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Deliverable 21.2

DETERMINANTS OF WC&OSH CONDITIONS CONNECTED WITH ECONOMIC CHANGE

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Abstract

In recent years, there have been widespread debates on the 'future of work' in Europe, as megatrends, such as technological change, globalisation and ageing of the population, have transformed countless jobs - which in turn calls for new skills. At the same time, many European countries are still recovering from the Great Recession. With the recent upsurge of unemployment still in mind, European citizens have raised concerns about what will happen to their job. It is against this background that this report explores the dynamics of new or emerging occupations, jobs, tasks and skills, and their identification in particular. To this end, the report starts with an extensive review of the literature, in order to reveal how these concepts are defined and measured. It then continues with an assessment of the strengths and limitations of the most commonly used methodologies and data sets and presents alternatives to both. Our focus is on the potential of web data from different sources, ranging from social media, over surveys, to online job boards and vacancies. The final chapters of the report present the results from a series of pilots that we carried out, each based on web data, with the objective to further our understanding of new occupations and skills. The report is concluded with a chapter that highlights one of these pilots; it examines skill mismatches by linking educational requirements from online vacancies to educational attainments of jobholders. We conclude that web data have much potential in this research area and can be highly valuable to provide policymakers with real-time information on ongoing trends.

This report constitutes Deliverable 21.2 'Determinants of WC&OSH conditions connected with economic change', for Work Package 21 of the InGRID project.

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InGRID 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

1.1 New occupations, jobs, tasks and skills: what is happening in Europe's labour markets and why is this important?

Europe's labour markets have undergone tremendous changes in recent years, stirring up widespread debates about the 'future of work' and raising concerns among citizens across the continent about what will happen with their jobs. Many fear that technological progress, globalisation and other factors will make jobs disappear or transform them in such a way that new skills are required (e.g. digital skills have been on the rise recently), which workers may not yet possess.

At the same time, new occupations, industries and ways of work are emerging (with new types of online labour as a prominent example). To date, it is not yet clear what the impact of this transition will be, nor do we already fully understand who will be (most) affected by it. Similarly, it remains unclear what the appropriate policy responses are - though history can serve as a guide in this regard.

These transitions are set against a background of very high unemployment in Europe, caused by the global crisis that started in 2008 and the subsequent Eurozone debt crisis. The crisis has considerably affected the lives millions of European citizens, putting issues related to unemployment, poverty and inequality high on policymakers' agenda. Even though nearly ten years have passed since the onset of the recession, many citizens are still suffering its consequences.

The InGRID research infrastructure project is devoted to these important issues. It aims to contribute to the objectives outlined in the EU2020 strategy by proving the scientific community with new and better opportunities to contribute to evidence-based policy-making in the area of inclusive growth. As part of the InGRID research project, we have researched the emergence of new jobs and skills and on how these can be identified using innovative methodologies and little explored, yet promising data sources.

In this paper, we document our research from start to finish: we first carried out an in-depth review of the current academic and policy literature, we then continued with an assessment of existing methodologies and pilots of new approaches, and we, finally, discussed the results obtained from this work. In addition, this report draws attention to one application that was developed in collaboration with the team from AIAS: a comparison of the educational requirements in vacancies and educational attainments of jobholders. More details on the different chapters of this report are provided below.

1.2 Structure of the report

The remainder of this extensive report is composed of four chapters, which each tackle the issue of new occupations, jobs, skills and tasks from different perspectives. The first three chapters are closely intertwined, each tackling the issue of the identification of new occupations and skills from different angles. Chapter 2 starts from an extensive review of the current academic and policy literature on new occupations and skills. The chapter first explores the conceptualisation of new occupations and skills in different disciplines. It reveals the difficulties involved in this process and explains how the existing literature has attempted to overcome them. The chapter further presents some initial details on the rapidly growing use of web data in labour market research. This chapter is a deliverable for *Task 21.2* of WP21 (*MS97*).

