then dedicated to an analysis of the traditional methods and data sources and the introduction of innovative methodologies and new web-based datasets to analyse these phenomena. These new data and methodologies are promising and contribute to the real-time identification of new occupations and skills as they arise. In that way, the report supports work on mismatch, skill gaps, over-education, school-to-work-transitions and other factors and furthers our understanding of the dynamics of the labour market.

This report constitutes Milestone 21.6 for Work Package 21 of the InGRID project.

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Integrating expertise in inclusive growth

European policy-oriented research can and must deliver useful contributions to tackle the Europe 2020 challenges of Inclusive Growth. Key tools in this social sciences research are all types of data earning statistics, administrative social data, labour market data, surveys on quality of live or working conditions, policy indicators. The project aims to integrate and optimise these existing European data infrastructures and accompanying expertise.

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1. Introduction

This State of the Art Report, which constitutes a milestone for **WP21** of the **InGRID research project,** aims to provide a *broad overview of the debate on the emergence of new jobs and skills in the 21th century*. The focus of the report therefore is on the labour market implications of the socio-ecological transition that Europe is experiencing. This transition is fuelled by megatrends such as technological progress, globalisation and climate change, which interact with and reinforce each other. New occupations are arising while others are becoming redundant. Along with new jobs, new skills are required that can be developed through formal education or on-the-job-training. Our basic task is to identify these new jobs and skills and to discern the ways in which they impact the economy. In order to answer these questions, one has to distinguish between occupations, tasks, jobs and skills and the ways in which new jobs and skills can be identified. Moreover, it is interesting to see how the academic world and the policy-makers approach these issues. As some issues are difficult to solve on the basis of the traditional methods and data, it is worth looking at novel methodologies and data sources that can be used to identify new jobs and skills and evaluate their impact on the labour market. These issues will also be discussed in this report.

To this end, the report is composed of five sections. Section 2 presents the societal drivers of new occupations and skills in the 21th century. The section discusses the *socio-ecological transition* that Europe is going through and its two types of underlying megatrends: *natural megatrends* (climate change, resource scarcity and energy transition) and *societal megatrends* (the increased use of ICT, demographics, shifts in the economic and political centres of gravity). The labour market implications of these two types of megatrends are examined more closely. Section 3 presents the academic discourse on the topic. The first part of the section introduces the definitions of occupations, jobs, tasks and skills and analyses the complex relationship between them. The second part of the section deals with the classification of occupations and skills. The third part of the section addresses new jobs and skills - in the form of occupational and skill change - in the 21th century. Section 4 complements the discussion of the academic discourse on new jobs and skills with an overview of the policy discourse and policy applications in this regard. This section focuses both on relevant international organisations and supranational bodies as well as the national level of government. Section 5 presents innovative methodologies and new data sources that can be used in empirical research on new occupations and skills. These methods and sources are embedded in a growing literature on the use of the web for (labour market) research. The section presents an overview of how the web developed into a research platform and lists several applications that use the Internet as a data source. In addition, attention is paid to the way in which the web can be used as a data source for the identification of new jobs and skills. Section 6 concludes this State of the Art Report with a brief summary of our main conclusions and an outlook for future research.

2. Societal drivers of new occupations and skills in the 21th century

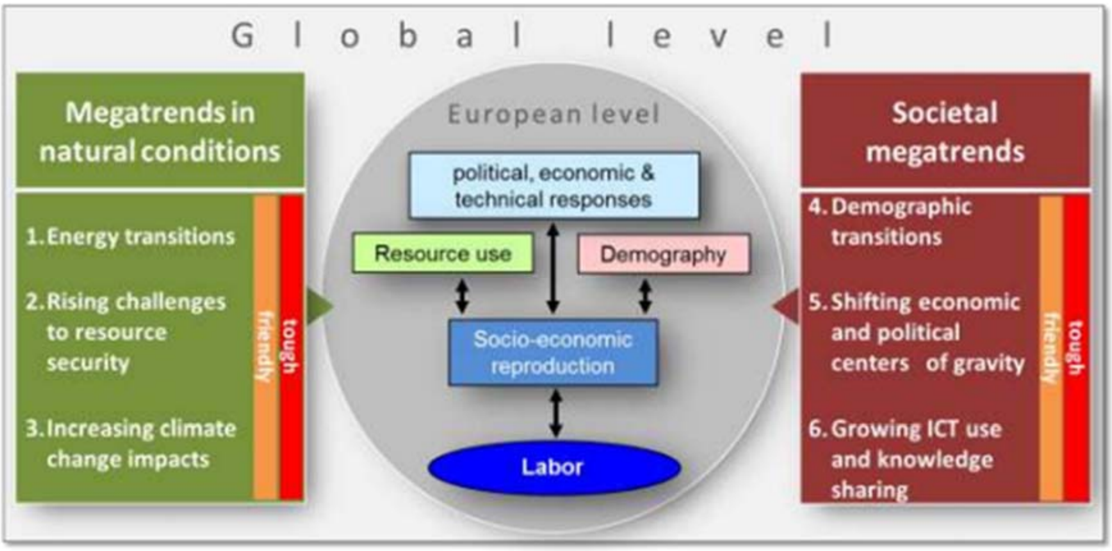
Since the start of the Great Recession, unemployment in Europe has soared. Despite signs of economic recovery for many indicators, the labour market conditions show only a rather moderate recovery, which differs considerably from one member state to another (European Commission, Spring Economic Outlook, 2015). Although economic growth is strengthening, it is unlikely to be sufficient to substantially lower the unemployment rates. In Europe, unemployment has been high for many years now. Since the 1970s, high unemployment levels have characterised many European countries (Sarfati, 2013). There was a small drop in the unemployment rates of some countries in the early 2000s, but this was quickly reversed by the end of the decade. A lot of research has been done on the causes and determinants of unemployment in Europe. Research has pointed to determinants such as labour mobility, skill mismatch, globalisation, market frictions, institutions and technological progress, among a variety of other factors.

The relationship between technology and employment has been a much debated topic in the last decade. The emergence of new technologies is often associated with the rise of new jobs, which commonly require a new set of skills from the workers performing them. An example is the introduction of the computer and the Internet, which created a whole range of new positions within firms (e.g. programmer, system administrator, IT support) and also facilitated the work of many other workers (e.g. clerical workers, typists). Furthermore, 'computer skills' are now being required for a growing number of jobs. In contrast, when new technologies emerge, certain functions become obsolete. In the example of the computer, one can think of cashiers that are increasingly being replaced by self-service registers (Frey & Osborne, 2013). This phenomenon is known as 'technological unemployment'. Although the issue of technology replacing labour has been around for centuries, the concept of technological unemployment was popularised by Keynes. He predicted widespread technological unemployment that is 'due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour' (Keynes, 1933, p. 3). A key question in this discussion is whether workers can easily switch to other jobs: do they have the right set of skills or are they able to acquire these relatively quickly (through formal education, on-the-job-training, life-long-learning)? The discussion on new jobs and skills therefore is strongly embedded in the literature on employment and technological change.

Technological progress and other societal changes have fundamental economic consequences, such as the emergence of new jobs. This idea dates back to classical economists, including Adam Smith, David Ricardo and Karl Marx (Kurz, 2010). The skill angle has also been well-covered since that time. Smith, for example, remarked that 'wages of labour vary with the easiness and cheapness, or the difficulty and expense of learning the business' (Smith, 2007). This understanding was further developed in later work, by Milton Friedman, Theodore Schultz, Gary Becker and Robert Lucas, and resulted in an extensive literature on the role of human capital. Abramovitz and David (2000) theorised that human capital is the driver of the post-Fordist economies, in a similar way as physical capital was the driver of the industrial-era economies.

Recent studies on labour market dynamics and on the emergence of new jobs and skills in particular, have identified several **megatrends** that are triggering these dynamics (Veselková & Beblavý, 2014). These megatrends are at the root of the socio-ecological transition that Europe is going through today. Socio-ecological transitions have shaped Europe in the past. In their paper, Veselková and Beblavý (2014) investigate two sets of emerging megatrends and their corresponding policy responses: **natural megatrends** and **societal megatrends**. Their analysis draws on the work by Fischer-Kowalski *et al.* (2012). Natural megatrends are trends in 'natural conditions' and comprise energy transition, resource security and climate change. Among the societal megatrends, Veselková and Beblavý (2014) consider population dynamics (demography), shifts in the economic and political centres of gravity and a growing use of IT and knowledge-sharing. Each of these megatrends presents a major challenge to the current production and consumption patterns and employment. That is why each of them is of interest to academics and policy-makers. Moreover, these megatrends interact with and reinforce each other, which a socio-ecological transition as a result. Nonetheless, the impact of the different trends on occupations and skills is likely to differ. Figure 2.1 shows the link between the socio-ecological transition and European society.

Figure 2.1 The interplay between the socio-ecological transition and European society

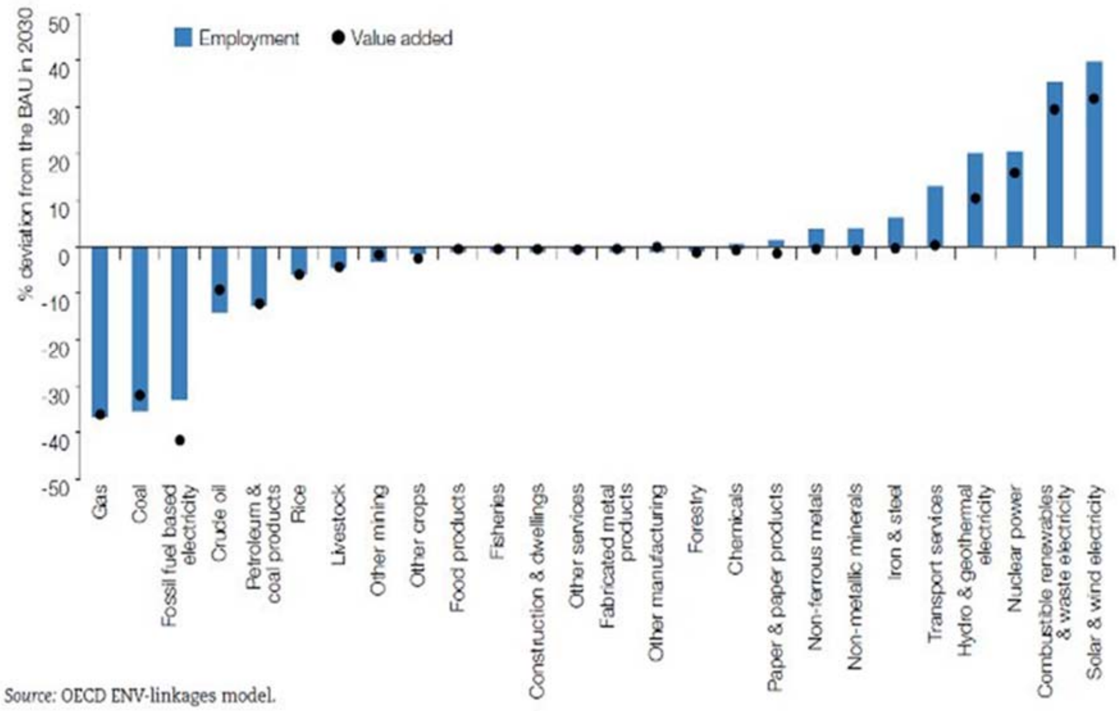


Source Fischer-Kowalski *et al.* (2012, p. 77)

A considerable amount of research on this topic has been conducted within the framework of the **NEUJOBS project**, which ran from February 2011 until January 2015. The project created a significant body of literature on the impact of the ongoing socio-ecological transition on the labour market (which is collected in two separate volumes of edited papers - Beblavý, Maselli & Veselkova, 2014; 2015). Since the speed and severity of the transition and its megatrends are unknown, however, different scenarios are explored to account for this uncertainty: a 'friendly' and a 'tough' version (for two timeframes: 2025 and 2050).

Research on the natural megatrends has often linked these phenomena to the hope of 'green' jobs. Greening the economy can boost job creation in areas such as waste, conservation, tourism and regulation. For example, a 2012 report estimated that close to 36 million jobs in the EU27 depend either directly (53%, of which about 10% are found in the environment-related tourism industry) or indirectly (47%) on the environment (ECORYS, 2012). Colijn and Behrens (2015) examine the relationship between energy, employment and economic growth. While decarbonisation will lead to job losses in the primary sector, a higher number of jobs are created in the power sector (due to a rising number of jobs in construction, installation and manufacturing and in operation and maintenance). The estimated net employment impact is thus positive. The reason for the growing number of jobs in the power sector is the higher labour intensity of renewables. Additionally, the renewable energy sector employs a higher share of skilled workers than most activities in primary fuels, according to Behrens *et al.* (2013). One can thus infer that the skill level of jobs is likely to go up as well. More details on the impact of greening on employment and the value added per sector are given in Figure 2.2 below.

Figure 2.2 Sectoral changes in employment with ambitious climate change mitigation policies, in percentage deviation from the business as usual scenario in 2030 (OECD countries)



Source OECD ENV-linkages model (OECD, 2015b)

Other work has addressed the labour market implications of the societal megatrends. The demographic shift has a potential to create jobs, particularly in the health care and social care sectors (Schultz & Geyer, 2015). The aging population will create more demand for labour in these sectors. Still, workers need to have the right set of skills to be able to be employed in these positions. In many countries, demand is already higher than supply for these occupations and this gap is expected to expand, because of the high average age of workers in health and social care. A related issue in this regard is that in many sectors workers are retiring later. To motivate workers to remain economically active, a change of position could be needed (e.g. a shift from manual to intellectual work). Such a change, however, often does require a new set of skills. That is why, policies to stimulate life-long learning are highly valuable (Ruzik-Sierdzinska & Radvansky, 2015). Technological progress is associated with job creation and job destruction, because productivity is becoming decoupled from employment and many routine jobs are automated (Autor *et al.*, 2003; Rotman, 2013).

As is clear from the brief overview above, the socio-ecological transition undoubtedly has an impact on the demand and supply side of the labour market. The megatrends are associated with job destruction and job creation, and with the emergence of new skills or the disappearance of skills that have become redundant. Occupational and skill changes are therefore interesting subjects to research in depth. In the remainder of this report, we will present the academic and policy discourse on these topics.

3. Academic discourse on new occupations and skills

This section introduces the academic discourse on new occupations and skills. The academic literature on jobs and skills is extensive and covers many contributions on job creation and destruction, skill upgrading, unemployment and wage inequality, among a wide range of different topics. As the structure of employment is constantly changing, and new jobs and skills are frequently arising, many researchers have tried to understand these dynamics (Goos *et al.*, 2009). This section therefore provides a review of this strand of the literature, focusing on the definition, measurement, drivers and consequences of new occupations and skills. In the first part of the section, the concepts of occupations, jobs, tasks and skills are clarified and the complex relationship between them is studied. The section then continues with a more in-depth discussion of occupational classification systems. The final part covers occupational and skill change in the 21th century. Note that there are also important links between labour, on the one hand, and inequality, growth and other fields, on the other hand. A further exploration of these links, however, is beyond the scope of this report.

3.1 Occupations, jobs, tasks and skills and the complex relationship between them

3.1.1 What is an occupation? What is a skill?

At the heart of the discourse on new jobs and skills lies the concept of occupations. An occupation can be defined as 'a grouping of jobs involving similar tasks, which require a similar skills set' (ESCO, 2015). It includes multiple jobs or job titles that have common characteristics. A job, on the other hand, 'is bound to a specific work context and executed by one person' (ESCO, 2015). In the latest edition of the International Standard Classification of Occupations (ISCO), the International Labour Organisation (ILO) identifies a job as a 'set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self-employment' while an occupation is 'a set of jobs whose main tasks and duties are characterised by a high degree of similarity' (ISCO, 2008). Tijdens (2010) uses the following definition: 'An occupation is a bundle of job titles, clustered in such a way that survey respondents in a valid way will recognise it as their job title; an occupation identifies a set of tasks distinct from another occupation; an occupation should have at least a non-negligible number of jobholders and it should not have an extremely large share in the labour force'. Elias (1997) goes back to the history of an 'occupation', which still has an impact on how the concept is regarded today. He maintains that occupations have clear space and time dimensions which can extend beyond the job that one holds. Damarin (2006) explains that occupations generally are regarded as a mechanism for dividing, allocating and directing labour. This view builds on the work of Abbott (1995), which lists three crucial occupational features: 'a particular group of people, a particular type of work and an organised body or structure other than the workplace itself' (pp. 873-874). This group of people can be distinguished by their skills, experience, culture, gender or race, while the group of tasks can be split according to products, activities, tools or customers (and other categories). Occupations, however, are considered as relatively stable across time and organisations. Occupations typically are presented in an occupational classification, in which they are grouped on the basis of similarity in terms of tasks, responsibilities, education and skill level.

Although the difference between an occupation and a job is clear in theory, it is not straightforward to disentangle these two concepts in practice. In fact, the two concepts can even coincide. An example is 'project manager', which can refer to a broader occupation or a specific job (e.g. project manager in an IT firm). In addition, in some cases, it is rather difficult to infer any information about a worker's occupation from the job title: a project manager in an IT firm and one working for a charity can have a very different set of tasks (depending on the work context). At the same time, two workers with the same occupation may have completely different job titles, e.g. astronaut, cosmonaut or taikonaut, notwithstanding that they perform similar tasks. Another issue is that given that an occupation is a group of jobs with similar tasks and skills, one may wonder how similar these actually have to be? Damarin (2006) further finds that when workers are asked to describe their jobs, many of them list multiple roles (that often vary across jobs and organisations). Some occupations can be distinguished through differences in education requirements or earnings. Because the distinction between occupations and jobs is not always clear, the concepts are sometimes regarded as 'interchangeable'. Moreover, there are many studies on the labour market and work that start from the concept of 'jobs' (without referring to occupations), while the term 'occupation' appears to be particularly important in specific strands of the literature. Tomaskovic-Devey (1995) explains that the concept is relevant for comparative work at the national or international level, precisely because occupations are independent from the specific work context, in contrast to jobs. Levenson and Zoghi (2010) maintain that occupations have a central role in the labour market. Both formal education and on-the-job training often are aimed towards a set of skills useful in different categories of jobs (i.e. occupations). Moreover, occupation-specific experience appears to be valuable in the labour market.

In each of the definitions of occupations and jobs listed above, the concepts of 'tasks' and 'skills' are present. These concepts therefore clearly are important building blocks in the literature as well. Acemoglu and Autor (2011) define a task as a 'unit of work activity that produces output (goods and services)' (p. 2) and a skill as a 'worker's endowment of capabilities for performing various tasks' (p. 2). In exchange for a wage, workers apply their skill endowments to tasks and generate output. Commonly, tasks are divided into routine and non-routines tasks (Baumgarten, 2015). Another definition for skills is given by the ILO; where a skill is 'the ability to carry out the tasks and duties of a given job' (ISCO, 2008). In ISCO, both the skill level and skill specialisation are considered. The European Commission uses 'skills' and 'competences' (ESCO, 2015). Both are defined according to the European Qualifications Framework. Skills are 'the ability to apply knowledge and use know-how to complete tasks and solve problems'. Competences refer to 'the proven ability to use knowledge, skills and personal, social and/or methodological abilities in work or study situations and in professional and personal development'. From a review of the concept and measurement of skills in the social sciences, Spenner (1990) concludes that increasingly skills are measured directly either via expert systems (e.g. Dictionary of Occupational Titles) or self-report measures. Correlations between both measures are high. Initially, skills commonly were assessed on a case-by-case basis but later large-scale surveys of employers and employees were used instead (Gallie *et al.*, 2003). Furthermore, the skill level of an occupation was often derived from the occupational classification. Occupational classifications, however, are not stable over time and reflect different bundles of tasks from one period to another (due to technological or organisational change) (Gallie *et al.*, 2003). For this reason, skill levels are often proxied by learning requirements in more recent work.

There are two caveats to this approach, however: it primarily focuses on initial knowledge acquisition and it ignores the issue of mismatch (Gallie *et al.*, 2003; Borghans *et al.*, 2001). Other ways to measure skills are standardised tests (PISA), wages, experience or other proxies (Elias & McKnight, 2001; Borghans *et al.*, 2001). Similarly to tasks, skills are commonly separated into groups (generic and occupation-related skills (Tijdens *et al.*, 2012), cognitive and non-cognitive skills (Brunello & Schlotter, 2011; Kureková *et al.*, 2015b). Tijdens *et al.* (2012) indicate that in contrast to generic skills, which are commonly measured via surveys, occupation-related skills are hardly ever measured in this way. In addition, they find that it is difficult to measure mismatch by comparing educational attainment and skill requirements of occupations.

Making the distinction between tasks and skills can be rather complicated. Workers of a given skill level can carry out a range of tasks, and at the same time workers with the same skill level can perform tasks of different levels of complexity. As workers need to possess the right set of skills to be able to do the tasks associated with their job, employers emphasise skills in the hiring process (Winterton, 2009). Additionally, there is a clear link between skills, tasks, jobs and occupations. Occupations are grouped on the basis of tasks and responsibilities, education and skills. Moreover, skills are often proxied by occupations or derived from the occupational classifications. This implies that when in doing research on one of these concepts, one also has to account for the other concepts. This notion is very important and will come back throughout the remainder of the report.

3.1.2 Occupations and skills in the academic literature

Occupations, jobs, tasks and skills are strongly intertwined and all are affected by the socio-ecological transformation. How are these four concepts used and analysed in the academic literature? In the social sciences, academic contributions covering all concepts are found but often these are discussed in a rather abstract way. Some of the concepts appear to be particularly important in certain strands of the literature. In this section, we present some examples of work on occupations and skills. Note that there is a vast body of studies on jobs and tasks in the literature as well. The strong link between jobs, occupations, tasks and skills and the 'interchangeable' way in which these concepts are sometimes used also becomes clear in Sections 3.1.3, 3.2 (on classifications) and 3.3 (a more extensive overview of the literature). Here, we present a number of papers that specifically cover occupations and skills.

While the concept of an occupation is absent in some strands of literature in the social sciences, it is a highly important concept in other branches. In this regard, Tijdens *et al.* (2012) point to the research on *education, vocational training, school-to-work transitions, and other areas* in which occupations are key. In their study, Tijdens *et al.* (2012) analyse how *work activities and skill requirements* are measured on the basis of occupations. For comparative research on this topic, a sufficiently detailed occupational classification is required (one going beyond the 4-digit level). Other work deals with a *single occupation or a set of occupations*. Recent work has concentrated on STEM (science, technology, engineering and mathematics) occupations, for example. Rothwell (2013) reports that there many STEM positions that require an associate's degree or less, in contrast to what one might expect. Unfortunately, these positions have been overlooked by policy-makers. Hanson and Slaughter (2015) document employment in STEM occupations in the United States. In the paper, the definition of an occupation is derived from the Ipums survey. Results indicate that employment in the STEM occupations follows the boom-bust cycle in the technology industry. In the US, foreign workers are strongly represented in STEM jobs, especially in computer-related occupations. The wage gap between native and foreign workers also is smaller in STEM than in non-STEM occupations, and earnings parity is reached much faster in the former as well. Pan (2015) evaluates gender segregation in occupations. Related work is embedded in the disciplines of sociology and psychology. In these fields, studies typically deal with gender, socio-economic or ethnic gaps and stereotypes in specific occupations (Byars-Winston *et al.*, 2015; Daniels & Sherman, 2015; Hauser & Warren, 1997; Shinar, 1975) and occupation-related features or issues (e.g. burnout, wages and working conditions, Maslach *et al.*, 2001; Narayanan *et al.*, 1999; Johnson *et al.*, 2005).

A related strand of literature deals with *occupational stability and mobility*. Gervais *et al.* (2014) focus on the latter. With a dataset on occupational mobility extracted from the Panel Study of Income

Dynamics (PSID),[1] the relationship between unemployment and occupations is examined. In the model, workers can learn in which occupation they are the most productive by sampling occupations over their careers (i.e. they are informed on the quality of the match). Younger workers are more likely to be in an occupation that is not a good fit and spend more time in transition between occupations. The PSID data are also used by Kambourov and Manovskii (2008) for an analysis of occupational and industry mobility in the United States. Mobility is high and it grew substantially during 1968-1997. It does not seem to be specific to a one-digit occupation. Kambourov and Manovskii (2008) further report that skills accumulated in a 3-digit occupation cannot be easily transferred to other 3-digit occupations (but this may not apply to all 3-digit occupations). At the same time, for other 3-digit occupations an even finer partition would be valuable. Another paper on occupational mobility is Groes *et al.* (2015), who use administrative data to study the phenomenon in Denmark. In their work, occupations are defined following the Danish occupational classification DISCO, which is based on ISCO88. Groes *et al.* (2015) detect that workers with the highest or lowest wages within their occupations have the highest probability of leaving it (U-shaped). Those with the highest relative wages within their occupation tend to switch to occupations with higher average wages; the opposite holds for workers with lower relative wages within an occupation. However, for some occupations the authors find that higher (lower) paid workers tend to switch when the relative productivity of the occupation sharply declines (goes up). Finally, Baumgarten (2015) relates outsourcing to occupational stability in Germany. While the overall effect is positive (stability is maintained), workers employed in occupations that are characterised by a low degree of non-routineness and interactivity suffer from greater instability.

In other work, *both occupations and skills* are explored. Fitzenberger and Licklederer (2014) consider *school-to-work transitions, skill formation and career guidance* of students graduating from lower-track secondary schools in Germany. Most students with poor grades appear to continue with pre-vocational training despite the fact that career guidance appeared to be effective (as students became more aware of their desired occupation). Virolainen and Stenström (2014) compare the system of *vocational training* in Finland with the systems of Norway, Denmark, Sweden, Germany and the United Kingdom. They report that completion of upper secondary education is the highest in Sweden and Finland, which could be due to the fact that in both countries both vocational and upper secondary education students are eligible for and proceed to higher education. In other words, vocational training is not a 'dead end' in these countries. The massification of higher education, however, complicates the transition of vocational education graduates to the labour market: there is increasing competition with higher education graduates (in all countries except for Germany, the completion of tertiary education has increased). Tyler *et al.* (1999) focus on the *cognitive skills* of young high school dropouts in the United States. They find that annual earnings are higher for young dropouts with higher levels of basic cognitive skills.

Caroleo and Pastore (2015) survey the literature on *educational and skills mismatch*. Mismatch can be of a horizontal (level of schooling is appropriate, the type of schooling is not) or vertical (over- or under education) nature. These issues have mostly been investigated from the supply rather than the demand side of the labour market. Theoretical work explains *over-education* on the basis of a set of models: the human capital theory (over-education results from a lack of skills gained through work experience), the job competition model (rigidity in demand for highly educated labour encourages students to acquire more education, which could be more than that requested), the assignment theory, job search models and career mobility models. Allen and van der Velden (2001) put the assignment theory to the test. Educational mismatches do not necessarily imply skill mismatches. Furthermore,

1 PSID is the The Panel Study of Income Dynamics. It is one of the longest running longitudinal household surveys in the world. In fact, the study was launched in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Information on these 18,000 individuals and their descendants has been collected on a continuous basis. Data on employment, income, wealth, expenditures, health, marriage, childbearing, child development, philanthropy, education, and numerous other topics are collected. It is directed by the University of Michigan and carried out by the Institute for Social Research. Data are available free of charge to researchers and analysts.

educational mismatches have a clear impact on wages, and only a small part of this effect is accounted for by skill mismatches. Skill mismatches, on the other hand, are important for job satisfaction and on-the-job search, in contrast to educational mismatches. For skills, there thus seems to be an extensive literature covering mismatch, overeducation, educational attainment, skill measurement and a variety of other subjects.

3.1.3 What are new occupations? What are new skills?

Among the economic consequences induced by the socio-ecological transformation that Europe is experiencing is the emergence of new jobs and skills. Occupations, jobs and tasks are constantly changing. New occupations arise when employers need workers to do tasks that have never been done before (Crosby, 2002). Initially, tasks may have been added to jobs that already exist. However, when tasks cannot be added to existing jobs or when these tasks are sufficiently different and become the primary job of a sufficient number of workers, then the new 'speciality' develops into an occupation of its own. The concept of a 'task' therefore is another fundamental building block in the literature. The introduction of new tasks is generally accompanied by changes in the skill demand. Crosby (2002) postulates that workers in new and emerging occupations generally combine basic skills with knowledge or experience in a subject related to the occupation. As is the case for the difference between occupations and jobs, making the distinction between tasks and skills can be rather a complicated process. We briefly pointed to this issue earlier, and it also became clear in the work of Acemoglu and Autor (2011). Workers of a given skill level can indeed carry out a range of tasks. Moreover, tasks are subject to change as a result of technological progress and changes in the labour market conditions. New occupations arise that strongly draw upon an existing set of skills or emerge because certain skills are applied to a new context (e.g. data analysis skills became more important in the social sciences). In this report, we therefore devote attention to jobs, tasks, skills and the relationship between them.

The identification of new occupations and skills is complex. A first important step is to identify which occupations already exist and which ones are relatively new. To this end, Crosby (2002) distinguishes between new, emerging and evolving occupations. The author thinks of evolving occupations as existing occupations with tasks that are changing drastically (for example, software engineers learning to program AI). New occupations, in contrast, have only recently materialised. The definition of 'recently', however, depends on the study. In the majority of studies, it means that the occupation is not included in the most current occupational classification system (Crosby, 2002). Emerging occupations have small employment numbers but are expected to grow larger in the future (and become easier to identify than completely new occupations, because some occupations are only noticed when they have grown sufficiently, e.g. massage therapists). From this work, one can see how existing occupations are changing (or evolving) into new occupations, which potentially grow larger and become more widespread throughout the economy. Among the factors driving the rise of new occupations, Crosby (2002) recognises the role of the socio-ecological transition (pointing out technological change, demographic shifts and social developments, the growing number of two-income households). She also points to changes in law and business practices. Nevertheless, it remains difficult to predict whether or not these drivers will bring about new occupations (i.e. surpassing the phase of being evolving occupations, which mainly have a skill dimension).

The distinction between new, emerging and evolving occupations can also be found in *other studies*. In some cases, these concepts are defined on the basis of the most recent occupational classification. In other cases, other measures are used. An overview of these studies is given by Crosby (2002). She concludes that to identify new occupations the majority of studies rely on surveys, employer interviews, trade publications, job postings (and the corresponding job titles), in addition to the current occupational classification. Some examples are given below. The US Bureau of Labor conducts a survey among employers to identify new occupations. Employers are provided with a list of common occupations, and asked to add missing occupations to this list. A lot of attention is devoted to occupations that are absent but show high employment numbers, or that emerge because of technological progress. In addition, the US Bureau of Labor also has a census, to which new job titles are added when detected in the coding process or at the request of experts. However, not all new job titles are added and a new occupation is not created for every new title in the census. In fact, job titles are organised within the existing occupations to the maximum extent possible. The Texas Career Development Resources office collects information via job postings, employer interviews, trade publications, among other sources. Traditional occupations included in the Standard Occupational Classification System (SOC) of 1980 that have seen substantial changes in terms of knowledge or skills are labelled 'evolving occupations'. 'Emerging occupations', on the other hand, are defined as occupations that are not identified in the SOC of 1980, but are 'new' (with new titles and new skills sets). The Minnesota Workforce Center also relies on employer surveys and on the 1980 SOC. It regards occupations as 'new' when they are characterised by work activities, skills and knowledge that are so new that they cannot be classified under the existing system. Evolving occupations, on the other hand, are existing occupations with rapidly changing skill sets, requiring new knowledge. The Department of Labor of the State of New York regularly issues a newsletter in which new and emerging occupations are discussed (https://www.labor.ny.gov/stats/enys_index.shtm). Recent examples of such occupations are bio-informatics technicians, energy brokers and Digital Forensics Investigators & Analysts. Another interesting paper is Lin (2011). In this article, the growth of 'new work' in the United States is documented on the basis of the growth of employment in newly introduced occupation codes in the Census. New occupational titles appear to belong to the following two categories: new titles associated with new technologies (e.g. web developer) and new titles associated with new personal services (e.g. stylist).

According to most of the literature, *new occupations therefore appear to develop out of existing occupations, or combinations thereof, at least to some extent.* Furthermore, the identification of new occupations is largely dependent on the introduction of new tasks (with a matching skill set) and the most recent occupational classification. However, even with an up-to-date list of occupations it remains difficult to predict which and how fast occupations will grow. Moreover, to identify a 'new' occupation, one needs to have a benchmark to weigh it against (i.e. to understand what 'new' really means). This raises the question whether the most recent occupational classification (from ISCO, ESCO or other institutions) actually is the most suitable benchmark. This issue will be discussed in more depth later. Nevertheless, keeping track of new, emerging and evolving occupations is important as this process may have implications for many domains of the economy and there is a clear link to the skill dimension. Many schools and colleges indeed try to adjust their educational programmes to developments in the labour market. Moreover, to transfer from one job to the next (given that many new occupations evolve from existing ones or are combinations of several existing ones, and require specialisation in certain tasks), workers need to have a set of skills to fall back on. Transferable skills, formal education and on-the-job training are therefore highly relevant.

The identification of new skills is somewhat less explicit in the academic literature, but from the work of Crosby (2002) and some of the other examples presented above it is clear that this -similarly to the identification of new occupations- strongly depends on the new tasks that are introduced. When a new task emerges, it often calls for new skills and new knowledge. Alternatively, this could also imply that existing skills and knowledge are combined in new ways. Other work has also pointed to the role of the drivers of new occupations or tasks for the introduction of new skills. For example, the advancement of information and communication technologies is accompanied by new forms of media, which means that 'new media literacy' can become an important skill in the future that did not yet exist. Similarly as for new occupations, new skills can be identified in a number of ways such as through surveys, interviews, skill classifications and case studies. Adler (1986), for example, takes the perspective of a manager, who has to assess the skill implications of technological change. On the basis of a case study for a large French bank, he demonstrates how new technologies introduced new tasks that in turn affect the skill demand (e.g. responsibility, interdependence and abstract skills became highly relevant in this case). Another way to identify new and emerging skills could be by monitoring the current skills needs and gaps and by anticipating the skill needs of the future. This approach will not reveal new skills in each case but could be a way to discover new skills nonetheless. Wilson and Zukersteinova (2011) provide an overview of four methods that are used to forecast future skill needs. A first method is based on formal quantitative models. This method is comprehensive, consistent and transparent, but is data intensive, costly and could give a false impression of precision and certainty. The second method is by directly asking employers about current and future skill needs. While this method is easy and direct, it could also be too specific, subjective, and inconsistent. A third method involves other qualitative approaches (e.g. focus groups, Delphi style methods and scenario developments). According to Wilson and Zukersteinova (2011), this method is holistic and direct but it could also be non-systematic, subjective and inconsistent. The final method comprises sectoral studies, regional and other observatories (qualitative and quantitative methods). This approach is holistic as well, but only covers the sector. Wilson and Zukersteinova (2011) find that quantitative modelling methods are used in general.

Importantly, the concepts of new and emerging occupations and the corresponding set of skills appear to be relatively clear from the papers listed above, but only a limited number of studies seem to explicitly cover this topic. Nevertheless, especially in terms of new skills, further clarifications and fine-tuning of the definitions could be helpful. The concept of a task also appears to be very important for both occupations and skills, but only little attention is paid to tasks in the literature. Moreover, to derive what a (new or emerging) occupation/skill is and how it can be identified/measured, academics strongly rely on policy documents and data sources. With these conclusions in mind, we continue with an analysis of occupational and skill classifications.

3.2 The classification of occupations and skills

A key concept in the debate on new and emerging occupations is the occupational classification. As illustrated above, occupations are generally regarded as new when they are absent from the most recent occupational classification used. The system of occupational classifications should therefore be explored in more depth. In this section, we introduce classifications of occupations and skills, and specifically focus on ISCO, ISCED, DISCO, ESCO, DOT, O*NET and SOC (see the short overview in Table 3.1).

Table 3.1 Overview of occupational and skill classifications

ISCO	International Standard Classification of Occupations (United Nations). ISCO is a tool for organising jobs according to the tasks and duties undertaken. Its aims are to provide: a basis for international reporting, comparison and exchange of occupation data; a model for the development of occupational classifications; and a system that can be used directly in countries without a national classification. In the most recent edition, jobs are categorised by occupation by the type of work done and ranked on the basis of the skill level and skill specialisation they require. In ISCO-08, nine different groups are distinguished.
ISCED	International Standard Classification of Education (United Nations). It is a tool to assemble, compile and report education statistics both within individual countries and internationally. It allows to map national educational classifications into an internationally comparable system. In ISCED, programmes are categorised by level of education on a hierarchical scale, which ranges from pre-primary education to the doctoral level. The classification scheme relies on both the levels and the fields of education. ISCED (2011) distinguishes nine education levels.
DISCO	European Dictionary of Skills and Competences (European Commission). DISCO is a comprehensive database of skill and competences terms (over 104,000) and sample phrases (over 36,000). In the database, skills and competences are classified, described and translated. Today, 11 languages are supported but the tool is being expanded to cover even more languages. DISCO is compatible with other European tools such as Europass and ESCO.
ESCO	European Skills, Competences, Qualifications and Occupations (European Commission, together with CEDEFOP). The ESCO classification consists of three pillars: skills and competences, qualifications and occupations. As such, it bridges the gap between education/training and work. Attention is also being paid to the link between them. ESCO further aims to contribute to labour mobility, online matching and shifting labour outcomes. ESCO's occupation pillar is linked to ISCO.
DOT	Dictionary of Occupational Titles (US Department of Labor). First published at the end of the 1930s, as a reference manual for the US Employment Service as it aimed to advance labour market matching. The dictionary contained occupational information as well as information on workers. The DOT has been replaced by O*NET in 1999.
O*NET	O*NET was introduced as an online version of the Dictionary of Occupational Titles (US Department of Labor). O*NET has developed into one of the most widely used databases for information on workers, occupations, the labour market, and so on by researchers, policy-makers, career centres and other labour market agents. The data are organised as a content model with six domains. One important advantage is that this extensive database is updated very regularly.
SOC	Standard Occupational Classification (US Department of Labor). First introduced in 1977 and is revised infrequently. It is used to categorise workers into occupational groups for the purpose of collecting, calculating, or disseminating data. There are 23 major groups, 97 minor groups, 461 broad occupations and 840 detailed occupations.

Changes in the occupational structure and the corresponding classification are driven by technological change, changes in consumers' preferences and changes on the supply side of the labour market (widespread higher education) (Elias & McKnight, 2001). The link between occupational classifications and skills/skills classifications is also clear from the articles of Elias and McKnight (2001) and Levenson and Zoghi (2010). Both papers report that common changes in the skill structure in an economy are studied with occupation-based measures. These measures are easily available and cover the range of skills needed to do a job. However, there are also caveats. Elias and McKnight (2001), for instance, report that detailed occupational categories are less reliable for skill measurement, because they are prone to coding errors. Levenson and Zoghi (2010) find the occupation-based approach too simplistic. They claim that the distinction between skills in the initial occupational classification schemes may not have been accurate. In addition, skills can vary considerably between jobs that are part of the same occupation and subject to changes over time (mean level and skill variation within occupations).

3.2.1 Definitions

The International Labour Organisation (ILO) defines an **occupational classification** as a 'tool for organising all jobs in an establishment, an industry or a country into a clearly defined set of groups according to the tasks and duties undertaken in the jobs' (ILO, 2015). According to the ILO, occupational classifications generally comprise two elements: the *classification system* (which outlines the system and includes occupational titles, codes and a description of the tasks involved) and a *descriptive component* (which can be regarded as a *dictionary of occupations*, because it provides details on tasks and duties, the goods and services produced, skill level and specialisation, and other items). In an occupational classification, jobs with the same set of tasks and duties are aggregated into occupations, which in turn are aggregated into occupational groups.

Much of the thinking about occupations was established in a relatively distant past. In the British Empire of the 19th century, the collection of detailed occupational data first started at the time of the census of 1884, which introduced an occupational classification scheme that comprised 12 classes (Woollard, 1998). This census was the first attempt to create an occupational classification, banding together jobs within an economic structure. This classification scheme was revised in 1851 by William Far, after which it was composed of 17 classes and 90 sub-classes. In the new scheme, occupations were classified on the basis of five main characteristics: (1) skill, talent or intelligence; (2) tools, instruments, machinery or structures; (3) materials; (5) processes; and (6) products. Of these five characteristics, 'materials' was deemed the most important one. To arrive at this classification of occupations, a standardisation of the millions of colourful job titles was necessary. This was not a straightforward process due to geographical and temporal differences, the practice to enlist multiple occupations and other obstacles (for more examples, see Woollard, 1998). For similar reasons, the earliest occupational classifications commonly had a clear local or regional dimension. In the 19th century, occupational classifications generally were associated with the industry in which the workers were employed (Levenson & Zoghi, 2010). Later, workers were no longer classified on the basis of the product they were making but rather by the kind of work they were performing. Herman and Abraham (1999) confirm that the basis for the categorisation of occupations shifted from industry to work characteristics.

The earliest classifications mainly served as a source of occupation-specific mortality rates, a device to make each occupation more manageable, and for actuarial purposes (Woollard, 1998). Later, occupational classifications were used to categorise the population by industrial and social class. Nowadays, occupational classifications are used by agents on the demand and supply side of the labour market because they provide valuable insights into the economic and social structure of society (ILO, 2015). Occupational classifications facilitate job search, applicant screening and matching, and inform job applicants on the job and skill requirements (Levenson & Zoghi, 2010). In addition, occupational classifications are often used for research. Detailed occupational descriptions hold information on tasks, requirements and working conditions. The classification structure itself can be used to support matching, and for labour market analysis and statistical purposes (ILO, 2015).

One of the main challenges of occupational classifications was how to convert them into a reliable measure of the dynamics of the labour market. This challenge dates back to the time when occupational classifications were first introduced. Even then, occupational classifications were criticised and often revised (Woollard, 1998). To date, this challenge still is largely unresolved. In fact, until the end of the Second World War, occupational classifications remained mainly regionally rooted. After World War II, a new set of occupational classifications were published, by (newly founded) political institutes and international institutions. These occupational classifications do account for cross-country differences.

The **classification of skills** has also received a lot of attention from researchers and policy-makers. Skill classifications became more prominent when it was clear that the traditional occupational classifications failed to reflect labour market transformation and interdependencies (Markowitsch & Plaimauer, 2009). Occupational and skill classifications can be regarded as complementary. Competences and skills have gained importance in matching in the last few years. In addition, a skills classification can strengthen the link between the education sector and other sectors in the economy and stimulate mobility.

3.2.2 ISCO and ISCED

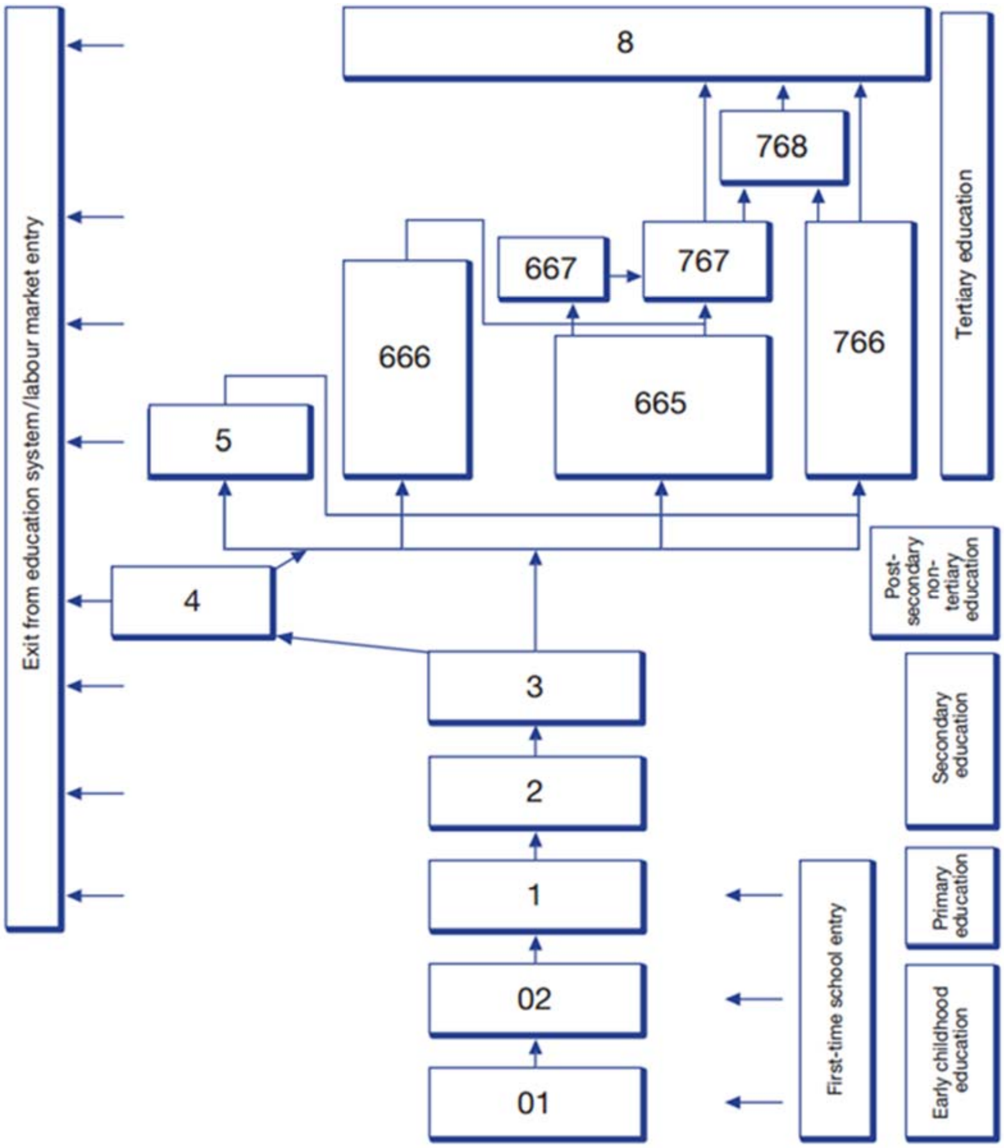
In the 1950s, the United Nations (UN) developed a more structured and internationally comparable occupation taxonomy. This taxonomy was at the root of the **International Standard Classification of Occupations** (**ISCO**), which was first published in 1958. The main goal of this classification was to map national classifications into a common internationally comparable taxonomy, thus enabling international comparisons and stimulating labour mobility (ILO, 1958). In ISCO, currently in the 2008 version, jobs are categorised by occupation by the type of work done. The distinction between major, sub-major, minor and unit groups within the classification is based on the 'skill level' and 'skill specialisation' that one needs to perform the tasks and duties of the job (ISCO, 2008). In ISCO 2008, a skill is 'the ability to carry out the tasks and duties of a given job'. The 'skill level' is related to the complexity and range of the tasks involved; accounting for the nature of the work, the formal education and experience needed, and the degree of on-the-job-training. 'Skill specialisation' refers to the type of knowledge applied, the tools, equipment and materials used and the nature of the goods and services produced. In ISCO 2008, this skill-based approach results in nine major groups, which are ranked on a hierarchical scale from levels 1 to 9: managers (level 1); professionals (level 2); technicians and associate professionals (level 3); clerical support workers (level 4); service and sales workers (level 5); skilled agricultural, forestry and fishery workers (level 6); craft and related trades workers (level 7); plant and machine operators, and assemblers (level 8); and elementary occupations (level 9). The 'armed forces occupations' (level 0) are excluded from the ranking due to the high degree of heterogeneity of skill demands across these occupations. Currently, ISCO still is the most widespread classification system of occupations, as evidenced by work done for the EurOccupations project. Nevertheless, there appears to be a lot of heterogeneity within individual occupations. Furthermore, the link between occupations and skills seems to be unclear.