Chapter 3is devoted to the methodologies that one can use to identify new occupations and skills. The chapter first discusses the traditional methods and data sources, pointing out their strengths as well as their limitations, while also providing more insights into their current use. It then continues with an overview of potential web-based data sources and innovative methodologies. The chapter further introduces the methodologies that we have piloted over the course of the InGRID project, which are presented by means of a series of case studies. In each case, the underlying web data sources are highlighted as well. This chapter was prepared as a deliverable for *Task 21.1* of WP21 (*MS97*).

Chapter 4 is dedicated to taxonomies. It presents the results from the case studies that we have conducted as part of the InGRID project, in each case very briefly recalling the methodologies and data sources used to make it easier for the reader. More specifically, the case studies assess the educational requirements of employers in the US (for the 30 most-frequently advertised occupations), IT skills requirements in non-IT jobs, the role of foreign languages skills in the Visegrad region and an occupations observatory (which is a new methodology that we piloted to capture new occupations using data extracted from online job portals for 11 EU countries). This chapter served as a deliverable for *task 21.1* of WP21 (*MS97*).

The fourth chapter of this report, Chapter 5, was prepared in close collaboration with the AIAS team. The chapter was prepared as a deliverable for *Task 21.2* of WP21 (*MS98*). It compares the educational requirements in vacancies with the educational attainment of jobholders obtained from survey data in the Czech Republic. The chapter first presents an overview of the difficulties related to the comparison of data from both sources, then outlines the methodology used and finally presents the results of the comparison. In this way, the chapter aims at contributing to a large body of work on skills mismatch.

The findings of these four chapters have been validated by means of a workshop, on which more details are presented in Section 1.2 (*MS99*). The final chapter, Chapter 6, of this report presents the main conclusions of our work.

1.3 Validating workshop

The results of the different chapters of this report have been validated in a workshop on '*Indicators for job quality, industrial relations, occupations and new skills and tasks*', which took place in Amsterdam on 7-8 November 2016 (hosted by AIAS). The aim of this expert workshop was to explore the state of affairs in the knowledge on job quality indicators, industrial relations indicators, occupational measurements, and new skills and tasks measurements. It also aimed at expanding an agenda for future research in these fields. The workshop included presentations of the findings of the research and technology activities undertaken as part of the InGRID's working conditions and vulnerability pillar as well as presentations by external experts.

The first day of the two-day workshop was dedicated to new skills and new jobs. In the morning, the focus was on *measuring occupations and tasks*. Three papers were presented and discussed. Kea Tijdens, coordinator of Work Package 21 in InGRID, presented '*Self-identification of occupation in web-surveys: databases and experiences*'. Malte Schierholz (IAB and MZES, Germany) presented his research '*Occupation Coding during the Interview*'. Stefano Visintin and Stephanie Steinmetz presented '*Measuring tasks in occupations*'.

In the afternoon, the focus was on *methodologies and taxonomies*. The first papers dealt with methodological issues. Karolien Lenaerts (CEPS) presented '*Prospects for utilisation of non-vacancy web data in labour market analysis'*. Miroslav Beblavý (CEPS) presented *'Using metadata to identify new occupations and skills'* and Antonio Lima (NESTA) presented *'A skill-based occupational classifier for web-based job ads'*. The three presentations were followed by a discussion. After the break, the papers focussed on taxonomy issues. Miroslav Beblavý (CEPS) presented '*The demand for general and IT skills in non-IT jobs in the US*'. Brian Fabo (CEPS) presented '*The demand for language skills in the Visegrad Four*'. Annemieke Biesma (Technopolis) presented '*The impact of game-changing technologies in the manufacturing sector*', again followed by a discussion.

The morning of the second day of the workshop focused on **job quality indicators**, and was chaired by Sylvie Hamon-Cholet (CEE). The first presentations concerned *'The Laeken indicators of QoW: lessons to learn*' by Greet Vermeylen (Eurofound), and '*It takes more than one measure: Capturing the multi-dimensionality of job quality with job types and multiple job quality outcomes'* by Guy Van Gyes, Anina Vercruyssen and Ine Smits (HIVA). Then, '*Measuring vulnerability to adverse working conditions: evidence from European countries*' was presented by Majda Seghir (CEE). The final presentation of the first session discussed '*Job Quality and Firm Size in Two Different National Institutional Regime'* (Zinaida Salibekyan, CEE). After the coffee break, a round table about job quality indicators was organised, chaired by Guy van Gyes (HIVA). A discussion followed with contributions from Francis Green (University College London), Sonja Drobnic (University of Bremen), and Greet Vermeylen (Eurofound).