The International Standard Classification of Occupations (ISCO) has not been without criticism since it was first launched. Elias (1997) summarises some limitations in his paper. Examples are issues related to the occupational data (quality, availability), the coding process (coding or interpretation errors, especially at a more disaggregated level) and the occupational classification itself (poor structure, based on concepts that cannot be operationalised, limited international comparability). Another interesting point that Elias (1997) makes is related to the concept of an occupation. This clearly has a time and space dimension, which implies that the social context and the type of questions and data sources certainly have an impact on the occupational data that are gathered. Moreover, the data collection and classification process are likely to affect the potential uses of the data afterwards. This issue should not be overlooked.

Along with the development of ISCO, the United Nations introduced the **International Standard Classification of Education (ISCED)**, which was first published in 1976 and is maintained by UNESCO. The most recent update was in 2011. The concept behind ISCED is highly similar to that of ISCO, i.e. to map national educational classifications into an internationally comparable system (ISCED, 1976). With ISCED, one should be able to compare education priorities and policies from governments all around the globe. As education systems differ vastly and are subject to substantial changes over time, ISCED is set up to allow for a certain degree of flexibility (as illustrated below). Similarly to ISCO, ISCED classifies programmes by level of education on a hierarchical scale, which ranges from pre-primary education to the doctoral level. The classification scheme relies on both the *levels* and the *fields* of education. ISCED (2011) distinguishes nine levels. These nine levels are the following: early childhood education (level 0), primary education (level 1), lower secondary education (level 2), upper secondary education (level 3), post-secondary non-tertiary education (level 4), short cycle tertiary education (level 5), Bachelor's or equivalent level (level 6), Master's or equivalent level (level 7) and the Doctoral or equivalent level (level 8). ISCED represents a complex structure of formal education while accounting for the differences between national systems.

This is shown in Figure 3.1, which displays potential educational pathways. As illustrated in the figure, national education systems commonly support multiple pathways from level 0/1 to level 8 in the classification. Especially the higher levels, i.e. level 4 and up, have subcategories that reflect the diversity of education systems and the different pathways that students may take. Indeed, most systems include branching paths, alternative programme sequences and second chance provisions (ISCED, 2011). All these education levels also lead to the exit from education option. In addition, ISCED (2011) comprises nine education fields: the general programmes (0), education (1), humanities and arts (2), social sciences, business and law (3), science (4), engineering, manufacturing and construction (5), agriculture (6), health and welfare (7) and services (8). Even though the level and field of education are taken into account, ISCED does not pay much attention to concepts such as lifelong learning, informal education or web-based education. Bohlinger (2013) points out that ISCED cannot be used to assess the competences of an individual as there is 'no direct relationship between educational programmes or qualifications and actual educational attainment' (p. 26). She notes that ISCED should be complemented with information on the traditions, functions and structures of the national system.

Figure 3.1 **ISCED 2011 - Potential educational pathways**



Source ISCED (2011)

3.2.3 DISCO and ESCO

Besides ISCO and ISCED, which were proposed by the United Nations, many other efforts have been made to design a classification of occupations/education/skills. At the European level, two initiatives are particularly interesting: the European Skills, Competences, Qualifications and Occupations (ESCO) and the European Dictionary of Skills and Competences (DISCO) projects. DISCO is a comprehensive database of skill and competences terms (over 104,000) and sample phrases (over 36,000). In the database, skills and competences are classified, described and translated (currently 11 languages are supported). DISCO cannot only be used for the analysis of competences and skills across occupations, but it also functions as a tool for other applications such as CVs, job advertisements and matching, and the description of learning outcomes.

In contrast to DISCO, the ESCO classification goes beyond the concepts of skills and competences. ESCO instead has the objective to capture the dynamics of the labour market and to bridge the gap between education and training, on the one hand, and work, on the other hand. To this end, the ESCO classification is being set up as a comprehensive classification that comprises three pillars and accounts for the relations between them. These three pillars are: (1) skills and competences (of a transversal, cross-sector, sector-specific and occupation-specific nature), (2) qualifications (awarded at the (inter-)national level, linked to tasks, technologies, occupations or sectors) and (3) occupations (structured hierarchically, linked to ISCO). As the final ESCO classification promises to be a rich data source that connects education with work and allowing for cross-country comparisons, it supports online matching and stimulates mobility. The development of ESCO is part of the Europe2020 strategy; the project has not yet been finalised. The first version of ESCO became available in the fall of 2013. Despite the potential advantages that ESCO can offer in comparison to ISCO, the database is not ready yet and it is unlikely to be without limitations either.

1.1.1 DOT, O*NET and SOC

Two other projects that are particularly interesting in this context are the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET) (both developed by the United States government). The Dictionary of Occupational Titles was first published at the end of the 1930s by the US Department of Labor. Data were collected through on-site observations of jobs while these were being performed. The DOT was originally designed as a reference manual for the US Employment Service, and consequently it was mainly regarded as a tool to promote labour market matching (Cain & Treiman, 1981). The dictionary holds information on different kinds of jobs and their main tasks. For each occupation, a definition and a classification code are available, in addition to scores on 44 characteristics (e.g. related to training times, working conditions and physical demands). Initially, especially information on the job content was included, but later workers' characteristics were considered too. Being created in the 1930s, the DOT mainly covered blue-collar jobs in manufacturing sectors. This, however, resulted in a severe over-representation of 'production jobs' in the dictionary in the second half of the 20th century (i.e. in terms of sampling, coverage and data representativeness) (Cain & Treiman, 1981). Other limitations of the DOT, according to Cain and Treiman (1981), are the lack of information on the hierarchy of jobs (level of authority and interrelations) and the fact that more recent versions largely take over the content from earlier versions. Stevens (1993) critically reviewed the DOT and the Standard Occupational Classification Manual (SOC). He mainly focuses on the incompatibilities between these two systems, with implications for e.g. labour market and occupational information systems, and work on competency and skills measurement. Stevens (1993) further calls for more communication and a better collaboration between the different branches of government. Other work has concentrated on the Standard Occupational Classification as well (e.g. Herman & Abraham, 1999). The SOC was first introduced in 1977 and is revised infrequently.

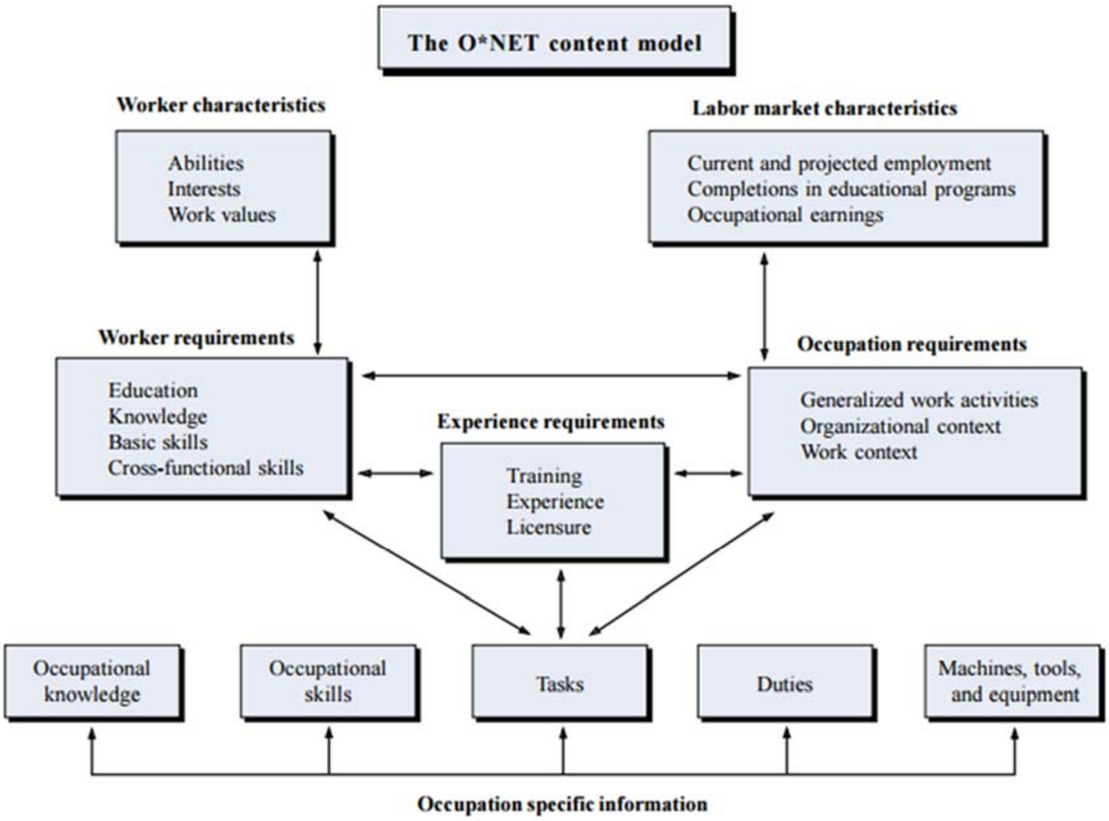
The Dictionary of Occupational Titles appeared for the last time in March 1999. It was regarded as obsolete and replaced by O*NET, an online database (instead of a book). Mariani (1999) describes the transition from the dictionary of occupational titles to the occupational information network. O*NET uses a standard occupational classification (linked to labour market data) and is specifically designed to better reflect the current state of the labour market, in which services and information are important concepts. O*NET serves two important purposes: it supports individuals in making education and training decisions and investments, as well as the business and community needs for a prepared and globally competitive workforce (NRC, 2010).

O*NET is organised as a content model with six domains (depicted in Figure 3.2): worker characteristics (which influence performance and one's capacity to acquire knowledge and skills), worker requirements (work-related attributes gained through education or experience), experience requirements (linked to specific work activities), labour market characteristics (or workforce characteristics, i.e. general characteristics of occupations or that influence them), occupation requirements (linked to specific occupations) and occupation-specific information (either apply to an occupation or narrowly defined job category) (NRC, 2010). Each of these six domains is composed of subcategories of occupational information. Examples are knowledge, experience, work activities, organisational context, and so on. One of the key differences between the DOT and O*NET is that the latter stresses skills, in addition to tasks - which are important in both - (Mariani, 1999). Seven groups of skills are considered: content skills, process skills, social skills, complex problem-solving skills, technical skills, systems skills and resource management skills. The first two skills in this list are basic skills; the last five are labelled transferable skills. Furthermore, the O*NET database bridges the gap between education and work, since it indicates the knowledge and training required for specific occupations. Other advantages of the system are that it provides up-to-date information and that users can organise the data as they want. Data for O*NET were gathered from the original DOT, through surveys and via occupational experts.

In O*NET, the identification of new and emerging occupations is based on two criteria that have to be met simultaneously: the occupation (1) involves significantly different work than other occupations in the database and (2) is not adequately reflected by the existing structure (O*NET, 2006). O*NET assembles 'background' information on these occupations, such as their development, employment numbers, education requirements, licensing and associations. O*NET focuses on the identification of new and emerging occupations in high-growth industries. Potential candidates are found by using a web-search methodology (i.e. searching the websites of sector associations and job portals, finding associations and educational programs) and by following leads from the US Department of Labor and the Employment and Training Administration. A selection of new and emerging occupations is then made, for which occupational profiles are constructed (classified as 'bright outlook' occupations). Examples of such occupations are baristas, industrial ecologists and video game designers.

The US National Research Council has also emphasised the value and usefulness of O*NET, as the database is used by a high number of individuals and organisation to collect information on workforce and career development, academic and policy research, etc. (NRC, 2010). O*NET has developed into a vital tool for many labour market actors.

Figure 3.2 The O*NET content model



Source Mariani (1999, p. 5)

3.2.4 Conclusions on occupational and skill classifications

Although occupational classifications have been a valuable tool for labour market analysis in the past, such classifications clearly do have drawbacks. When we return to the concept of an occupation and its time and space dimensions (as explained by Elias, 1997 and discussed above), one may wonder if occupational classifications are the most appropriate tool to capture the current market dynamics. Given that occupational classifications are only rarely updated,[2] they may not provide up-to-date information on the emergence of occupations and skills. If a new occupation is identified as one that is not included in the most recent (ISCO) classification, one may ask whether this occupation is actually new, or whether it is not included because the classification was last updated more than ten years ago. This is particularly relevant in sectors and firms that are characterised by substantial and swift changes. Importantly, the rapidly changing sectors and firms are very likely to be those that are most affected by the socio-ecological transition (e.g. health care, IT, digitalisation, high-tech manufacturing) - i.e. precisely the labour market dynamics that researchers, policy-makers and other stakeholders (such as the education sector) are interested in. Moreover, if new occupations are only identified as ‘new’ several years after they first emerged, it may be difficult to discover where they first emerged (which sector), how they dispersed through the economy (speed, which sectors were reached first, which sectors followed later) and whether they are indeed new. The implications of these issues potentially are considerable. For example, this time lag clearly precludes a prompt response from policy-makers and impedes schools to align their programmes with the demand of employers on the labour market. Similar issues arise when skill classifications are updated irregularly or insufficiently

2 ISCO was released/updated in 1958, 1968, 1988 and 2008; ISCED in 1976, 1997 and 2011.

detailed. One of the main goals of this report, therefore, is to consider alternative methodologies and data sources to identify new occupations and new skills. For this reason, we focus on the Internet and evaluate its potential as a data source for the analysis of these dynamics. More details are provided in the following sections.

3.3 Occupational and skill change in the 21th century

In this section, occupational and skill changes are discussed in depth, with the aim to identify their drivers and consequences. This analysis is not limited to the changes that occurred in the 21th century, but instead also considers historical trends. This allows us to better understand whether these labour market dynamics are completely new or whether they are part of a longer history of similar changes. As Katz (1972) notes, there has been a vast increase in the number of distinct occupations between the 19th and 20th century. Abbott (1995), in contrast, noted that occupations are relatively stable across time and organisations. The section covers job polarisation, skill-biased technological change and other hypotheses. At the end of the section, an outlook towards the future is presented.

3.3.1 Occupational and skill change in the past

Studies on the history of occupational and skill change often depend on **case studies** to illustrate how occupations and skills were affected by specific factors in the past. One of the main reasons for this is that data on this period are hard to come by.

Chin *et al.* (2006) focus on the **Second Industrial Revolution** at the end of the 19th century. The basis for their work is the literature on technological change and its implications during this period. Early work had reached a broad consensus that technological progress was skill-replacing (i.e. de-skilling). This is confirmed by Frey and Osborne (2013), who explain that technologies increasingly substituted for skills (by task simplification) as artisan shops were replaced by factories and **steam** power was adopted. The introduction of steam power along with major developments in continuous - flow production -production parts became identical and interchangeable -, also gave rise to **assembly lines**. A well-known example is the Ford Motor Company assembly line, where work that was previously performed by one person was now divided among many workers. Frey and Osborne (2013) conclude that in the 19th century, physical capital was a relative complement to unskilled labour but acted as a substitute for relatively skilled labour.

The view that technological progress in the 19th century was de-skilling was later challenged by several studies that presented a more nuanced interpretation. In their paper, Chin *et al.* (2006) make use of a unique data set on merchant mariners. With this data set, they analyse the impact of technological change on the demand for skills and the wage structure in the sector. The results of their analysis suggest that technological progress in the merchant industry had *skill-biased* as well as *skill-replacing* aspects. As the sail was replaced by steam, the occupation of 'sail-maker' became obsolete. Moreover, moderately-skilled able-bodied seamen were replaced by low-skilled engine room operators. Both effects are examples of skill-replacing technological change. Still, the introduction of steam on merchant ships also called for highly skilled engineers on board the ships (which was a new occupation at the time) and able-bodied seamen, mates and carpenters earned a premium relative to workers in similar occupations on sail ships (this could be interpreted as a reward for skill). Chin *et al.* (2006) conclude that the overall impact of the introduction of steam appears to be de-skilling and that the wage structure in the merchant shipping industry became wider.

Frey and Osborne (2013) consider the period of **electrification** at the end of the 19th century/the beginning of the 20th century as a very important period of technological change. The switch from water and steam power to electricity lowered the demand for unskilled manual workers (as many steps of the production process were automated) but raised the demand for skills (skilled blue-collar production workers and white-collar non-production workers - which have higher educational attainment (see Allen, 2001). This was also supported by progress in continuous-flow and batch production and by a collapse in transport costs. An interesting case is presented by Gray (2013), who examines the electrification of the manufacturing sector in the United States at the beginning of the 20th century (when steam was being replaced by electricity). This electrification was accompanied by important productivity gains, which were due to a more efficient use of labour and the introduction of the assembly line, among other factors. What impact did electrification have on the distribution of skills? On the basis of a dataset on the task content of occupations, Gray (2013) shows that electrification resulted in a 'hollowing out' of the skill distribution (known as 'job polarisation', affecting workers in the middle of the distribution, see Section 3.3.2.1). More specifically, the demand for high-skilled blue-collar tasks declined, the demand for low-skilled manual tasks remained stable and the demand for clerical and managerial tasks increased. Gray's results contradict earlier research such as Goldin and Katz (2008), who reported that electrification gave rise to skill-biased technological change. Goldin and Katz (2008) also showed that the downward trend in the education premium during that period was caused by the growing supply of educated workers.

Along with the technological developments that shape the labour market, education has changed dramatically. In the US, this was first reflected in an increasing number of workers with a high school degree (Frey and Osborne, 2013). Recently, it became even more prominent during the 'computer revolution' (which started in 1960, with the first commercial uses of computers, and rapidly grew in the 1990s with the introduction of the Internet). Since the 1980s, educational wage differentials and wage inequality have grown a lot. Frey and Osborne (2013) note that this is often explained by the stronger complementarity between capital and skills that results from the computer revolution. Computerisation raises demand for clerical skills, similarly as the introduction of office machines in the beginning of the 20th century, but it can also lead to automatisation (Autor *et al.*, 2003). Frey and Osborne (2013) therefore conclude that computers have caused a shift in the occupational structure of the labour market: 'the result has been an increasingly polarised labour market, with growing employment in high-income cognitive jobs and low-income manual occupations, accompanied by a hollowing-out of middle-income routine jobs' (p. 12). Akerman, Gaarder and Mogstad (2015) analyse whether the adoption of broadband internet is accompanied by a higher labour productivity and wages. Results suggest that the adoption of broadband internet is associated with a deterioration of the productivity and labour market outcomes of unskilled workers (substitute routine tasks). For skilled workers, broadband internet appears to enhance their productivity and labour market outcomes (complements non-routine tasks).

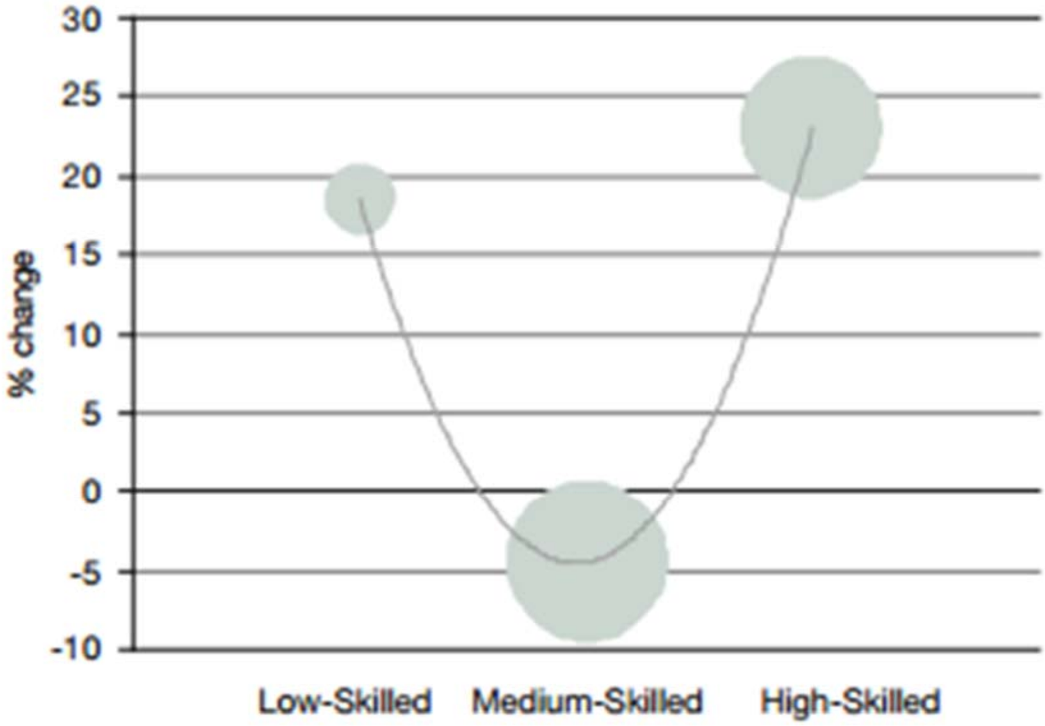
3.3.2 Occupational and skill change in the 21th century

3.3.2.1 Job polarisation

As indicated above, one of the most remarkable characteristics of new jobs and new skills, at least in the context of developed economies, is their polarised nature. The polarisation of labour (or jobs) is a phenomenon where the demand for labour does not rise linearly with the skill level but rather resembles a U-shaped function (as illustrated in Figure 3.3). Instead, there is a polarisation in favour of both low-skilled and high-skilled jobs. Job polarisation has been found in the US (Autor, Katz & Kearney, 2006; who also show that wages have been polarising there), Japan (Ikenaga & Kambayashi, 2010), the UK (Goos & Manning, 2007), Germany (Spitz-Oener, 2006; Dustmann *et al.*, 2009) and other European countries (Goos *et al.*, 2009). In their work, Gallie *et al.* (2003) discuss the polarisation of skills. Skill polarisation can occur at the occupation level: where workers in lower occupational classes face skill stagnation or depreciation, the opposite holds for worker in higher occupational classes because their employers tend to investment in on-the-job training. Skill polarisation could also arise on the basis of contractual status, in a core-periphery setting. At the core, we find full-time permanent workers, who are offered skill training; at the periphery we find part-time and temporary workers.

Job polarisation has received attention from academics and policy-makers. Many studies have been conducted on the causes and consequences of the phenomenon. Among the possible causes of job polarisation are technological change and globalisation, both of which mainly impact routine jobs (Autor *et al.*, 2001; Blinder, 2009). Importantly, especially the jobs in the middle of the distribution are affected (Maselli, 2012). The demand for high-skilled employment has been on the rise for many years, and a similar trend is detected for low-skilled jobs (especially in the service sector) (Maxwell, 2006). Low-skilled service jobs, however, commonly offer minimal levels of job quality and job security, low wages and few possibilities for advancement. These jobs therefore tend to come attached with *negative selection stigma* and are difficult to fill (as many unemployed try to avoid such positions, particularly if before they held low-skilled manufacturing jobs that offered a higher wage) (Lindsay and McQuaid, 2004). Furthermore, while low-skilled service jobs are sometimes referred to as *deskilled* due to the very low barrier to entry; in many cases they tend to be quite demanding in terms of social and language skills and - in some cases - even in terms of formal education.

Figure 3.3 Changes in demand for jobs per ISCO skill level



Source Maselli, 2012

The *up-skilling* of some occupations combined with *de-skilling* associated with many new jobs (especially those in the low-skilled segment) complicates thinking about the labour market structure. This problem, however, is difficult to address. The issue also became clear in the EurOccupations project, which measured internal consistency of a wide range of occupations and found little grounds to assume that workers in the same occupation groups actually perform similar tasks (Tijdens *et al.*, 2012). For these reasons, efforts have been made to include more dimensions into the thinking about jobs (e.g. computer use). In addition, there is a separate stream of literature that is focused on skills rather than jobs (Tijdens *et al.*, 2012) as well as work that aims to bridge the gap between jobs and skills on the basis of novel data sets (Tijdens, 2010; Fabo & Tijdens, 2014). These efforts will be discussed in more detail below. Gallie *et al.* (2003) further report that during 1986-2001, there is a clear rise in the qualifications demanded by employers. There also was a drop in the amount of positions that do not require any education or training and in the number of positions that only require very brief training.

What is driving occupational and skill change? Oesch (2013) explores different possibilities on the basis of a supply-demand-institutions framework. This framework is embedded in the canonical model of the labour market, which attributes changes in the skill premium and skill-upgrading to shifts in the relative demand or supply for skilled workers, and to labour market institutions. Oesch (2013) detects an occupational 'upgrading', i.e. the average occupation has become higher-skilled and better paid. This upgrading could be driven by demand-related factors (skill-biased technological change, routinisation), supply-related factors (changes in skill supply, immigration) and institutions-related factors (de-standardisation of work contract). In another paper, Oesch and Rodriguez (2011) explore the drivers of polarisation on the basis of the same framework. In the remainder of this section, several of these theories are explored in more detail.

3.3.2.2 Skill-biased technological change

Before many researchers set out to address the issue of job polarisation, the literature focused on another - yet very closely related - issue. This issue was the global increase of wage and employment inequalities between skilled and unskilled workers that has been documented in several contributions. Many of the early contributions have attributed these rising inequalities to skill-biased technological change (Mendez, 2002; Chin *et al.*, 2006; Oesch & Rodriguez, 2011, among other publications). This view has been challenged in later work, as explored in more depth below. Most work has focused on the developed economies (e.g. Juhn *et al.*, 1993; Nickell & Bell, 1996), but there are also studies that cover developing countries. One example of the latter is Conte and Vivarelli (2011), who examine the occurrence of skill-enhancing technology import and find that this significantly raises the demand for skilled workers (while it does not affect the demand for unskilled workers). Katz and Murphy (1992) mainly attribute the increasing wage inequality in the US between 1963 and 1987 to skill-biased technological change within sectors (resulting from computerisation; see Krueger, 1993). Alternative drivers, such as labour allocation shifts between sectors and globalisation, appear to be less important. In a recent paper, Weiss and Garloff (2011) relate skill-biased technological change to unemployment and wage inequality in Europe and the US. Whereas skill-biased technological change is associated with increasing wage dispersions in the United Kingdom and the United States, it raises unemployment in continental Europe. Antonietti (2007) reviews the literature on the relation between skills and technology. He concludes that technology is a complement of non-routine, non-manual tasks and a partial substitute for repetitive manual tasks.

3.3.2.3 Other hypotheses

Skill-biased technological change, however, cannot explain the phenomenon of *labour market polarisation* that characterises many economies today and that was discussed in detail in Section 3.3.2.1. In fact, the evidence of job polarisation in favour of high-skilled and low-skilled jobs is inconsistent with the hypothesis of skill-biased technological change (Autor *et al.*, 2003; Wright & Dwyer, 2003; Goos & Manning, 2007; Jung & Mercenier, 2014). These papers suggest that employment growth has taken place in the low-paid personal service jobs and in the high-paid professional and managerial jobs, while employment in average-paid production and office jobs has disappeared (Oesch & Rodriguez, 2011). That is why a number of alternative explanations have been put forward since the early 1990s. Chin *et al.* (2006), for example, consider labour market frictions and computerisation. From his review of the empirical literature, Antonietti (2007) concludes that early studies have relied mostly on sector- and firm-level data, while more recent work used work-level data or even job-level data. The latter appears to present a more complex picture of the underlying dynamics.

In their seminal paper, Autor *et al.* (2003) propose an alternative theory of technological change to explain job polarisation: '**routinisation-biased technological change**'. Routinisation-biased technological change entails that technology (computers in particular) can replace labour in routine tasks but not in non-routine tasks. Routine tasks are defined as codifiable tasks that involve a step-by-step procedure. One of the main features of this theory is that it shifts the focus from *skills* to *tasks*. In the model, technology affects the returns to tasks rather than skills. The plausibility of this theory as an explanation for job polarisation has been confirmed by Goos and Manning (2007), who show that routine tasks indeed are concentrated in the centre of the distribution (using data for the UK). Moreover, Acemoglu and Autor (2011) demonstrate that the variance in the growth of US wages since the early 1980s can be attributed to changes in inter-occupational wage differentials. Other work also stresses the importance of this phenomenon during the First Industrial Revolution (Oesch, 2013).[3]

Another potential explanation for the recent labour market polarisation is related to changes in **international trade** (or **globalisation - see** Jung & Mercenier, 2014). In this regard, work on two dimensions has been particularly important: trade in intermediates (Feenstra & Hanson, 1999) and offshoring (Grossman & Rossi-Hansberg, 2008; Blinder, 2009; Ebenstein *et al.*, 2014; Helpman *et al.*, 2012). In this literature, the idea of trade in tasks has also been highly relevant.

In addition to these factors, **demand-side** factors can have an impact on the labour market as well (Jung & Mercenier, 2014). Shifts in the composition of demand (e.g. because of population aging, non-homothetic preferences) have been investigated by Manning (2004) and Autor and Dorn (2009). The latter examine employment growth in service occupations.

In an interesting contribution that was published last year, Jung and Mercenier (2014) compare the impact of these different explanations on the distributions of employment and wages. First, the authors model a 'closed economy' to examine the impact of skill-biased technological change, routinisation-biased technological change and demand shifts. The model only provides empirical support for the second hypothesis. When an 'open economy' model is used, Jung and Mercenier (2014) conclude that labour market polarisation is likely to be jointly induced by routinisation-biased technological change and by globalisation. Nevertheless, the authors find that the within-group and overall wage inequalities - which are changing disproportionately- can only be accounted for by routinisation-biased technological change. Another paper that compares several potential explanations for polarisation is Goos *et al.* (2009). These authors study job polarisation in 16 European countries in the period 1993-2006, with a focus on three hypotheses: routinisation, globalisation and offshoring, and wage inequality. They find clear evidence of routinisation, while the results for offshoring and inequality are less convincing.

Oesch and Rodriguez (2011) point to the role of **institutions** in Britain, Germany, Spain and Switzerland. In all four countries, they detect a pattern of occupational upgrading, as the strongest employment growth is found at the top of the distribution. Furthermore, in all countries employment declined more in average-paid than in low-paid jobs. Importantly, wage-setting institutions do appear to filter the pattern of occupational change: countries only experience a trend towards polarisation if wage-setting institutions facilitate the creation of low-paid interpersonal service jobs. This may be more the case in Britain and Spain than Germany and Switzerland.

A final hypothesis to take into account is that of **Schumpeterian creative destruction** (Immergluck, 1999; Mendez, 2002). The emergence of new highly-skilled jobs can result in creative destruction. An example of this is the finance industry. This industry used to employ many clerks focused on interacting with clients, but many of these jobs has been disappeared due to increased automatisation and a stronger focus on areas such as secondary mortgage markets (Immergluck, 1999).

Technological change in the past and the present has clearly had its labour market implications, as evidenced by many studies. Frey and Osborne (2013) summarise the conclusions of this literature as follows: technological progress has been accompanied by substantial changes in the occupational

3 In this context, computerisation, routinisation and automatisation have a similar meaning.

structure throughout history, but it has not resulted in widespread technological unemployment as predicted by Keynes (1933). This is due to the fact that technological progress has two opposing effects on employment: a *capitalisation effect* (employment grows in highly productive sectors) and a *destruction effect* (technology and labour are substitutes) (Aghion & Howitt, 1994). Frey and Osborne (2013) argue that in the past the former has been dominant. The impact of capital deepening on the relative demand for skilled labour has *changed substantially throughout history*. In the 19th century, manufacturing technologies and skilled labour were substitutes. The 20th century was characterised by job polarisation, caused by computerisation. Other work has related these conclusions to education and training. For the United States, Rauscher (2015) explores the link between educational expansion and occupational change over the period 1850-1930. Results suggest that compulsory school attendance laws and the educational expansion are associated with skill-biased technological change, a higher average occupational standing and an expanded occupational distribution. Education can change the occupational structure.

A question that still remains unanswered, however, is **what the future will look like**? In their paper, Frey and Osborne (2013) suggest that although the capitalisation effect historically has been dominant, this does not necessarily apply to the future. In fact, computerisation is no longer limited to manual and cognitive routine tasks but is being extended to non-routine tasks as well. This development is supported by the recent advancements related to 'big data' and robotics (e.g. robots' senses and dexterity). Frey and Osborne (2013) estimate the probability of computerisation for 702 occupations in the United States. They find that about 47% of total US employment is at high risk of computerisation. The transportation, logistics, office and administrative support and production occupations are at high risk. Interestingly, a vast share of the service occupations is likely to be computerised in the future as well. Frey and Osborne (2013) further document a negative relationship between the probability of computerisation and wages and educational attainment. In a related paper, Beaudry *et al.* (2013) show that the demand for skills in decreasing. For the 21th century, Frey and Osborne (2013) predict a truncation in the current trend towards polarisation: further computerisation is limited to low-skill and low-wage workers, who will switch to tasks that are not susceptible to computerisation. To this end, workers will have to acquire social and creative skills. Education and skills will remain important in the future for all workers. Another example of this is the incredible growth in STEM jobs in the past decade and the clear emphasis from policy-makers on STEM skills. As a result, educational institutes worldwide have introduced STEM-oriented training programmes and are stimulating students to opt for STEM training.

Finally, in a recently published article, Autor (2015) predicts that polarisation will not continue indefinitely. He argues that although some of the *tasks* in middle-skill jobs are susceptible to automation, many of the *jobs* in this segment of the distribution will still demand a mixture of tasks from across the skill spectrum. Moreover, the tasks bundled into the middle-skill jobs cannot be unbundled so easily, without causing a substantial decline in job quality. Autor (2015) therefore maintains that many middle-skill jobs will combine routine with non-routine tasks in the future. These jobs are not offshorable. In these jobs, workers continue to have the comparative advantage (e.g. problem-solving skills, interpersonal interactions). Autor (2015) concludes that the emphasis of human capital investment should be on the production of skills that are complemented rather than substituted for by technological change.

3.4 Conclusions

In the section, we have shed some more light on the academic discourse on new jobs and skills and focused on how occupations and skills have been transformed through history. The section clearly shows that occupational and skill changes are not new phenomena. In contrast, they appear to have a permanent nature and are (predominantly) driven by technological progress. The technologies at the core of these advancements appear to differ (e.g. the steam engine, computers and robots). What also differs is the labour market impact that technological progress has. In this regard, the issues of de-skilling, up-skilling and job polarisation have been discussed. This conclusion is supported by Gray (2013), who states that the electrification episode in the beginning of the 20th century 'mirrors the more recent polarisation of the US labour force associated with computerisation' (Gray, 2013, p. 360).

One may wonder whether the concept of an occupation is still relevant, given that the most of the literature appears to emphasise tasks and jobs. In the past, occupations were regarded as the dominant form of work organisation (Damarin, 2006). This view has been challenged by the emergence of large multi-divisional firms and Fordist mass production, which caused many occupations to become part of a large organisational structure. However, organisations are also subject to change (more flexible work forms, web-based work), which in turn could affect occupations. Damarin (2006) focuses on web labour, which has a modular structure; i.e. multiple roles are combined in ways that vary substantially across projects or organisations. In a way, this is similar to the flexible practices in other sectors such as job rotation. Damarin (2006) argues that the existing literature largely neglects this issue. Nevertheless, the concept of occupations is still relevant as occupations remain task-based mechanisms to divide of labour.

From this overview of the academic literature, we conclude that occupations, jobs, tasks and skills are strongly related and intertwined. This notion is also reflected in the many theoretical and empirical contributions that deal with several of these concepts simultaneously. In the literature, occupations, skills, jobs and tasks are all important (in some branches more so than in others) and rather clearly defined. Nevertheless, some of these concepts are used as synonyms rather than as distinct concepts (e.g. occupations and jobs). The identification of new occupations also is relatively clear, but we did not find any reference that clearly defines what a 'new skill' is. Nevertheless, if we connect new skills to new tasks and new occupations, we are able to cover new skills as well. In addition, in a lot of the academic work, occupations, jobs, skills and tasks are studied in a rather abstract way. Academic studies strongly draw on the methodologies and data sets of the policy-makers and institutions, which suggests that there are clear links between the academic and policy worlds. This link will be further explored in the next sections.

4. Policy discourse and policy applications related to new jobs and skills

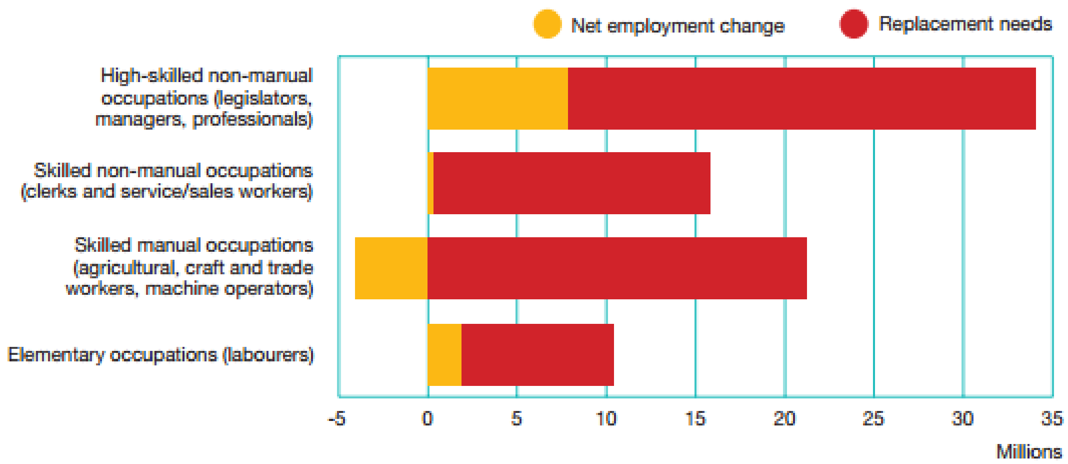
4.1 Policy discourse

4.1.1 International organisational and supranational bodies

The academic debate on new jobs and skills has a policy counterpart, composed of many contributions from international organisations and the European Commission. On 16 December 2008, the **European Commission** (EC henceforth) published a memo entitled '*New Skills for New Jobs: Anticipating and matching labour market and skills needs*' (European Commission, 2008). In the memo, the Commission outlines the two main objectives of the project: (1) to ensure a better match between skills and labour market needs and (2) to improve Member States' capacity to assess and anticipate the skill needs of its citizens and firms. In other words, the Commission focused on two aspects: skill upgrading and skill matching. Already in this memo, the issue of new jobs and new skills was linked to the socio-ecological transition. Moreover, the EC stresses that skills are not only acquired through formal education and training, but also through informal training, on-the-job-learning and work-related experience.

The objectives that were sketched out in this initial memo became part of a larger report published in 2010, entitled '*New Skills for New Jobs: Action Now*' (prepared by the Expert Group on New Skills for New Jobs for the European Commission). Among the challenges identified in the 2010 report are the lack of skilled workers in Europe (about 33% of Europe's population aged 25-64 has no or low formal qualifications, drop-out rates are too high) and the lack of workers with the 'right' skills (causing mismatches, skill gaps and shortages). The report formulates four recommendations to tackle these issues. The first one is to improve services and incentives for individuals and firms to acquire, upgrade and make the best use of skills. The second recommendation is to bridge the gap between education, training and employment. The third one is to develop the right set of skills and the final recommendation is to better anticipate the skill needs of the future (for this labour market information is key). This report was based on a prediction of demand for different occupations made by the European Centre for Development of Vocational Training (Cedefop), which, though based on ISCO, recognises the non-linear nature of demand for skills caused by job polarisation.

Figure 4.1 **Projected demand in different groups of occupations until 2020**



Source European Commission, 2010, based on data from Cedefop

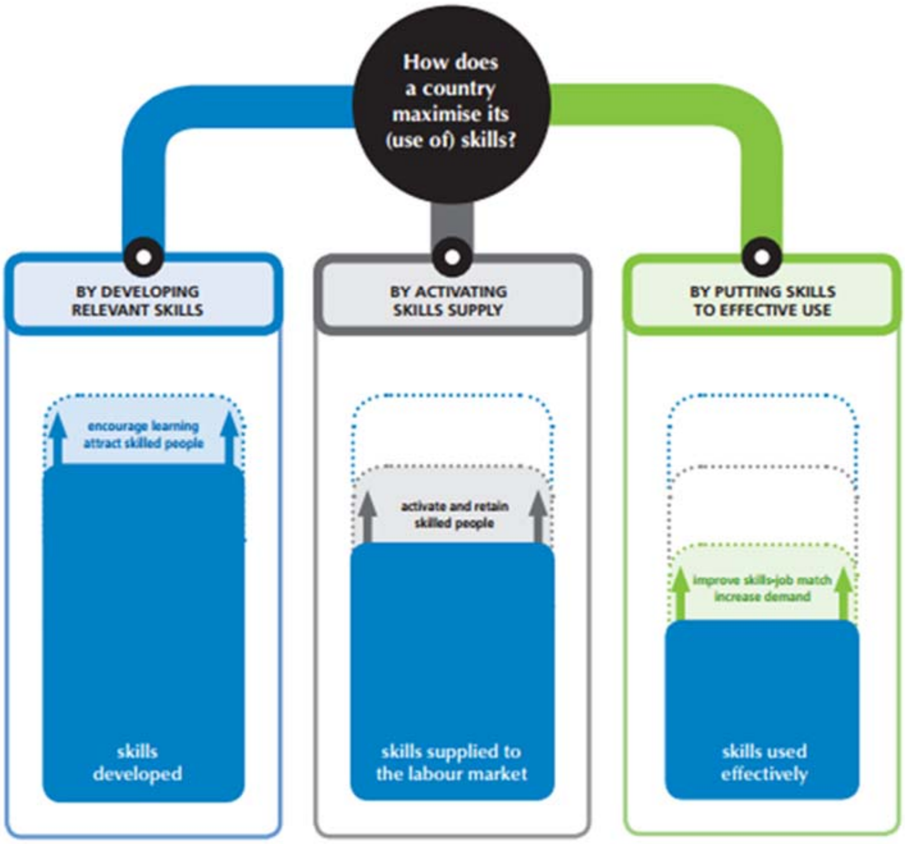
In 2010, the European Commission continued the discussion on new jobs and skills with the '*Agenda for new skills and jobs*', which is part of the Europe 2020 strategy. The aim of this agenda is to reach the EU's employment target of 75% of the working-age population. Other goals of the initiative are to reduce the early school-leaving rate below 10% and to increase the number of young people enrolled in higher education or vocational training to at least 40%. As part of the *New Skills for New Jobs* initiative, the Commission sets out to promote a better anticipation of the future skill needs, develop a better matching between skills and labour market needs, and bridge the gap between education and work. Some practical measures towards this objective are: ESCO, the European Qualifications Framework, forecasts by Cedefop, an analysis of emerging trends at the sector level and the development of sectoral skill councils, and ongoing research with the OECD and ILO. In addition to the 'Agenda for new skills and jobs', the Europe 2020 strategy encompasses two other flagship initiatives: '*Youth on the move*' and '*European platform against poverty and social exclusion*' (Europe2020). The former has the objective to improve the employability and education, decrease unemployment and increase employment of young people. To meet these objectives, the EU will better align education and training with young people's needs, stimulate international mobility and facilitate the transition from education to work. Note that a lot of these efforts are targeted at tertiary education, for example in the Erasmus+ programme. These initiatives suggest that the debate on new jobs and skills is high on the agenda of European policy-makers and within the European institutions.

At the European level, a lot of work on occupations and skills is done by Cedefop (the European Centre for the Development of Vocational Training). An example of this work is *Skillsnet*. This network, established in 2004, aims to connect researchers and experts active in the early identification of skill needs or forecasting and in the transfer of research results on this topic into policy and practice. Other examples are the *EU Skills Panorama*, employer surveys and skill forecasts. In order to forecast the skill needs and gaps of the future, Cedefop uses national accounts data to perform macroeconomic projections based on the E3ME model (to assess sectoral employment prospects across Europe) (Cedefop, 2008). These data are combined with data from the European Labour Force Survey (sectoral employment trends can then be regarded by occupation and qualification). Many countries carry out skill forecasts as well but the approaches used are fairly different (Wilson & Zukersteinova, 2011).

Meanwhile, the **Organisation for Economic Cooperation and Development** (OECD) has also invested in the issue. The flagship initiative of the OECD is the 'Survey of Adult Skills', as part of the Programme for the International Assessment of Adult Competencies (PIAAC). The survey measures the key cognitive and workplace skills that individuals need. More specifically, the survey assesses the proficiency in literacy, numeracy and problem-solving skills (in technology-rich environments) of adults in the context of their socio-economic status (for 33 countries). It evaluates the availability of these skills and their use at work and at home. In this way, it provides valuable information for educators, policy-makers and labour economists. With the survey, the OECD aims to support the development and implementation of national skills strategy. The results of the survey are presented in the OECD Skills Outlook. The findings of the first survey are reported in the Skills Outlook for 2013 (OECD, 2013). The survey reveals that more education is not necessarily associated with better skills, and that skill acquisition beyond formal education (at work or at home) is becoming increasingly important. In the 2013 Outlook, the connection between new jobs and skills and the socio-ecological transition is made as well. The most recent edition of the Skill Outlook is entitled '*Youth, Skills and Employability*' and again builds on the Survey of Adult Skills. To enhance the employability of youth, a comprehensive approach is required that encompasses education, social and labour market policies and coordination between public policies and the private sector (OECD, 2015). The 2015 report further recommends to ensure that all young people level school with a range of relevant skills, to assist school leavers to enter the labour market, to dismantle the institutional barriers to youth employment, to identify and help young people who are not employed or in education to re-engage, and to facilitate better matches between young people's skills and jobs.

The broad OECD Skills Strategy is outlined in a larger document entitled '*Better Skills, Better Jobs, Better Lives: A Strategic Approach to Skills Policies*'. This strategy is shown in Figure 4.2 and comprises three pillars that are equally important. The first pillar is 'Developing relevant skills'. The idea behind this pillar is to arrive at a skills supply of a sufficient quantity and quality. The second pillar entails 'Activating skills supply'. The aim of this pillar is to re-integrate inactive individuals into the labour force to ensure that all available skills are used. The third pillar comprises 'Putting skills to effective use'. In this pillar, the focus is on skill-matching. Importantly, the OECD reports that new skills often are developed informally (e.g. through work experience). Moreover, the OECD is also concerned about the deterioration of skills that are not put to use. Throughout the report, there therefore is a strong emphasis on life-long learning. Note that the OECD also publishes the OECD Employment Outlook. In the 2015 edition, attention is paid to minimum wages, job quality, wage inequality, among other subjects (OECD, 2015c).

Figure 4.2 **The OECD skills strategy framework**



Source OECD (2012)

The OECD's approach to some extent complements the approach of the European Commission. Similar to the Commission, the OECD focuses on new jobs with high skill requirements. Nonetheless, while the Commission concentrates on the areas where job creation happens and infers the demand for high skilled workers, the OECD focuses on the development of the skills themselves. Unlike the Commission, the OECD does not stress so much the importance of the higher education, noting that both many skills are developed in both working and non-working contexts, while they tend to decline with time, particularly if workers do not use their proficiency. For that reason, the OECD particularly stresses the importance of life-long learning - a point, where there is an agreement with the Commission.

The importance of skills and preparation for the high-skilled jobs of the future has been stressed by the **International Labour Organisation** (ILO) as well. In 2011, the ILO prepared a G20 training strategy entitled '*A Skilled Workforce for Strong, Sustainable and Balanced Growth*'. During the Great Recession, many G20 countries opted for education and training to address some of the labour market challenges provoked by the crisis. The ILO strategy considers the lessons that were learned from these experiences, but also looks at the future: how can education and training programs be adapted to meet changes in skill requirements and improve access to training and skills development? To this end, the ILO strategy centres on qualitative education, a smooth transition from school to work, skill matching, life-long learning, the anticipation of the skills of the future, among other elements. The OECD also prepared a report for the G20 (OECD, 2010).

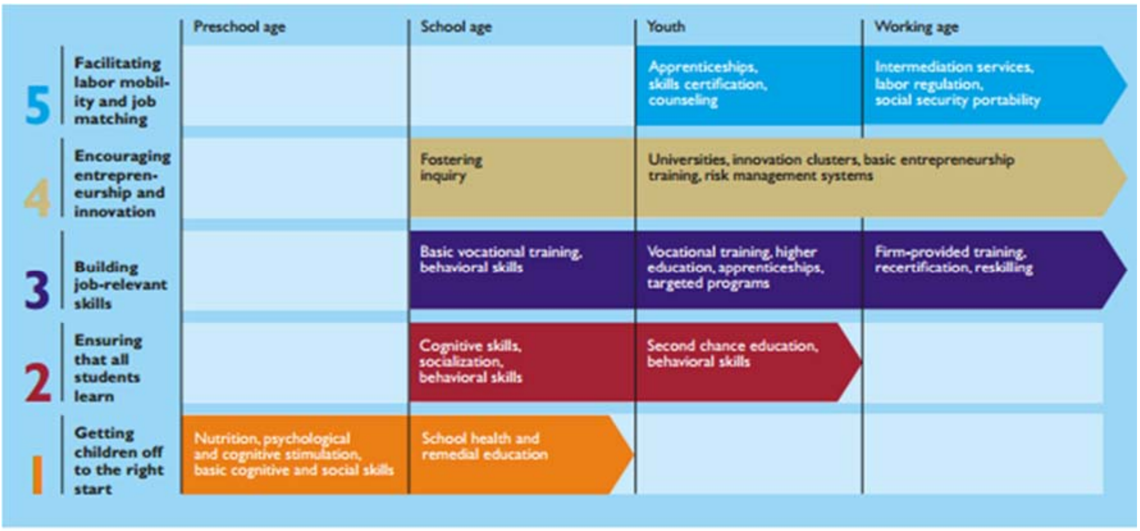
In 2012, **UNESCO** published a report entitled '*Youth and Skills: Putting Education to Work*' in which a more global perspective is taken. In the report, pathways to a better future for young people all around the world are explored. To this end, the 10 most important steps to be taken are summarised.

These steps are: (1) provide second-chance education for those with low or no foundation skills, (2) tackle the barriers that limit access to lower secondary school, (3) make upper secondary education more accessible to the disadvantaged and improve its relevance to work, (4) give poor urban youth access to skills training for better jobs, (5) aim policies and programmes at youth in deprived rural areas, (6) link skills training with social protection for the poorest youth, (7) make the training needs of disadvantaged young women a high priority, (8) harness the potential of technology to enhance opportunities for young people, (9) improve planning by strengthening data collection and coordination of skills programmes, and (10) mobilise additional funding from diverse sources to meet the training needs of disadvantaged youth (UNESCO, 2012). Similarly to the other reports discussed, the UNESCO report emphasises the importance of skills for the labour market and economic progress, but also for other aspects of life (e.g. social mobility, equality and health).

Finally, the **World Bank** has proposed the STEP (i.e. Skills Toward Employment and Productivity) framework, which is carefully explained in a report entitled '*Stepping up the skills: for more jobs and a higher productivity*' (World Bank, 2010). In the report, the World Bank stresses the importance of skill development in emerging and developing economies. The STEP framework comprises five interlinked steps: (1) getting children off to the right start, (2) ensuring that all students learn, (3) building job-relevant skills, (4) encouraging entrepreneurship and innovation and (5) facilitating labour mobility and job matching (Figure 4.3). Three key elements of the framework are: behavioural skills (e.g. entrepreneurship, creativity, and teamwork), path dependence (early investments make later efforts more productive) and labour market clearing.

The overview provided in this section illustrates that international organisations and supranational bodies are closely following the academic debate on new jobs and skills. Many of them have created a series of reports in which they link the socio-ecological transition to the challenges that many economies are facing today; and the solutions proposed for these challenges are related to skills (development, use, and response to the current and future needs of employers, and so on).

Figure 4.3 STEP strategy through the worker's life cycle



Source World Bank (2010)

4.1.2 National states level

At the national level, attention has been paid to the new jobs and skills debate as well. This section provides an overview of some of the initiatives that have been taken at the country level. However, this overview is not exhaustive, because of the large number of countries and initiatives that exist. For this reason, we have opted to mainly focus on Europe and present some examples.

In the United Kingdom, the UK Commissioner for Employment and Skills (UKCES) published a series of papers covering the state of the labour market in the country, the supply and demand for skills and the future expectations in this area. This body of literature was summarised in an overview paper published in 2014 entitled 'The Labour Market Story: An Overview' (UKCES, 2014). The main challenges identified in these papers are the polarisation of the labour market, the falling wages and labour productivity, the fact that the UK is not keeping pace with its competitors in terms of investment in low and intermediate skills and (structural) skill gaps (despite relatively high investments in education). The report predicts that jobs at the intermediate skill level will continue to fall, resulting in an hour-glass shaped labour market. Jobs in the services industries are likely to expand, while the opposite holds for jobs in utilities and manufacturing.

Meanwhile in Germany, the focus is strongly on life-long learning and other efforts to retain the competitiveness of aging population. The flagship effort is the bi-annual published regular expert report, the *Bildungsbericht*, on the state of education in the country. The most recent Bildungsbericht was published in 2014 and discusses different education levels in Germany (Bildungsbericht, 2014). One of the sections is dedicated to training and learning in adulthood. In France the reports on jobs and skills are produced less frequently, but the coverage of the issue is still quite prominent. The main activity are the '*Les métiers en ...*' published by the Centre d'Analyse Stratégique in collaboration with the Ministry of labour. The latest, published in 2012, covers the period up to 2020 (Centre d'Analyse Stratégique, 2012). The report focuses on polarisation of occupations and increased presence of women on the labour market. It also deals with the further progression of high-skilled jobs and jobs in the health and social service sectors. Italy has identified the skill mismatch and rigid education system as the key challenge in Italia 2020 (Italia 2020). Sweden has invested in several policy initiatives in the area of life-long learning based on the skills and jobs supply and demand prediction *'Trender och Prognoser 2008: befolkningen utbildningen arbetsmarknaden med sikte på år 2030'* made by the Swedish statistical office (Swedish Statistical Office, 2014). In 2005 a book was published entitled 'Labour Market Research and Policy Making in Flanders' (by Jan Vranken). This book is composed of an overview of several policy papers that bridge the gap between labour market research and policy measures in Flanders, Belgium. One of the key topics under examination was the issue of life-long learning (Vranken, 2005). Other important topics include the transition from school to work, mobility and the labour market in the 'new economy' (which discussed e-work, new production concepts, new businesses and new occupations). The countries in Eastern Europe often lag behind their Western counterparts in terms of the transition towards the service economy and related developments. For Poland, there is the *Strategia Rozwoju Kapitału Ludzkiego*, which heavily stresses catching up with the Western Europe in terms of labour market participation of the citizens (Poland, 2013).

Going beyond Europe, in the United States, perhaps surprisingly, there is no clear policy document summarising the government's stance towards the issue of future jobs and skills supply and demand. The closest reports are the Occupational Employment Projections, the Job Outlook in Brief and the Education Outlook, published by the US Bureau of Labour Statistics (the 'outlooks' are not exactly reports, but refer to a website where one can find more information in the form of shorter articles). The first report was last published in 2013 and explores the expected developments in the coming decade (up to 2022) (US Bureau of Labour Statistics, 2013). The main areas discussed are job creation in the health care sector and growing demand for highly educated workers. The last Job Outlook was published in 2012; the last Education Outlook appeared in 2008. Outside of the Western world, the debate generally reflects the need for a more qualified workforce, although it is often centred on locally important issues. In China, for example, the focus in on the move away from the labour-intensive economy by developing creative skills, a strategy outlined in the National Plan for Medium- and Long-term Education Reform and Development (2010-2020) (UNESCO, 2010). Similar aspirations were put forward in the Indian National Skills Policy as well as an extension of coverage particularly in terms of primary and secondary education (India, 2009), which is also a focus of UNESCO's Dakar Framework for Action (UNESCO, 2000).

This overview confirms that also at the national level, attention is paid to the issue of new jobs and skills. Depending on the national challenges, the focus can differ. This is particularly clear when the approach of developed countries is compared with that of emerging and developing nations.

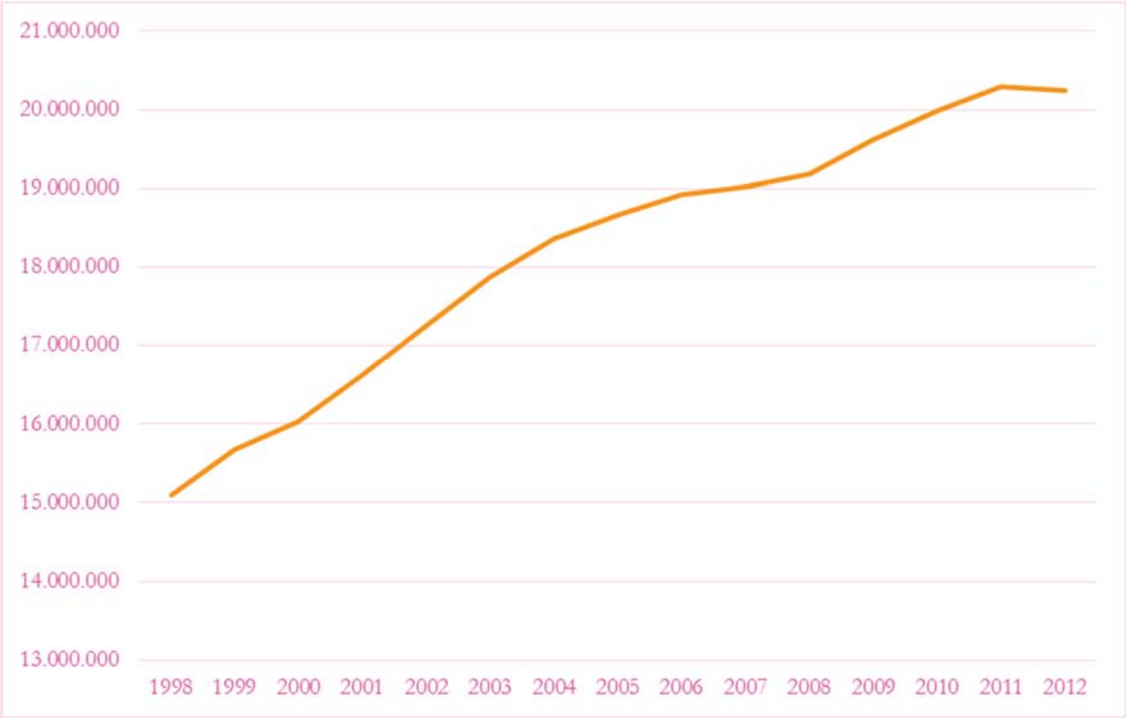
4.2 Public policy applications

The extent to which this thinking has been reflected in the actual policies in the European Union varies between member states, because education and labour market policies are still strongly connected with the national level of the EU political system. Nonetheless, the EU members are cooperating with each other and with the EU-level institutions to develop policy responses to the labour market challenges that they face. Labour mobility within the EU is an important aspect of matching demand and supply on the labour market. Free movement of labour is one of the four main freedoms of the EU and since the beginning of 2014, when the temporary restrictions for Bulgarians and Romanians were lifted, all EU citizens can choose to reside and work in any other EU member state. Still only 3% of Europeans live in a European country other than their own (Barslund & Busse, 2014). The EU has been trying to increase this figure through the EURES project, which combines job vacancies from all EU member states and uses the standardised classification systems of jobs, skills, competencies and qualifications to ease the accessibility throughout the EU. More details on EURES are provided in Section 5.2.4.3. EURES targets workers, and to some extent students.

In contrast, the Erasmus+ programme was mainly designed to stimulate the international mobility of students, and to some extent workers. Erasmus+ facilitates student exchanges, and further support education and life-long learning initiatives between the EU and associated countries (European Commission, 2015). Additionally, the Youth Guarantee policies are being introduced in all member states to ensure that all young Europeans have access to meaningful education, training or work opportunities. The objective of these policies is to ensure a smoother transition from school to work (European Council, 2013). Another form of worker mobility is from outside of the EU. It is also important to consider migration, especially on the country-level. Recently, several European countries have implemented policies to attract highly skilled migrant workers. Typically, these policies aim to identify and offer preferential treatment for highly skilled immigrants, particularly if they are able to find employment or generate substantial income through self-employment (Kahanec & Zimmerman, 2011). These efforts are comparable with activities of other major economic powers, such as the US Green Card system.

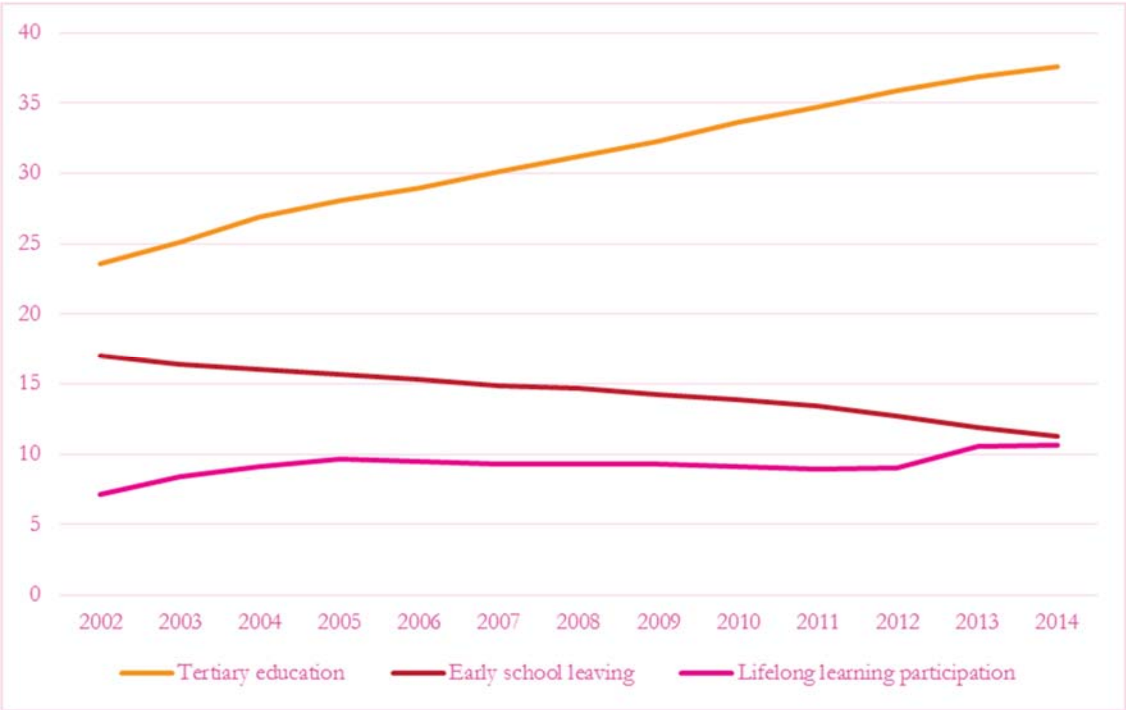
As indicated above, education policies are largely shaped on the national level, despite the prominent role of the EU in some areas. In the past decade, the EU member states have invested heavily in access to higher education. The number of participants in tertiary education in the EU28 has grown from 15 to 20 million between the years 1998 and 2012 (see Figure 4.4). This strategy of 'massification' of tertiary education embraced by European states has resulted in a dramatically changed structure of the European labour force. While in 2002 less than one out of four working Europeans had a college degree, currently over a third of the European population has attained tertiary education. At the same time, governments successfully tackled the issue of early school leaving: the share of young people not in education without at least a secondary education has dropped from 17% to 11% over the time period. Although the share of people participating on life-long learning remains just above 10%, it has more than doubled since 2002 (see Figure 4.5).

Figure 4.4 Number of tertiary education students in EU28



Source Eurostat (Data before 2003 are own estimates based on Eurostat)

Figure 4.5 Developments on European labour markets



Source Eurostat

4.3 Conclusions

From this overview of the policy literature, we conclude that occupations, skills, new occupations and new skills are important subjects to policy-makers. There is a large number of policy documents outlining new strategies, targets and methodologies to track changes in the labour markets. On the skills side, we find a multitude of studies on matching, skill mismatches, skill gaps, overeducation, vocational training and so on. Especially in the policy reports, education is a key topic, and in nearly all of them the labour market is linked to the education sector. On the jobs side, attention is devoted to the labour market implications of technological and demographic changes, polarisation and related concepts. Again, due to the strong relation between occupations and skills, both concepts are considered in the majority of the reports. In the academic literature, there are many papers that also cover both concepts at the same time, but other work focuses in more detail on one or the other.

In the policy reports, the definition and identification of occupations, jobs and skills are clear. A similar conclusion applies to the concepts of new occupations, jobs and skills. These concepts are used in a lot of papers, although often no definition is listed as to what a new occupation or skill is. Nevertheless, generally similar methodologies and data are used as in the academic field (e.g. case studies, surveys, classifications, modelling). The underlying concept of a task also appears in a number of reports (in the description of how and why new occupations emerged). In addition, occupations, jobs, skills and tasks are often studied in an abstract way. What also appears from this overview, however, is that especially policy-makers are pushing the debate on new occupations and skills. This is clear from the many recent reports that consider the measurement of jobs and skills, mismatch, skills gaps, predictions and other topics. Policy-makers seem to be particularly forward-looking, in comparison to academics. Another interesting point is that especially the skill angle seems dominant in the policy literature; in some of the reports, the analysis of new occupations and jobs clearly serves as a way to support policy-making on skills.

5. Towards an innovative methodology and new data sources for the analysis of new occupations and skills

In order to identify new jobs and skills, one needs to rely on a solid methodology and a reliable dataset. From our discussion of the academic and policy discourse, it is clear that the commonly used concepts, methodologies and data appear to fall short. In the academic literature, there are only a few studies that clearly define new occupations, jobs and skills (without reverting to an abstract representation of these concepts or considering solely the evolution of employment, job or vacancy statistics), and very often they rely on occupational classifications, trade information, case studies, surveys or interviews. This approach, however, seems insufficient to capture new trends and dynamics that extend beyond the local or regional level (especially in rapidly changing industries).

There appears to be a stronger interest on the policy side in the subject of new jobs and skills than in the academic world. Both at the national and the international level, a multitude of reports and strategies towards new jobs and skills can be found. Still, a lot of work done by policy-makers uses the same or similar data sources and methodologies as the academic studies and again the underlying concepts are not always clear (in practice, data and classifications are typically made available by policy-makers). In this regard, the academic and policy worlds clearly are connected and the interplay between them is significant: academic studies provide support for policy contributions and vice versa. However, some of the issues and limitations of the traditional methods and data sources already became clear in the previous sections of this report, raising the question of what alternative methodologies and data sources could be used instead. In this section, we evaluate the potential of web-based data sources and methodologies for labour market analysis and for the identification of new jobs and skills in particular. Our analysis is inspired by and embedded in the recent, rapidly advancing literature on Internet-based labour market research (see Askitas & Zimmermann, 2009; 2015). This section is devoted to the advantages and limitations of traditional and web-based data sources.

5.1 Labour market analysis: Traditional methods and data sources

Woods and O'Leary (2007, p. 4) define labour market information as 'all quantitative and qualitative information that relates to labour markets'. It is composed of six parts: macro labour force (e.g. demographics), labour demand (e.g. vacancies), occupational supply (e.g. new entrants to labour force), occupational characteristics (e.g. job skills), education and training information (e.g. programme descriptions) and classifications and crosswalks (e.g. industry). In many countries, labour market information is initiated and made available by the government. Several international institutions and other organisations also provide labour market information. Labour market data offered by the government or international institutions are considered to be more accurate, better structured and more complete than data from other sources.

Traditional sources such as the CPS or Census have the further advantage of being based on a randomly selected sample of the population ('representative'). A disadvantage of traditional data sources, however, is that statistics commonly are distributed with a lag. Some databases are not updated regularly, or are, in contrast, frequently revised. In addition, data often are assembled from administrative sources or via surveys, which could result in a small sample size or even lead to data unavailability for sectors or regions with a limited coverage (Wright, 2012). For many less-developed countries, labour market data are simply absent or of a low quality (Shapiro, 2014). According to Damarin (2006), **new and emerging occupations are difficult to analyse**, precisely because they are not well reflected in the existing data sources and lack the coherent institutions and cognitive categories that facilitate data collection. We already pointed to this notion before: using occupational classifications to identify new occupations, and the corresponding set of new skills, clearly has serious limitations.

5.2 Innovative methods and web-based data sources for labour market analysis

One solution to address the issue of time lags in the more traditional databases is by using *real-time labour market data*. The concept of real-time labour market data mainly refers to the availability of job advertisements, CVs and resumes online (Dorrer *et al.*, 2012). This information can be found on public and private websites, such as online job portals and company websites. With real-time labour market data at hand, one can infer trends in labour demand, supply, and matching, observe (changes in) education and skills requirements, and identify new or emerging occupations.

With the advancement of the Internet, the web has developed into an interesting platform for data collection and analysis (Benfield & Szlemko, 2006). Web-based data can be used to overcome some of the issues related to traditional datasets. Researchers argue that the Internet enables them to compile large, diverse and more representative datasets in an easy, fast, flexible and relatively inexpensive way. In addition, since the Internet has become intertwined with every aspect of life, it allows us to capture dynamics that are difficult to grasp otherwise (Askitas and Zimmermann, 2015). In fact, at the end of 2014 almost 3 billion people had access to the Internet (ITU, 2014). Globally, close to 44% of households have Internet access at home. It is thus not very surprising that the number of studies that use web data has soared (across a range of disciplines).

The use of online data in the social sciences and for labour market analysis has been advocated by Kuhn and Skuterud (2004), D'Amuri and Marcucci (2010) and Askitas and Zimmermann (2009; 2015). Autor (2001) identifies three ways in which the web has affected the labour market: how firms and workers search for each other (e.g. passive candidates, on-the-job search); how labour services are delivered (e.g. skills are being required online); and how local labour demand is shaped (e.g. e-commerce). Job search, recruitment and matching have indeed transformed dramatically with the growth of the Internet (EC and ECORYS, 2012; Kuhn, 2014; Kuhn and Mansour, 2014). Carnevale *et al.* (2014) and Askitas and Zimmermann (2015) conclude that matching has become more efficient since search and matching frictions are reduced. Both job seekers and employers benefit from this transformation of the search and matching process and the labour market data that have become available (Carnevale, *et al.*, 2014). Job seekers can easily look for vacancies and get more insight into employers' requirements. They can upload their CV on a job board or social network and interact with potential employers and their current employees. Companies and recruiters, on the other hand, are able to promote vacancies at a low cost. Branding, an increased visibility and a larger outreach are additional advantages. Besides its relevance for employers and job seekers, real-time labour market information is also valuable for the education sector. As Dorrer *et al.* (2012) point out, education institutes can adjust their programmes to developments in the labour market, to (proactively) address skill mismatches. Similarly, Carnevale *et al.* (2014) suggest that universities benefit from the information posted on online job portals, because this facilitates the detection of new jobs as well as new education and skill requirements. For these reasons, online vacancy, CV and *resumé* data are important for workforce agencies and policy-makers too (Carnevale *et al.*, 2014).

5.2.1 How did the Internet develop into a research platform?

As indicated above, the web has become an interesting research subject and a tool for data compilation. Hooley *et al.* (2012) therefore distinguish between research that covers the Internet and studies that make use of the Internet to conduct research, but note that these two domains actually are strongly connected. The earliest studies were mostly of the first type and focused on the social dimension of the Internet (Freeman, 1984; Finholt & Sproull, 1990). Shortly after these first studies were done, work that made use of the web to perform analyses emerged (Kiesler & Sproull, 1986; Kehoe & Pitkow, 1996; Foster, 1994; Welch &Krantz, 1996). As the field expanded, new methodologies and data collection methods were developed, which often were strongly embedded in the existing methodological framework and enriched with insights from technological progress. Currently, Internet research methodologies have transformed into a separate research field (Hooley *et al.*, 2012).

Online research can take many forms. In their book, Hooley *et al.* (2012) concentrate on four types: surveys, interviews and focus groups, ethnographies and experiments. **Surveys** were among the first research activities performed online. In fact, the first recorded email survey was done in 1986 (Kiesler & Sproull, 1986) and the first recorded web surveys in 1994 (Kehoe & Pitkow 1996). Compared to the traditional paper-and-pencil methods, online surveys have the advantage of being flexible, fast, low-cost and easy to set up. Data can be collected from a larger and more diverse sample, which has a positive impact on data accuracy. At the same time, the anonymity of the respondents is ensured. Web surveys are also easier to analyse than traditional surveys. Disadvantages of online surveys include sample bias, measurement error, non-response and dropout, and other technical and ethical issues.

For the United States, there are two Internet Panel Surveys that we want to present here: RAND's American Life Panel (ALP) (6,000 participants) and the Understanding America Study (UAS) panel (2,500 participants, CESR, University of Southern California). Both panels are representative for the US population of ages 18 and up. Online **interviews and focus groups** have developed more slowly. This work mainly concerns asynchronous email interviews, although limited work does consider synchronous interviews and focus groups (O'Connor *et al.*, 2008; Foster, 1994; Gaiser, 1997 and 2008; Murray & Sixsmith, 1998). Online interviews and focus groups are more flexible and cost- and time effective, but they do require technical competence of the participants, shift the power balance in their favour and constrain the researcher from observing any non-verbal communication. Online ethnographers examine how humans live and interact online. Research typically deals with social interactions on online communities, networks, gaming, discussion groups, bulletin boards, blogs and social media (Doostdar, 2004; Herring & Paolillo, 2006; Hookway, 2008; Boellstorff, 2006; Boyd & Heer, 2006; Thelwall, 2008). Lastly, **online experiments** have been used in a variety of fields, beyond the boundaries of the social sciences. Some examples of work in this area are Weigend (1994), Krantz and Dalal (2000) and Musch and Reips (2000). In her recent study, Pallais (2014) performs an experiment on oDesk - an online marketplace - to test the hypothesis that young workers have a higher probability of being unemployed than older workers because of barriers to labour market entry. oDesk is also used by Pallais and Sands (forthcoming), to examine why referred workers have higher chances to be hired, and by Horton (forthcoming), to investigate the role of recommendations (which appear to raise the probability of being hired).

Horton *et al.* (2011) perform a set of experiments on Amazon Mechanical Turk (MTurk). More specifically, the authors replicate three classic experiments online and prove that such experiments are valid and beneficial to researchers. Besides oDesk and MTurk, there is another platform on which researchers can perform online experiments: TESS (Time-sharing Experiments for the Social Sciences). Researchers can submit proposals for experiments (which are peer-reviewed). When a proposal is approved, TESS does the experiment free of charge on a representative sample of US-based adults. Horton *et al.* (2011) demonstrate that online experiments are more flexible, faster, cheaper and easier to conduct than real-life experiments, and allow for a broader scope. The sample of participants that one can reach is also more diverse and larger. These features improve the quality of the study.

5.2.2 What are the advantages and limitations of web-based data?

The **advantages and limitations of web-based data** are documented in a series of papers. Web data allow researchers to fill the gaps where traditional data sources are absent or weak (e.g. due to a low coverage or quality, specialised markets) (Shapiro, 2014). In addition, data can be collected in real time (or almost; i.e. no lags or revisions), which means that current labour market trends are detected. Online, researchers can assemble large, diverse and potentially more representative datasets. Because an increasing part of the population is active online, sampling may become unnecessary in the future (Askitas & Zimmermann, 2015). Other advantages are that data collection and analysis are easy, fast, flexible and relatively inexpensive and that logistical issues associated with traditional sources can be avoided (e.g. tedious data entry prone to errors) (Benfield & Szlemko, 2006; Mang, 2012; Wade & Parent, 2001; Kennan *et al.*, 2006).

Another advantage of web data is that they facilitate research on **self-employment**, which is a key driver for entrepreneurship and job creation and may become even more relevant in the labour market of the future. This is also highlighted in a recent OECD report: the web is a catalyst for business innovation, across all sectors of the economy, but it is not easy to study these dynamics (OECD, 2014). At the same time, self-employment is difficult to measure on the basis of traditional data sources (because data are lagged and the definition of self-employment differs across data providers, see Fairlie & Robb, 2009). Many datasets either cover information on the owner or the business, but not on both. Web data can be a solution, as users can indicate in their profiles whether they are self-employed and information on the business can be found online.

Furthermore, online portals and social networking sites facilitate **on-the-job search**. Stevenson (2009) reports that the 77% of the people who use the web for job search are employed. These employed job seekers are more likely to leave their current job, transition from employment to employment and have better negotiation positions vis-à-vis their employer. Stevenson (2006) already concluded that the Internet leads to better matches for the employed (e.g. higher wage growth when changing jobs). Kuhn and Skuterud (2004) assess which unemployed workers look for a job online and whether they became reemployed more quickly. Online job search seems ineffective in reducing unemployment stints. However, negative selection on unobservable variables could also explain the results (e.g. poor networks).

With regards to online vacancy data, several other advantages can be listed (Shapiro, 2014). For example, vacancy data comprise real job titles, job descriptions, education and skill requirements, and other information at a detailed level. In this regard, Shapiro (2014) points to the issue of occupation codes, which do not necessarily correspond to actual jobs in traditional labour market sources and often are outdated or incomplete (e.g. emerging occupations are not yet included in the list and while the structure is maintained over time, it no longer reflects reality). Another advantage is that one can track the time it takes to fill particular job openings. This gives an insight into the match/mismatch of labour supply and demand (for specific occupations, industries or regions; see Shapiro, 2014).

Web data, however, are also characterised by a **number of limitations** (Benfield and Szlemko, 2006; Shapiro, 2014; Leithart, 2013; Carnevale *et al.*, 2014). For example, there are ethical (e.g. privacy) and technical (e.g. familiarity with a computer) issues. Online data and job vacancy data in particular are, by their very nature, incomplete. There are several reasons for this observation. The first is that not all job openings are posted online. In addition, not all available jobs are advertised, as recruitment also occurs through internal and informal channels. This implies that for some jobs a vacancy is never published. Even if all job vacancies would be advertised online, it seems unlikely that one would be able to assemble all of them into a single database. Moreover, vacancies are often duplicated and some jobs are of a seasonal nature. It is therefore difficult to count the number of vacancies posted online at a certain point in time, and this is even more so when a time series of comparable samples has to be found.

Job advertisements do not always state all skills and qualifications required for the position. A related issue is that firms commonly create their own advertisements, which means that these vary greatly (little standardisation). Another issue is that a vacancy does not necessarily correspond to a real job opening. In some cases, employers just publish vacancies online to gather resumes and CVs. Vacancies can also be biased towards specific regions, industries or applicants. Carnevale *et al.* (2014), for example, find that although between 60% and 70% of job openings in the US are advertised online, 80% of them require no less than a Bachelor degree. They further detect a bias towards industries and occupations that mainly employ high-skilled, white-collar workers (STEM occupations are also strongly represented). Autor (2001) further points to adverse selection of job applicants (applying for a job is cheap and easy; therefore job seekers apply for many jobs, for which they could be over- or under-qualified). His paper also has a segment on geography and inequality. Although job search is cheaper, markets are integrated and labour services can be delivered online, this is not necessarily beneficial to all groups. Selection really is an important issue for web data (Carnevale *et al.*, 2014; Kearney & Levine, forthcoming). Websites or online platforms could attract specific users, which affects data representativeness. Moreover, not all job seekers use the Internet in their job search. With these obstacles in mind, the quality, consistency, accuracy and volatility of web datasets should be examined (Carnevale *et al.*, 2014). Data cleaning will be important. Another limitation is that vacancies only represent a small part of the entire labour market (Wright, 2012). In fact, vacancies do not even coincide with the full labour demand (Carnevale *et al.*, 2014). That is why many studies combine data extracted from the web sources with data from traditional sources; these sources often are regarded as complementary (Dorrer *et al.*, 2012; Wright, 2012; Carnevale *et al.*, 2014).

Other work has focused on the **methodological issues** that are associated with web-based job vacancy data. In a recent study, Kureková *et al.* (2015) conclude that the main issues of vacancy analyses are related to the representativeness of the data source and the extent to which findings can be generalised. The issue of data representativeness is not new to the literature, yet few possible solutions have been put forward. The representativeness of a sample of job advertisements is difficult to assess, given that the total population of vacancies and its structure are unknown. Furthermore, vacancy data are not missing at random; missing values instead result from the sampling procedure selected. Kureková *et al.* (2015) explain this as follows: online vacancies are a sample of the population of vacancies; missing values thus stem from the vacancies that were never advertised online. Some earlier studies therefore compared the sample of vacancies with a representative dataset that describes the labour market structure from the Labour Force Survey (see Jackson, 2007; Štefanik, 2012a; 2012b). Alternative approaches involve data diversification, using additional datasets (from administrative sources) and conducting further analyses to better understand the bias. In the literature on surveys, weighting techniques are commonly used to improve representativeness (post-stratification weighting and propensity score adjustment) (Steinmetz *et al.*, 2009). Propensity score adjustment is suitable to adjust socio-demographic, attitudinal and behavioural differences, while post-stratification corrects for demographic divergences. Weighting, however, cannot be applied to vacancy data as the population of vacancies and its structure are unknown.

In their contribution, Kureková *et al.* (2015) therefore propose several methods to alleviate this issue. First, they note that the reliability and representativeness of data should be assessed at the country-level (via the market share of the job portal from which vacancies are collected) and in the context of the research focus. Second, a model-based approach, embedded in the literature on missing data, can be used to tackle the sample bias. At the heart of this approach is the idea that estimating a population mean from a sample mean is similar to predicting a population mean (Royall, 1992). More precisely, a model is set up to determine the missing values. The model is based on the density of the variable with the missing values, and conditional on a set of variables that describe the survey design and a set of parameters. The best-fitting model is selected on the basis of selection criteria and estimated using Bayesian techniques or maximum likelihood. In the case of vacancies, data on the features from advertised jobs and on the variables that determine whether or not a vacancy is posted online are necessary (e.g. firm size). Kureková *et al.* (2015) corroborate previous work by Gosling *et al.* (2004), de Pedraza *et al.* (2007), Steinmetz *et al.* (2009) and Štefanik (2012a).

Despite these limitations, online labour market data and vacancies data in particular have been recognised as a promising source for future research. These data can further our understanding of the labour market and provide an answer to a wide range of questions: How do new occupations emerge and spread throughout the economy and how do education and skill requirements differ across industries and change through time? Moreover, the amount of studies using web data and novel methodologies is clearly on the rise. This trend suggests that the field is likely to expand (Kureková *et al.*, 2015). Hooley *et al.* (2012) also expressed the view that web-based research in the social sciences is inclined to advance. This is especially relevant in the context of jobs and skills, given the importance of online job search and recruitment.

5.2.3 Which web-based data sources can be used for labour market analysis?

Which web-based data sources allow us to study the emergence of new occupations and skills in the economy? A first data source that could be particularly useful in this case is a dataset extracted from online **job portals**. Many online job portals are not limited to vacancies, but instead also collect CVs and offer salary comparisons, employer evaluations and career advice. We distinguish between national job boards and the European job portal EURES. With regard to the former, we also make the distinction between job vacancy analysis and CV analysis. Earlier studies on this topic have mostly worked with data obtained from private job portals (Capiluppi & Baravalle, 2010; Štefánik, 2012a; Kuhn & Shen, 2013). Note that one could make the distinction between online job boards and **other online labour market intermediaries** like oDesk, Amazon Mechanical Turk (MTurk), CoContest and TaskRabbit. Most of the work on these intermediaries has focused on MTurk, an online marketplace through which employers offer tasks that require human intelligence (i.e. work that computers are unable to do). Horton (2011), for example, studies the fairness of MTurk employers. Buhrmester *et al.* (2011) evaluate MTurk's potential as a data source in psychology and the social sciences. Other studies cover oDesk (Ghani *et al.*, 2012; Pallais, 2014). Maselli and Fabo (2015) use CoContest to evaluate the potential income that designers can earn via the platform.

Research seems to be more limited for other online intermediaries. Another well-known potential data source is data obtained from **web surveys**. Surveys such as those of the WageIndicator Foundation and Glassdoor collect data on salaries, working conditions, company and employer reviews. Online surveys have proven their value as research platforms in the past and should therefore definitely be considered for labour market analysis as well. Other sources include **Google Trends** and **social networks**. These sources are sometimes overlooked, but do contain useful information regarding the labour market. More specifically, new job opportunities are often posted on companies' Facebook page or Twitter profile, while job candidates set up a profile on LinkedIn in order to connect with potential employers. Social networks can reduce search frictions. Google Trends serves as an excellent tool to detect new trends and discover the occupations and skills that are on the rise. In the following sections, these potential data sources are discussed in more depth.

How can researchers **access the data from these sources**? One possibility is that data are made available on the website of interest or that of a partner organisation (as is the case for WageIndicator, where data are available through IZA). Some data are collected by private companies and are sold to interested researchers.[4] Another possibility is to opt for a 'web crawling' or 'spidering' technique. Carnevale *et al.* (2014) provide detailed information on this technique. Job advertisements can be assembled into a database by means of a 'spider' (or web bot) that crawls the Internet. Commonly,

4 An example is http://www.textkernel.com/

the set of websites to be crawled is carefully selected to ensure the representativeness and completeness of the dataset. As a second step, the set of advertisements is processed: data are extracted from the database and parsed into smaller fragments, which in turn can be coded. This is a complex step in which the structure and the content of the job advertisement are highly relevant. To this end, a detailed taxonomy of variables and words is very useful. In addition, semantic analysis and text mining are often required to support the coding process. Similarly, on some websites researchers can query the API to extract data. Examples of articles that use the spidering technique to compile a database of job advertisements are Capiluppi and Baravalle (2010) and Kuhn and Shen (2013).

There are several **barriers** that may impede data collection from online job portals (Shapiro, 2014). Job advertisements are generally not standardised (although several job portals do use a specific template), which complicates the identification and parsing process. As a result, the information that is contained in each advertisement may vary to a large extent. While some advertisements are very detailed, other job posts do not even provide essential information such as the sector, company name, the education or skill level required and so on. Online portals commonly do not store their information, which precludes historical analyses (Kureková *et al.*, 2015). Most advertisements are published on multiple websites, which necessitates a de-duplication step during the data collection process (Carnevale *et al.*, 2014). These issues clearly present a challenge to the identification of new jobs and skills, as this crucially depends on the job title and description in the advertisement.

5.2.4 Online job portals

This section examines the potential of online job portals as a data source for labour market research, and particularly for research on the rise of new occupations and skills. The section comprises three main parts. The first two parts assess the potential of national job boards and focus on vacancies and CVs respectively. The third part discusses the European job portal EURES. From the overview presented below, we conclude that online job portals in fact serve as an excellent data source for the analysis of new occupations and skills, because of the broad and detailed information that they comprise. In fact, one cannot only extract information from the advertisements and the CVs, the occupational structure and 'tag system' of the job portal are highly informative too. Job boards can be public or private, general or specialised (targeting only a sub-set of the population). Furthermore, many online portals have transformed from 'job sites' into fully fledged 'career communities', that collect and provide data on contracts, wages, working hours and company reviews. A comparison of different job portals can reveal insights as well, including which (new) occupations arise, where they appear first, and how they spread through the economy (across time, industries and countries).

5.2.4.1 Vacancies

Job portals or - more generally - employment websites connect the demand and supply side of the labour market. As finding and responding to an advertisement often is the first step, job portals are a valuable source for labour market research, especially in the light of the advancement of technological progress (Kureková *et al.*, 2015; Carnevale *et al.*, 2014; Kuhn, 2014; Kuhn & Mansour, 2014). Job advertisements shed more light on the qualifications and skills that employers are looking for. Web data, in comparison with traditional data sources, have the advantage of being more detailed and providing information that may not have been available before.

At the heart of the online job portals are the vacancies or job advertisements, published by employers looking for qualified applicants to fill a position in their firm. Many of these websites, however, also allow job seekers to post their CV and resume, provide job-search or career advice and other information (such as average wages by sector or legal advice on employment contracts). Some well-known examples of job portals are Monster.com, Careerbuilder.com and Glassdoor.com. Job portals can list domestic positions and/or jobs abroad. Although many portals cover all sectors and occupations, there also are a lot of job boards that specifically target a narrow selection of sectors or jobs (some examples are itjobs.com and euroeconomistjobs.com) or that focus on a specific region (e.g. jobsinberlin.eu). Job seekers benefit from using online portals as they can browse through a high number of positions, use search criteria to find a position that matches with their profile and get a better understanding of employers' requirements (Carnevale *et al.*, 2014). For firms and recruiters, job boards offer many advantages too, such as the ability to list job openings on targeted websites while keeping advertising costs low. Carnevale *et al.* (2014) further note that online job boards also serve as a useful tool for workforce agencies and colleges, as they facilitate the identification of emerging occupations, or new education and skill requirements.

Job portals are useful to explore the emergence of new occupations and skills for several reasons. These reasons are related to the data offered through these portals, such as the *occupational classification used* and the *information provided by the job advertisements themselves*. First, job portals are typically structured in a way that allows job seekers to easily find similar jobs to the one they are looking for. To this end, the portals rely on an occupational classification to structure their database and facilitate job search. In some cases, advertisements are assigned to a specific category ('tagged') by the advertiser. The list of tags can be published online or stored in a library which is called by search API. Job portals generally update these tags quite regularly, to capture changes in the labour market. The Slovak job portal profesia.sk, for example, included about ten new occupations every year between 2011 and 2014. In other cases, job portals do not use the tags system but associate occupations purely on the basis of keywords in the job description. This approach, however, is more prone to errors. The underlying occupational classification is a good data source to capture the occupational structure in a region at a certain point in time. These classifications can easily be compared with occupational classifications from other sources, such as ISCO and ESCO, to identify new occupations (e.g. what is missing in the official lists?). By combining the occupational classification with more detailed information extracted from the job vacancies or with labour market information from other sources, new occupations and new job titles can be found and further analysed.

Second, evidently, the job advertisements themselves also contain a lot of information that can be used to detect new occupations and skills. An advertisement typically comprises a job title, description (e.g. responsibilities, tasks), requirements (e.g. level and type of education, skills) and other information (e.g. details on the position, firm or industry; such as salary, company name and field of activity). In their study based on online advertisements, Burning Glass, Carnevale *et al.* (2014) detect more than 70 'data fields' in a single job post. By collecting a sample of advertisements, one can find new job titles and identify new tasks and skills required. These jobs may be completely new or already exist in different countries or sectors. As new occupations arise because new tasks are introduced in the economy (Crosby, 2002), which require a new set of skills, a careful analysis of job advertisements is a good start. A comparison of the skill requirements can shed light on these dynamics. Creating an occupational structure from job titles, however, is not straightforward especially in a cross-country setting (Tijdens *et al.*, 2012).

Empirical applications

Some recent literature uses job advertisements for labour market analysis. This current stream of literature is closely related to previous work that relied on **printed job advertisements**. Jackson *et al.* (2005) and Jackson (2007), for instance, work with job advertisements published in newspapers to test a number of sociological theories. Their work focuses on the merit selection hypothesis and on the link between social mobility and education in the UK. Despite the methodological issues that were raised by Kureková *et al.* (2015) and discussed in more detail above, the authors do not appear to be concerned by data representativeness and the extent to which results can be generalised. This issue also appears in a number of other studies that are presented in this section.[5] Dörfler and van de Werfhorst (2009) examine the merit selection hypothesis for the case of Australia, on the basis of

5 For a more detailed discussion, see Kureková *et al.* (2015).

advertisements published in newspapers between 1985 and 2005. In their work, the field of study is considered too. Importantly, Dörfler and van de Werfhorst (2009) opt for a multivariate regression approach to account for the fact that some skills levels may be under-represented in their database. Barnichon (2010) created an index from printed and online job vacancies, based on the Conference Board's Help-Wanted Index (HWI) that only covers job advertisements printed in major newspapers.

Other studies exploit **online job advertisements** instead. In an early study, Backhaus (2004) examined how firms describe themselves to job seekers in their recruitments materials (or, in other words, how do firms go about company branding and which marketing materials are used with that objective in mind). To this end, she obtained a sample of job advertisements from Monster.com. Kuhn and Shen (2013) use a data sample that comprises millions of job listings extracted from the third-largest Chinese job portal (through web 'spidering') to analyse gender discrimination in the recruitment of workers. The database is supplemented by firm-level data. Kuhn and Shen (2013) detect gender discrimination, but note that it is less problematic for positions that require highly-skilled workers. The sample that these authors have is extensive, but not completely representative due to a bias towards younger, highly educated workers, and towards private sector jobs with higher remuneration levels. Yet, no action has been taken to address these issues. Other articles concentrate on the Chinese labour market as well. In another paper, Shen and Kuhn (2013) consider the effect of over-qualification of job candidates on the basis of web data. Data representativeness again is not discussed and results are presented in a generalised manner. In other studies, Maurer-Fazio and Lei (2015) consider discrimination based on gender and facial attractiveness in the Chinese labour market, while Maurer-Fazio (2012) looks into ethnic discrimination. Martínek and Hanzlík (2014) combine data from job portals with data obtained from the Ministry of Labour and Social Affairs to study labour market dynamics in the Czech Republic. Masso *et al.* (2013) take a different approach and use job board data to study occupational mobility of return migrants in Estonia. Marinescu (2015) uses Careerbuilder to investigate geographical mismatch in the US, while Marinescu and Rathelot (2015) rely on this portal to study unemployment insurance.

Another strand of literature applies job portal data to perform research on **skills**. Kureková *et al.* (2012), for example, discuss the formal qualifications and other skills requested for low- to medium-level skilled occupations in Slovakia. These authors maintain that their results can be considered generalisable to the Slovak labour market, because the job portal from which the data are assembled covers a substantial market share. In another recent paper, Kureková and Žilinčíková (2015) explore whether low-educated workers and student workers are competitors for the same positions. Their results suggest that this does not appear to be the case, as they have different skill sets that actually are complementary. Other papers focus on the skills requirements in the IT industry. Wade and Parent (2001), for example, look into the relationship between performance and job skills, while Huang *et al.* (2009) differentiate between business, humanistic and technical IT skills.

More specifically, Wade and Parent (2001) compile a database of job advertisements for web-masters, to which data gathered via a web survey are added. They also apply multivariate regression techniques. Capiluppi and Baravalle (2010) crawl the popular website Monser.com to investigate the potential mismatch between the skills required for IT staff and those developed in education or training programs in the UK. Kennan *et al.* (2008) compare skills requirements for librarians in Australia and the US, on the basis of a set of advertisements published online and in the printed media. They find that skills requirements vary greatly across these two countries and through time. With a sample of vacancies from Burning Glass, Hershbein and Kahn (2015) provide evidence for upskilling: employers require more in areas with higher unemployment rates. Using a similar approach and dataset, Sasser Modestino *et al.* (2014) examine changes in employers' demands during the Great Recession (2007-2012) and the subsequent recovery (2010-2012). In bad labour markets employers are more demanding, both in terms of education and experience. Kudlyak *et al.* (2012) rely on matched applicant-vacancy data from SnagAJob to assess how job seekers' behaviour changes during their job search. In another contribution based on SnagAJob, Faberman and Kudlyak (2014) report that job seekers' search efforts decline with search duration. Finally, in a recent report, Rothwell (2014) uses data from Burning Glass to study job advertisement duration time and skills requirements, focusing in particular on STEM positions.

From this brief overview, we conclude that there are several articles on occupations and skills that make use of vacancy data obtained from online job portals. Some other examples are Tijdens *et al.* (2015b) and Fabo and Tijdens (2014). Kureková *et al.* (2015) find that most studies obtain data from private job portals, which are then used to explore a wide range of research topics in a single country setting. Methodological issues do not appear to receive much attention. Although online job boards and their job advertisements have been used extensively to study the dynamics of the labour market, researchers have to be aware of the limitations of these data sources (for more details, we refer to Carnevale *et al.*, 2014 and Kureková *et al.*, 2015). Not all vacancies are posted online, not every job opening creates a vacancy and not all vacancies are actually (new) jobs. In addition, online job listings appear to be targeted towards more highly-educated applicants looking for white-collar and STEM jobs in sectors with high skill requirements (Carnevale *et al.*, 2014). Furthermore, job advertisements' data are highly volatile and may be inconsistent. In many papers, therefore, job advertisements are combined with other labour market information and educational data sources. Dunlop (1966) compares the advantages and disadvantages of vacancy analysis. According to this author, job vacancy data can be regarded as the counterpart of unemployment series and can be used as a measure of economic fluctuations. Vacancy data can support labour allocation, labour administration and the development of (re-)training programmes. Nevertheless, job opportunities are made available in a variety of different ways. Moreover, vacancy data do not allow capturing the internal labour market and self-employment.

5.2.4.2 CVs

An increasing number of job portals enable job seekers to make a profile and/or upload a **CV** or a **resume**. Online job boards are no longer simply platforms on which employers and recruiters can post new vacancies, but instead are developing into 'career communities'. On many job sites, job seekers can post a CV, find career advice and interview techniques, look for training courses or internships, discover information on salaries and benefits, and make use of several other features. Monster.com, for example, allows users to post a resume and cover letter, and further offers resume writing and distribution services. In addition, the website has a salary calculator, a tool to look for education or training opportunities and a blog (on which a range of topics are discussed, including networking and job search advice). Indeed.com and CareerBuilder.com are two other examples of job portals on which job seekers can upload a resume. It therefore does not come as a surprise that comprehensive career communities, such as Glassdoor.com, are popular among job seekers and employers.

Job seekers can benefit from uploading their CV or resume to a job portal, as this can help them to attract the attention of employers to their profile. For employers, on the other hand, these resumes are very valuable too. Many websites allow employers to browse through CVs. On indeed.com, for instance, employers can sort CVs by location, company, job title and years of experience. In order to analyse the emergence of new occupations and skills, information extracted from CVs can also be an interesting data source. CVs are fairly detailed and provide an overview of the qualifications and skills that the job seeker has (both in terms of formal education and other skills). They also contain a list of (previous) job titles and positions, in some cases even with a detailed description of what the job entailed. In addition, by keeping track of the profiles that receive the most attention from employers, one can identify the skills and qualifications that are highly in demand (by region or sector).

Empirical applications

The analysis of CVs is commonly embedded in the study of recruitment and selection. On this note, many studies point out that online recruitment has gained in importance in the last few years. As there are many CV-related studies, only a few examples will be discussed here. Cañibano *et al.* (2008), for instance, perform a CV-based analysis to evaluate researcher mobility. Other work introduces ways to covert a CV into a resume (Haseltine, 2013). Some studies use CVs and resumes obtained from online job boards. Masso *et al.* (2011) study the relationship between labour mobility and the innovative performance of firms. To this end, they use a dataset comprising 261,000 resumes of job seekers, obtained from the leading Estonian online job portal. This dataset is then combined with data from the Community Innovation Survey.

Masso *et al.* (2011) find that a high level of innovativeness is associated with higher inter-firm labour flows (both at the firm-level and the industry-level). Štefánik (2012a; 2012b) aims to analyse the demand and supply of university graduates with a dataset obtained from the Slovak job portal profesia.sk. From this job board, he extracts job vacancies as well as CVs. His focus on the labour market segment of the university graduates is motivated by the idea that for this segment data representativeness is less problematic. As an additional check, Štefánik (2012a; 2012b) compares his vacancy data with data from the national Labour Force Survey and excludes occupations that are not equally presented in both sources. Three occupations are studied in his work: accountants, programmers and sales managers. Examples of the skills considered are language skills, database skills and programming skills. Štefánik (2012a; 2012b) finds large differences in the skill requirements across the three professions. Agrawal and Tambe (2014) use online resumes to track workers' career paths, focusing on workers previously employed in firms acquired through leveraged buyouts.

5.2.4.3 **EURES**

EURES[6] is the European Union's Job Mobility Portal, which was established in 1993. The portal assembles job vacancies across the EU in a standardised way. In addition to these vacancies, EURES aims to provide information, advice and job matching services to employers and job seekers and to stimulate labour mobility. The portal has a large network of EURES advisers (more than 850) to assist both job-seekers and employers wanting to recruit abroad. To job-seekers, EURES offers the opportunity the search for a job by browsing through job vacancies in 31 European countries (which are updated in real-time). Job-seekers can select an occupation, enter a job title, select their preferred contract (full-time or part-time) and indicate one or more countries and regions of interest. Job-seekers can also create a CV on the website that can be retrieved by employers and by the EURES Advisors. EURES has a separate page for recent graduates. Another interesting feature of the portal is the 'your first EURES job' scheme, that targets young people who are interested in finding a job, traineeship or apprenticeship abroad. EURES also has a 'skills and careers' page, on which learning opportunities are listed (which can be searched by education level, subject and location). This page integrates the information from PLOTEUS, the Commission's Portal on Learning Opportunities throughout Europe. For employers, EURES provides detailed information on recruiting abroad as well as the possibility to look for job candidates via the portal. More precisely, employers can browse through the CVs that are uploaded on the website, advertise jobs or find information on the labour market of the countries they are interested in. Employers can also discover the steps involved in the recruiting process and participate in information and recruitment events. EURES collaborates closely with the national public employment services as well (they post their vacancies on the portal); employers can therefore also benefit from their services. In order to facilitate labour mobility across countries, the EURES portal further has a 'Living and Working' section that provides an overview of administrative, practical and legal issues that are related to mobility. In fact, for each country labour market information, living and working conditions and free movement are discussed. A wide range of topics are addressed, such as the cost of living, taxation, social legislation, health, finding accommodation, where jobs are available and how the labour market operates.

6 See https://ec.europa.eu/eures/public/homepage

Empirical applications

Even though EURES is a European-wide job portal where researchers can access vacancies, CVs, and labour market information, there are hardly any studies in which the portal serves as a data source. More precisely, to the best of our knowledge, only Kureková *et al.* (2015) use a dataset obtained from EURES. They exploit the cross-country dimension of the EURES portal to evaluate employers' skill demand in the Czech Republic, Denmark and Ireland. The authors conclude that skill demand differs greatly across these three countries, which points to the role of domestic institutions and structures.

1.1.2 Google Trends

Google Trends (www.googletrends.com) was launched in 2006. The service is based on Google Search and analyses a percentage of Google web searches. In particular, Google Trends allows users to check how often search terms, or combinations thereof, are entered relative to the total number of searches performed (by region, across time). When multiple search terms are entered, the relative popularity of these terms is compared. More precisely, on the web page, there is a search button allowing users to type in their search term of interest (e.g. occupations, or skills, or both). Google Trends displays the interest in this search term over time (is it on the rise or declining?), by region (global, national or regional level, depending on country), and related searches (split out into topics and queries, e.g. if one looks for 'skills', related searches are 'social skills', 'job skills', skills tests'). A normalised volume of queries is provided, which are presented in a graph. Spikes in the graph are associated with news headlines, when possible. However, to protect the privacy of its users, Google does not publish results for the search terms, for which there are insufficient observations. Trends data exclude searches made by very few people, duplicate searches and special characters. Searches and search outcomes can be manipulated by Google and one has to keep in mind that it is a company that develops content, sells advertisements and promotes its sub-brands (e.g. Yahoo Finance). This could particularly affect small- and medium-sized firms, which see their search ranks worsen and lose significant amounts of traffic. Moreover, organisations and large companies are able to manipulate search results too, to maximise traffic and exposure.

Google Trends further has lists of 'hot searches' and 'hot topics'. The former tracks the Google searches that are rising the fastest at the moment while the latter captures trending terms in the news and on social media. Google Trends also features top stories that can be filtered by region and topic (e.g. business or health). In 2008, Google launched Google Insights, an extension to Google Trends. Google Insights allows users to track words and phrases that are entered into search boxes and analyse results. The tool was integrated into Google Trends in 2012. All datasets can be downloaded in the .csv format.

There are some important caveats to Google Trends. As only a sample of searches is used and searches for which there are insufficient observations are excluded, Trends data could be affected by **sample bias** (in small samples, only random draws with enough observations are shown) (Kearney and Levine, forthcoming). A second issue is **sampling variability** (problematic for standard error calculations when data are treated as fixed rather than random variables). To address these issue, the authors repeat their searches on Google Trends several times and calculate the average of the indices (to reduce the sampling variability). Another shortcoming of Google Trends data is that demographic information is not available. As temporal and geographic variations are sources of variation that labour economists typically rely on, the above issues are important to account for.

Empirical applications

Google Trends serves as a data source in a large number of contributions. One of the most well-known applications is **Google Flu Trends**. In an influential article published in Nature, Ginsberg *et al.* (2009) explain how Google Trends can be used to improve the early detection of seasonal influenza by monitoring search engines like Google. This approach seems to work well because of the high correlation between the percentage of doctor visits and the relative frequency of specific queries on Google. The authors can predict weekly influenza activity in the US (with a time lag of one day). Other studies have used Google Trends to examine health-related topics as well (e.g. papers that extend or improve Ginsberg's method or focus on other diseases).

The strand of literature that relies on Google Trends for **forecasting and now-casting** is extensive too. Choi and Varian (2012) show that Google Trends is a useful tool for predicting the 'present' (in the form of subsequent data releases, i.e. the short-term future), due to the correlation between queries and economic indicators. They illustrate this result with the examples of travel, retail sales, home sales and automotive sales. Carriere-Swallow and Labbe (2013) work on a related topic, focusing on automobile purchases in Chile. Preis *et al.* (2013) relate Google queries to stock market dynamics and show that losses are often preceded by a growing volume of specific stock market search terms. In a recent publication, Chen *et al.* (2015) evaluate to what extent Google search queries can be used to 'now-cast' business cycle turning points during the crisis of 2007-2008. Schmidt and Vossen (2012) use Trends data to account for special events in economic forecasting. In another paper, Preis *et al.* (2012) link queries, and whether they refer to the future or past, to countries' economic success. Constant and Zimmermann (2008) use Google Trends to measure economic and political activities, while Askitas and Zimmermann (2009) and Choi and Varian (2009) use it to predict unemployment.

Other studies use Google Trends for **behavioural analysis**. In a series of articles, Stephens-Davidowitz uses Google Trends to explore topics such as racism, religion, prejudice and health. Rode and Shukla (2014) use a Google search query to examine racial differences in labour market outcomes in the US. The authors provide evidence for racial prejudice: in metropolitan areas with more racially charged searches, black-white gaps in annual income, hourly wage and annual hours worked are wider. This result appears somewhat stronger for less-educated workers. Another relevant paper is Kearney and Levine (forthcoming), who combine data from Google Trends, Twitter and two other sources to examine how media images affect adolescents' attitudes and outcomes for the case of MTV's reality TV show '16 and Pregnant'. Interestingly, the TV series appeared to raise the amount of Google searches and tweets on birth control and abortion. Moreover, the show is associated with a 5.7% reduction in teen births in the 18 months after its introduction. Kearney and Levine (forthcoming) do point to potential endogeneity: the interest in '16 and Pregnant' is likely higher in areas where the teen birth rate is higher, or where it is rising or falling more slowly. While the former can be tackled via geographical fixed effects, the latter is addressed with an instrumental variables (IV) strategy, in which ratings are instrumented with ratings of any MTV show broadcasted during the same time in the previous period.

5.2.5 Social networking sites

In the last few years, many studies have appeared that are concerned with social networking websites. Whereas initially researchers were mainly interested in the social networks themselves, as evidenced by the report on online ethnographies in Section 3, attention has recently shifted towards their role as a research platform and data source. Social networks indeed commonly have a very large user base covering individuals, firms, and other organisations. User profiles often contain rather detailed information about current and past work experience, educational attainment and other qualifications. Information about the behaviour and preferences of individuals can easily be obtained from these sites. In addition, firms and organisations often set up profiles on these networks as well, through which they can interact with current employees and interested job applicants, and provide details on their positions and work environment. Social networks can also reduce search frictions. In many cases, information is publicly available. Acquisti and Fong (2015a; 2015b) investigate how information available on job applicants' profiles affects their interview invitation rates. A third of employers searched online for information on the candidates. Results also suggest that employers in the

Republican parts of the US have a significant bias against Muslim candidates and in favour of Christian applicants.

From the social networks, researches can compose a database that comprises occupations, job titles, experience and qualifications and other labour-related variables. In this section, three social networks are presented: LinkedIn, Facebook and Twitter. Social networks should not be overlooked, as they can further our understanding of search and matching on the labour market. The presentation of these sites draws on the information provided on their websites.

5.2.5.1 LinkedIn

Of the social networks discussed here, LinkedIn (www.linkedin.com) is the one that is the most obvious candidate to serve as a data source for labour market analysis because of its focus on professional networks. By enabling users to set up profiles, connect with other users and find or list job openings, LinkedIn aims to 'connect the world's professionals to make them more productive and successful' and to 'transform the ways companies hire, market and sell'. LinkedIn was founded in 2002 and became available online in the spring of 2003. About 4,500 users signed up to the website during the first month. Since then, LinkedIn has developed into the largest global online professional network, connecting over 364 million users (including employers and companies, recruiters, employees and job seekers) in over 200 countries and territories. In the first quarter of 2015, over 75% of LinkedIn's new users were not US-based. The website currently supports 24 languages. In Europe, LinkedIn has more than 89 million users. Two new users sign up every second. LinkedIn is publicly held and generates revenues from Premium Subscriptions, Marketing Solutions and Talent Solutions. In the United States, 28% of the adult Internet users use LinkedIn (Duggan *et al.*, 2014). The site is particularly popular among college graduates, higher-income households and the employed. LinkedIn is the only platform where people aged 30-64 are more likely to be users than those aged 18-29 (Duggan *et al.*, 2014).

Because LinkedIn holds profiles of companies, job seekers and recruiters, it is an interesting platform to analyse labour market dynamics. Firms can use LinkedIn to set up a 'Company Page' on which they can post job opportunities or create dedicated 'Career Pages' for this purpose. LinkedIn users can go through company pages to find job opportunities, use the general search options LinkedIn that offers or connect with recruiters. Since 2011, users can even apply for jobs directly by using their profile as a resume when they click on the 'Apply with LinkedIn' button on job listing pages. Another feature is the option to establish or become a member of an interest group (e.g. Java Developers). User profiles of employees and job seekers further comprise valuable information on their education level and skills. In the fall of 2012, LinkedIn added a feature through which users can comment on each others' profiles and endorse each others' skills. From this it is clear that LinkedIn reduces search frictions, as job seekers (employed or unemployed) can easily find positions in their organisation or sector of interest, and employers can easily browse through a large set of profiles to find their ideal candidate (also passive candidates are available). LinkedIn therefore is a good starting point for labour market analysis. For 94% of job candidates (two-thirds of recruiters), LinkedIn is the most important social network for job hunting (candidate sourcing) (Right Management, 2015).

Empirical applications

Currently, most of the work on LinkedIn covers the **platform** itself. For example, there are several studies that examine how LinkedIn can be used effectively in selection and recruitment or other business processes (Caers and Castelyns, 2011; Bonsòn & Bednárová, 2013; Rangel, 2014 and Zide *et al.*, 2014; from the perspective of job seekers and employers). Other work focuses on the company itself (e.g. Jarrow *et al.* (2011) discuss LinkedIn's stock price). On the other hand, there are only a few contributions in which LinkedIn **serves as a data source**. An interesting example is State *et al.* (2014), who examine migration to the US among professional workers of different education levels with a database of geo-located career histories from LinkedIn. Boucher and Renault (2015) use a dataset compiled by HiQ Labs, which comprises many job titles and LinkedIn profile summaries, to construct a job classification. Gee (2015) takes vacancies published on LinkedIn to do an online experiment covering over 2 million job seekers. She demonstrates that reporting the number of previous applications increases the likelihood of application, especially among female job seekers. Tambe (forthcoming) examines how labour market factors shape early returns to investment in big data technologies such as Hadoop on the basis of LinkedIn. Other studies, of which several are related to the analysis of jobs and skills, can be found on http://data.linkedin.com/publications.

A final set of applications that are worth mentioning, are embedded in the '*Economic Graph*' challenge. The LinkedIn Economic Graph challenge was launched in 2012 and sets out to create an economic graph within a decade (i.e. to digitally map the world economy). For this challenge, teams were invited to propose how they would use data from LinkedIn to perform research on a wide range of topics related to the job market. Some 11 teams were selected, of which at least five work specifically on occupations or skills. These teams' research topics are: 'Text Mining on Dynamic Graphs' (aid firms to find skill sets that match their needs), 'Your Next Big Move: Personalised Data-Driven Career Making' (aid workers to acquire skills for job they are interested in), 'Identifying Skill Gaps: Determining Trends in Supply and Demand for Skills' (on skill gaps and other labour market challenges and opportunities), 'Forecasting Large-Scale Industrial Evolution' (on industrial changes and emerging skills) and 'Bridging the Skills Gap by Transforming Education' (on efficient matching and education).

5.2.5.2 Facebook

Facebook (www.facebook.com) is a well-known online social network that was launched in 2004. On Facebook, users can set up a profile on which they can post messages, photos and videos, update their status and make use of other features. User profiles can be public or private. On their profile, users can share their employment status or occupation, education level, family situation, skills, interests and hobbies and all kinds of other information. Users can connect with others by becoming 'friends', in which case they receive notifications when a friend updates his/her profile (via the 'news feed'), are able to send messages or chat. Since 2004, users have the possibility to create or become a member of a (private) Facebook group (e.g. related to their work). As of 31 March 2015, Facebook had 1.44 billion monthly active users. The average number of daily active users during the month of March was 936 million. About 83% of the daily active users do not reside in the US or Canada. These numbers reveal that Facebook has an extremely large global user base. The website also has a much larger network of users than any of the other social networking sites discussed in this report. Duggan *et al.* (2014) find that Facebook is the most popular social network: it is used by 71% of online American adults. Women are particularly likely to use Facebook compared to men (66% of men, 77% of women have a profile). Facebook is a publicly held company that mainly generates revenues through advertising.

Companies, recruiters and other organisations can also create a Facebook profile. This possibility was introduced in 2007 and is known as 'Facebook Pages'. Facebook Pages are public profiles held by celebrities, businesses, organisations, and brands. On their profile, companies can present themselves to users, interact with them, introduce new products and post job vacancies. On this note, there are also many job portals that have their own Facebook page through which they look for new talent, share job opportunities and offer career advice. Some examples are Indeed and Monster. In 2012, Facebook launched a job board, the 'Social Jobs Partnership Application', which is the result of collaboration with the Department of Labor, the National Association of Colleges and Employers, the Direct Employers Association and the National Association of State Workforce Agencies. The introduction of the application was motivated by the outcome of a survey that was performed by the

National Association of Colleges and Employers (NACE), which targeted 530 employers and recruiters in the spring of 2012.[7] This survey revealed that (1) 50% of the employers used Facebook in the hiring process, (2) almost 90% of the companies noted that recruiting via Facebook is more cost effective than through other channels and (3) especially networking and referrals are key features to find new employees (e.g. engaging in a network with a candidate after he/she 'liked' the company's Facebook page). By using the application, recruiters can post job opportunities which can be sorted by location, industry and skills. When the application was first launched, it combined job offers from BranchOut, the Direct Employers Association, Jobvite, Monster and Work4Labs. The goal of the project is to facilitate the process of finding and sharing jobs via Facebook. A final option that firms and recruiters have to search for job candidates is to exploit Facebook Graph Search (Headworth, 2014). Facebook lowers search frictions (users can easily connect with an employer of interest or join a group, employers can browse through profiles and discover interesting candidates more easily, via groups).

Empirical applications

There are many studies on the topic of Facebook, but at first glance, only a few studies exist that use Facebook data to address labour market dynamics, occupational change and the emergence of new jobs and skills. Overall, the literature is extensive and covers different fields. Some examples are health-related issues, network analysis, and education. Wilson *et al.* (2012) examined the research on Facebook in the social sciences. Their analysis is based on 412 articles published up until the first of January in 2012. Wilson *et al.* (2012) classified these articles into five categories that reflect five research questions: (1) Who is using Facebook, and what are users doing while on Facebook?, (2) Why do people use Facebook?, (3) How are people presenting themselves on Facebook?, (4) How is Facebook affecting relationships among groups and individuals?, and (5) Why are people disclosing personal information on Facebook despite potential risks?. The bulk of the articles addressed the fourth question (impact on social interactions). These research questions are also particularly interesting to get more insight into labour market dynamics and recruitment and selection. Some work has been done on these issues, from both the perspective of job seekers and the perspective of employers and recruiters. Research confirms that Facebook is becoming an increasingly popular tool to screen job applicants (Karl *et al.*, 2010a, 2010b; Kluemper & Rosen, 2009). This, however, implies that employers and recruiters can also evaluate job applicants on other criteria, such as their gender or race or 'inappropriate' material on their profile (Kluemper & Rosen, 2009, Bohnert & Ross, 2010). Kelkar and Kulkarni (2013) discuss the usefulness of Facebook from the labour supply side. While pointing out the possible advantages that Facebook has for job seekers, Kelkar and Kulkarni (2013) do find that only a small number of members actually use Facebook to look for jobs and networking purposes. In addition, the authors criticise the Social Jobs Application, because it tends to yield inconsistent and ineffective results and does not appear to add much to what is already available on the job portals' websites. From this study, one can conclude that Facebook has the potential to serve as a source of recruitment and selection, but this potential has not yet been exploited to its full extent. Two other examples of work on Facebook are Gee *et al.* (2015a) (on the link between job transmission and Facebook) and Gee *et al.* (2015b) (on weak ties).

Facebook therefore appears to be an interesting and valuable data source that has been used for labour market research but not, to the best of our knowledge, for the analysis of (new) occupations and skills. Wilson *et al.* (2012), however, note that data crawling techniques are becoming less effective due to stricter privacy settings.

7 The survey is available at:
http://naceweb.org/uploadedFiles/NACEWeb/Connections/social-jobs-partnership-executive-summary.pdf

5.2.5.3 Twitter

Twitter (www.twitter.com) is a micro-blogging website through which users can send and read short messages (no more than 140 characters) called 'tweets'. Whereas these messages can be read by anyone, only registered users can send out tweets. Users are 'connected' to each other when they follow or are followed by other users. Moreover, messages sent out by one user can be re-tweeted by others. Tweets can cover any topic and can be grouped by topic or via hash tags. Twitter also keeps track of 'trending topics' (global and regional trends, using an algorithm that accounts for the location and interests of users). Twitter was launched in 2006 and has grown substantially ever since. About 500 million tweets are sent each day, most of which are accessible for public view as tweets are publicly visible by default. As of 31 March 2015, Twitter had 302 million monthly active users. Twitter supports 33 languages and 77% of its accounts are held outside the United States. These numbers clearly illustrate that the website has a global user base. Twitter's mission is to 'give everyone the power to create and share ideas and information instantly, without barriers'. This idea is put into practice through following and followers, re-tweeting and the public nature of the service.

Twitter can be used by job seekers, employers or companies and recruiters and is therefore a useful tool in the analysis of the labour market. Job seekers can use Twitter to get more information on companies, discover job openings and find out more about the qualifications required, by following these firms, and they can interact with current employees. Moreover, job seekers can also use the general 'search' function to find new vacancies. Companies, on the other hand, cannot only turn to Twitter for marketing purposes and sales, they may also use the website to tweet about new job vacancies and look for employees. Such tweets often consist of a job title, a brief description of the position and a link to a web page with more information. In addition, companies can use Twitter to strengthen their profile and spread information to clients and (potential) employees. A further option that companies have is to work with third parties, for example 'Tweet My Jobs', to share their job vacancies (Schawbel, 2012). Recruiters can also rely on Twitter to find new talent, through their own account, by becoming a member of groups or following users. Another feature that is particularly useful in this regard is the option to embed a web link in the company's or recruiter's Twitter profile page, which directs job seekers to their full website. Furthermore, many job portals, such as CareerBuilder, Indeed, Simply Hired and Monster, have their own Twitter accounts through which they share job listings and offer job search and career advice. As Twitter messages are fairly short, employers generally will not use Twitter as their main recruiting tool, but rather as a part of a whole recruitment strategy (Larsen, 2011). Duggan *et al.* (2014) suggest that 23% of the US adults online use Twitter. The site is particularly popular among those younger than 50 and the college-educated.

Empirical applications

Even though Twitter was only introduced in July 2006, there already exists an extensive literature on the micro-blogging website. Academics and other researchers from many different fields have taken an interest in Twitter, which resulted in a high number of studies on a variety of topics (including but not limited to the field of computer and information sciences, physics, linguistics and economics). This interest is motivated by the scale of the database (the large amount of users and tweets) and its time dimension. In a recent article, Williams *et al.* (2013) focus on Twitter-based research to identify and classify the types of studies that are being done. From their review of the literature, they conclude that generally the following four elements are covered: the message, user, technology, and concept. Other elements that are considered in some papers are the domain (e.g. education, health, business and security), data and research method. For a sample of 575 papers on Twitter published between 2007 and 2011, the authors show that most research deals with the content of Tweets followed by work on the users (together they represent 80% of the papers). Some more specific examples of recent work on Twitter are the paper by Achrekar *et al.* (2011) on the prediction of flu trends, by Murth (2015) on elections, by Yu and Wang (2015) on sentiments in tweets during the World Cup of 2014, and by Sashittal *et al.* (2015) on brand entification.

Despite the large number of topics covered, research on the relation between Twitter and labour market dynamics and the use of Twitter data to identify or classify occupations and skills is limited. Kearney and Levine (forthcoming) use Google Trends and Twitter, but find that the latter is harder to access than the former. Historical data cannot be accessed, nor is there information on the frequency of tweets on the site. A library of past tweets can be obtained, but this library is difficult to manipulate due to its size and format. Data can be obtained through third-party vendors. Other limitations are that geographical information is difficult to obtain and that information on demographics is unavailable. Only a few papers seem to use Twitter for the behavioural analysis.

In February 2014, Twitter launched a pilot project called '*Twitter Data Grants*', which consisted of a call for proposals for research institutions to collaborate with Twitter staff and get access to public and historical data. Six teams were selected to join in the project: a team from the Harvard Medical School/Boston Children's Hospital (on foodborne gastrointestinal illness surveillance), NICT (on a disaster information analysis system), University of Twente (on diffusion and effectiveness of cancer early detection campaigns), UCSD (on measuring happiness of cities), University of Wollongong (on urban flooding in Indonesia) and University of East London (on the relationship between Tweets and sports team performance). Before the Data Grant programme was launched, free access to data was limited to the last seven days. The difficulty in accessing Twitter data also spurred several papers on this topic, such as Kwak *et al.* (2010), who describe how they 'crawled through' Twitter to examine Twitter's topological characteristics. Note that Twitter, in contrast to the other platforms described in this report, is mainly relevant for the demand side of the labour market as users only have very limited profiles. One option, however, is that job seekers can spread their resume via Twitter in the hope of attracting companies' and recruiters' attention.

5.2.6 Online web surveys

Web-based surveys have already been discussed in the earlier sections of this report. Here, we focus on Glassdoor and WageIndicator. Both sources are well-known and attract a large number of users and participants in their surveys. The surveys cover labour-related factors, such as wages and work conditions. However, as participation in surveys is voluntary, researchers have to be aware that this may have implications for the sample obtained in the end. Examples of potential issues are the information on specific questions may be missing or that only a part of the population is reached. The latter may result in low response rates, as suggested by Benfield and Szlemko (2006). Other issues to keep in mind, regarding the completion of the surveys, are the (computer) literacy of the participants and the 'rapport' possible with the respondents (authenticity, credibility of the questions and answers).

1.1.2.1 Glassdoor

Glassdoor (www.glasdoor.com) is a very popular career community website that was first launched in 2008. Although the website operates as a job board, Glassdoor actually goes beyond the more traditional job portals as the company also targets employers and recruiters, as well as career centres and libraries. The company is based in the US and managed to develop into one of the largest job sites there, but its user base is rapidly expanding towards a more global audience. In fact, Glassdoor currently has over 30 million members in over 190 countries worldwide.

The Glassdoor website is organised into **six categories**. The first four categories are oriented towards job seekers and employees, while the last two target firms and recruitment agencies. Each of the first four categories enables job seekers to upload their resume. The first out of the six categories is '**jobs**'. Similarly to the more traditional job portals, Glassdoor functions as a job portal on which millions of vacancies are listed. Job seekers can browse through these job openings to discover which firms are hiring and which positions are available on the labour market. On the website, job seekers have the opportunity to look for open positions by location, job title, occupation or key words.

Glassdoor also presents them with a list of popular and related searches. The second category is **'companies'**. Job seekers can look for firms in a specific location and are redirected to a detailed company page if they click on a firm. On a company page, job seekers can upload or read company reviews, find CEO approval ratings, discover the salaries that the firm offers for specific roles, ask questions to current or former employees, find office photos and other information, read interview tips, and so on. One of the innovative features of Glassdoor is that all this information is provided by former or current employees of these firms. This is in line with the company's focus on transparency. The website covers more than 400,000 firms worldwide. To write a company review, users need to have an account. Users are only allowed to write one review, per firm worked at, per year. Reviews are published anonymously. Firms have no information on the identity of the employee that posted the review, and cannot manipulate or remove reviews. Before a review is published, it has to be approved by Glassdoor. Reviews that do not meet the guidelines are not published (e.g. reviews should be balanced, cannot disclose trade secrets). Employers can respond to reviews and flags reviews that do not meet the guidelines, are inappropriate or fraudulent. The third category on the website is **'salaries'**, which can be viewed for specific positions. The fourth category targeted towards job seekers is **'interview'**. As indicated above, job seekers can find information on the interview style, level of difficulty, sample questions and other information (for interviews in different firms, for a variety of jobs). Since much of the information provided on the website is filled out by former and current employees, Glassdoor clearly has a 'web survey' dimension.

Glassdoor further aims to attract employers. The two remaining categories therefore are **'employers'** and **'post a job'**. On the website, employers can set up an 'Enhanced Employer profile', on which they can share their history and discuss their activities, promote new vacancies, or post a link to their Facebook account. Glassdoor offers employers effective recruiting and employer branding solutions via 'Glassdoor for Employers'. Employer branding implies that employers can keep track of the candidates who are looking into their company and the reputation that their firm has on the website (and ways to improve this). Job advertising involves listing a single or all available jobs; target job seekers; using analytics to get better matches (and to discover which advertising works best). Glassdoor has more than 2,000 clients and partners for which they do employer branding promotion, job advertising (especially to candidates who may not have been aware of the position), or both. Glassdoor also offers solution for companies in specific sectors, such as tech, telecom and SaaS companies; banking and finance companies; and consulting companies. Finally, note that Glassdoor also reaches out to **career centres and libraries**. The idea here is that career centres and libraries can offer unlimited access to the website to their students without having to post information of their own.

According to Glassdoor, users of all ages and backgrounds are on the site. Moreover, the average company rating is 3.4 (on a 1-5 scale). Some 70% of the employees indicate 'OK' or 'satisfied' when asked about their employer. A survey of over 4,600 Americans revealed that 2,201 of them use Glassdoor (Osterhaus, 2014). About 50% consult Glassdoor at the start of their job search, to identify top employers. Osterhaus (2014) reports that especially job seekers aged 55-64 and those earning between $25,000 and $49,999 annually are active on the site. Most respondents live in urban or suburban areas. Glassdoor seems to attract users of all ages and income levels. As Glassdoor engages more users and companies, representativeness may increase further.

Empirical applications

There are numerous studies that use data extracted from Glassdoor.com to study the labour market. In many cases, data on wages or other information that are posted on Glassdoor.com are used to complement a more extensive analysis. An example of this is a study on the opportunities of females in IT by Thiele (2014), who uses Glassdoor to find the median wages for a number of IT professions (including software trainers, system programmers, network technicians). Massimino *et al.* (2015) use Glassdoor.com to come up with employee satisfaction rates. Other publications refer to Glassdoor as a source where individuals can find information on interview techniques, firms and their skill requirements and other useful tips. An example of this is an article by Kaplan (2014) published in Nature, on how to prepare for job interviews. Another example is the work by Lauby (2013), who considers the rising popularity of Glassdoor.com as an example of the increasing importance of employer/career branding. Chandra (2012) uses Glassdoor data on the work-life balance ratings across firms, to compare Eastern and Western perspectives on work-life balance. American and European companies rank higher than Indian companies as they pay a lot of attention to this issue.

Glassdoor also has its own research team of economists and data scientists: **Glassdoor Economic Research** (http://www.glassdoor.com/research/). Given that Glassdoor gathers an enormous amount of real-time data on different labour market aspects, the website is a unique and rich data source. Such data have been difficult to collect in the past, especially on such a large scale. Recent studies published by this tram deal with hiring times, jobs affected by the introduction of a minimum wage, the link between salary and employee satisfaction, salary transparency, cities' recovery after the crisis measured by unemployment, jobs and wages, company culture, among a variety of other topics. The website will offer downloadable data in the future and supports 'Job Tools'. The latter are two interactive map-based tools that can be used by job seekers nationwide. The first tool is the 'Job Explorer', through which job seekers can find where their skills are in demand. The second tool is the 'Apprenticeship Finder' that can be used to explore apprenticeship and career opportunities. For the second tool, job seekers can view on a map in which states there are many apprenticeships opportunities (high to low), by clicking on a state, job seekers can zoom in and find out where in the state the opportunities are available. For example, in the state of California, there were 5,704 apprenticeship jobs available at the end of July, most of which were concentrated in the areas around San Francisco, Sacramento, San Diego and Los Angeles and in Silicon Valley. The first tool is the job explorer. Here, job seekers can select a job category or type in a key word to view on a map where these skills or jobs are concentrated. In the state of California, this resulted in a number of 94 'programming skills' jobs and 44,556 'programmer' jobs. The tool indicates the 'top cities' with these jobs, and lists 'other jobs you should consider' (for the 'programmer' job, jobs are: senior programmer, consultant, software engineer, and programmer analysts).

5.2.6.2 WageIndicator

WageIndicator consists of a series of websites that are operated by the WageIndicator Foundation. These websites are available in about 80 countries and support their main national languages. The WageIndicator Foundation is a non-profit organisation that was founded in 2003. The idea behind WageIndicator is that, to understand global labour market trends, comparative and up-to-date micro-level data are necessary. Such data can be collected in an easy and relatively cheap way through online surveys. By setting up national websites and asking each visitor to complete the web survey, information on a range of labour market topics can be obtained. As similar questions are asked across all countries (in the national languages, adapted to national specificities), a large sample that allows cross-country comparison can easily be assembled. WageIndicator uses web-marketing, collaborations with partners and search engine optimisation to attract visitors to its websites.

WageIndicator mainly relies on web surveys to obtain labour market data. In countries with poor Internet access paper-based surveys are used instead. The WageIndicator survey contains questions on occupation, industry, wages and bonuses, contributions and entitlements to social security, contracts, working hours and overtime, working conditions and intensity, well-being and satisfaction with job and pay. Other questions are more related to the demographics of the respondent, i.e. age, country of birth, religion, household composition and education. The web surveys are run on a continuous basis. The survey is targeted towards the labour force, which includes employees, self-employed, informal workers and unemployed individuals. Participation is voluntary and there is a price incentive to stimulate participation. This implies, however, that individuals with no internet access, that are illiterate or do not speak the nations' main languages are underrepresented in the surveys. WageIndicator data should therefore mainly be used for exploratory analyses as they are not representative for the full population. Occasionally, customised web surveys are used, for instance to target specific industries or occupations.

The national WageIndicator websites are generally organised into three pillars. The first pillar is **'pay'**. This pillar presents up-to-date information on real wages and minimum wages, to which visitors can compare their own salary. Note that WageIndicator has a database of minimum wages and also runs cost of living surveys. The site further holds information on the relation between the minimum wages and the poverty line and on public sector wages. The second pillar is **'law and advice'**. This pillar provides visitors with current information about labour laws and collective agreements (collected in a separate database as well). On these web pages, visitors can also find replies to commonly asked questions about labour legislation. The third pillar, **'career'**, comprises interview and training advice.

The data that results from WageIndicator surveys are organised as a single dataset for period 2000-2005 and into annual releases from 2006 onwards. Each dataset comprises continuous variables, project variables and META variables (questionnaire version, case identification, survey completion e.g.). With the exception of the META variables, all variables are numerical and on a nominal or scale measurement level. Only computed variables are available (not the source variables). The open-ended survey questions are not available in the dataset; neither are the time stamps; but both can be requested. The WageIndicator data are distributed through the data archive of IZA (IDSC). Researchers can easily obtain these datasets to perform their own labour market analyses.

Empirical applications

Because the datasets collected through the WageIndicator project are very rich, they have been used in numerous studies on a wide range of labour-related topics. Many of these studies have been done by members of the **WageIndicator Foundation**. Some examples of this work are: the paper by Munoz de Bustillo and de Pedraza (2010) on job insecurity in five European countries, by Tijdens *et al.* (2013) on the remuneration of health workers in 16 occupational groups and 20 countries, by Zofkova and Stroukal (2014) on the wage penalty of motherhood in the Czech Republic, by Steinmetz *et al.* (2014) on the impact of working time and wages on retention among health workers, by Besamusca and Tijdens (2015) on collective bargaining agreements in developing countries and by Guzi and de Pedraza (2015) on subjective well-being. Other studies are of a more methodological nature, such as the work by de Pedraza *et al.* (2010) on continuous volunteer web surveys in Spain and by Tijdens (2014) on dropout rates and response times of an occupational search tree in web surveys. The importance of methodological research should not be underestimated, as it contributes to lower dropout rates and improvements in web survey quality.

These examples, however, represent only a small sample of the work that is based on WageIndicator data. On the website of the WageIndicator Foundation, a longer list of articles is provided. The first studies date back to 2001. More recent work involves a study on skill mismatch among migrant workers (Visintin *et al.*, 2015), on self-identification of occupations in web surveys (Tijdens, 2015), on workers and labour market outcomes of informal jobs in formal enterprises in sub-Sahara Africa (Tijdens *et al.*, 2015) and on bonus payments in India's formal sector (Varkkey *et al.*, 2014). Other work covers WageIndex analyses (to map the workforce, wages and working conditions in specific countries; Fabo and Sedlakova, 2015), the value of web data in developing economies (Tijdens & Steinmetz, 2015), among many other topics.

5.3 Conclusions

From this overview of the strengths and weaknesses of the traditional and web-based data sources, we conclude that online data are an interesting and highly useful tool for labour market analysis and the identification of new jobs and skills. Although research has mostly focused on the analysis of vacancies, CVs and resumes, and online surveys so far, data obtained from Google Trends and social networks can support the analysis of new and emerging occupations and skills as well. Web-based data sources clearly offer some important advantages compared to traditional sources, such as a fast, easy and inexpensive data collection process and the availability of large, diverse samples.

6. Conclusions

What are new occupations? What are new skills? How are they measured? And what differences do we observe when the academic and policy literature on these topics are compared? These questions are at the heart of this State of the Art Report. In both the academic and the policy literature, the concepts of *occupations*, *jobs*, *tasks* and *skills* are clearly defined. The relationship between each of them is complex, which implies that these concepts could be difficult to disentangle in practice. In many studies, several of these concepts are therefore studied simultaneously. In some branches of the academic literature, occupations are more important than jobs or tasks, while the opposite holds for other strands. There is an extensive literature on skills as well. Nevertheless, in the bulk of the academic work, occupations, jobs, tasks and skills are analysed in a rather abstract way. In the policy literature, we find a large number of contributions on both topics: occupations and jobs on the one hand, and skills on the other hand. Commonly, these concepts are studied simultaneously in this literature as well.

In contrast, only a few studies explicitly define *new occupations, jobs, tasks and skills* and only a limited number of academic contributions explicitly study them. We do find many contributions on occupational and skill change, but again in most of them these concepts remain rather abstract. In general, the identification of new occupations and new skills in this literature draws on *surveys, interviews, classifications, forecasts, trade literature or other data sources*. The policy literature, on the other hand, does pay a lot of attention to new jobs and skills, as reflected by the high number of reports on the topic. The skill dimension seems to somewhat dominate the job dimension in many of them. The *concepts of new occupations and skills are derived in a similar way and based on similar data sources as in the academic literature*. Again, there are only a few reports that present exact definitions of new occupations and skills. A comparison of the academic and policy literature further reveals that there is an overlap between the two fields, in terms of methodologies, data and conceptualisation. Nonetheless, both fields would benefit from clearer definitions and a more refined and up-to-date measurement. This calls for alternative methodologies and data sources, such as web data, which are also explored in this report. Web data are increasingly used for labour market research; it is a rapidly advancing research field and highly promising for the identification of new skills and occupations. This is an important topic, because new occupations and skills are among the consequences of the socio-ecological transition and related to mismatch, skill gaps, overeducation, school-to-work-transitions and other factors. A clear, fast identification of these new occupations and skills therefore is extremely relevant, and further steps towards this goal should be taken in the academic and policy literature.

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InGRID
Inclusive Growth Research Infrastructure Diffusion

Referring to the EU2020-ambition of Inclusive Growth, the general objectives of InGRID – Inclusive Growth Research Infrastructure Diffusion – are to integrate and to innovate existing, but distributed European social sciences research infrastructures on 'Poverty and Living Conditions' and 'Working Conditions and Vulnerability' by providing transnational data access, organising mutual knowledge exchange activities and improving methods and tools for comparative research. This integration will provide the related European scientific community with new and better opportunities to fulfil its key role in the development of evidence-based European policies for Inclusive Growth. In this regard specific attention is paid to a better measurement of related state policies, to high-performance statistical quality management, and to dissemination/outreach activities with the broader stakeholder community-of-interest, including European politics, civil society and statistical system.

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

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