After lunch the workshop's focus shifted to the topic of the *conceptualisation of the social dialogue/industrial relations: the indicators challenge* (chaired by Guy van Gyes (HIVA)). Two presentations were given: '*Key dimensions of industrial relations: a new conceptual framework*' (Christian Welz, Eurofound) and '*Dimensions of industrial relations and efficacy of social dialogue'* (Bernd Brandl, Durham University). The last part of the second day addressed the issue of *measuring social dialogue/industrial relations: the indicators challenge*, and was chaired by Maarten Keune (AIAS). Two presentations were delivered: '*Potentials of the ICTWSS database and the global WageIndicator Labour Law Database*' (Kea Tijdens, AIAS) and '*Potentials of the European Company Survey'* (Guy Van Gyes, HIVA).

2. What are the new occupations and the new skills? And how are they measured? The state-of-the-art in the academic and policy literature

Prepared by Miroslav Beblavý, Mehtap Akgüc, Brian Fabo & Karolien Lenaerts

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, overeducation, school-to-work-transitions and other factors and furthers our understanding of the dynamics of the labour market.

2.1 Introduction

This state-of-the-art report, which constitutes a deliverable 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 policymakers 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 2.2 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 2.3 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 2.4 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 2.5 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 2.6 concludes this state-of-the-art report with a brief summary of our main conclusions and an outlook for future research.

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

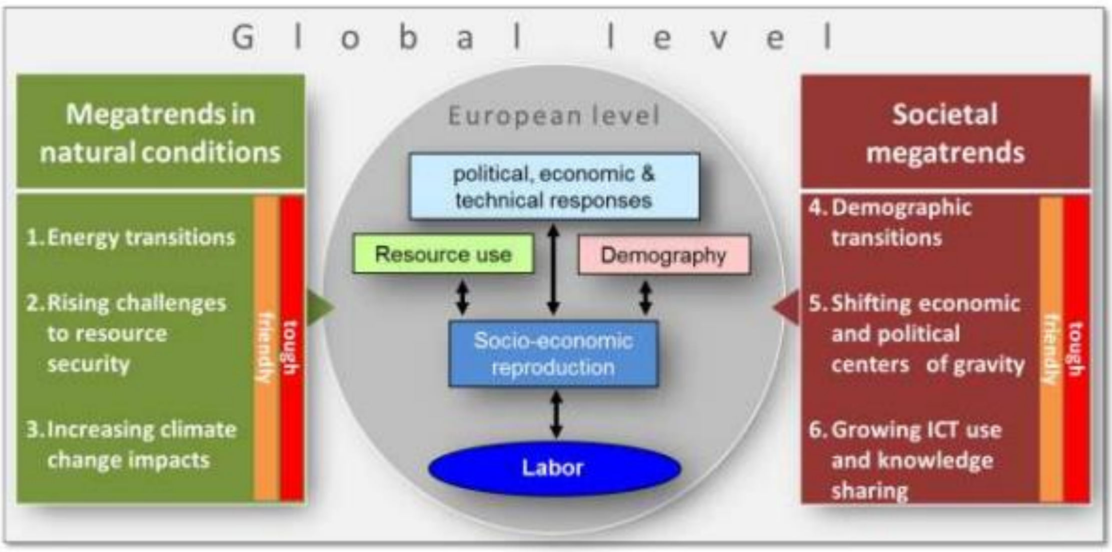
Since the start of the Great Recession, unemployment in Europe has soared. Despite signs of economic recovery for many indicators, the labour market conditions show only a rather moderate recovery, which differs considerably from one member state to another (European Commission, Spring Economic Outlook, 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 & 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 & 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 & 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 policymakers. 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 Socio-ecological transition and its megatrends

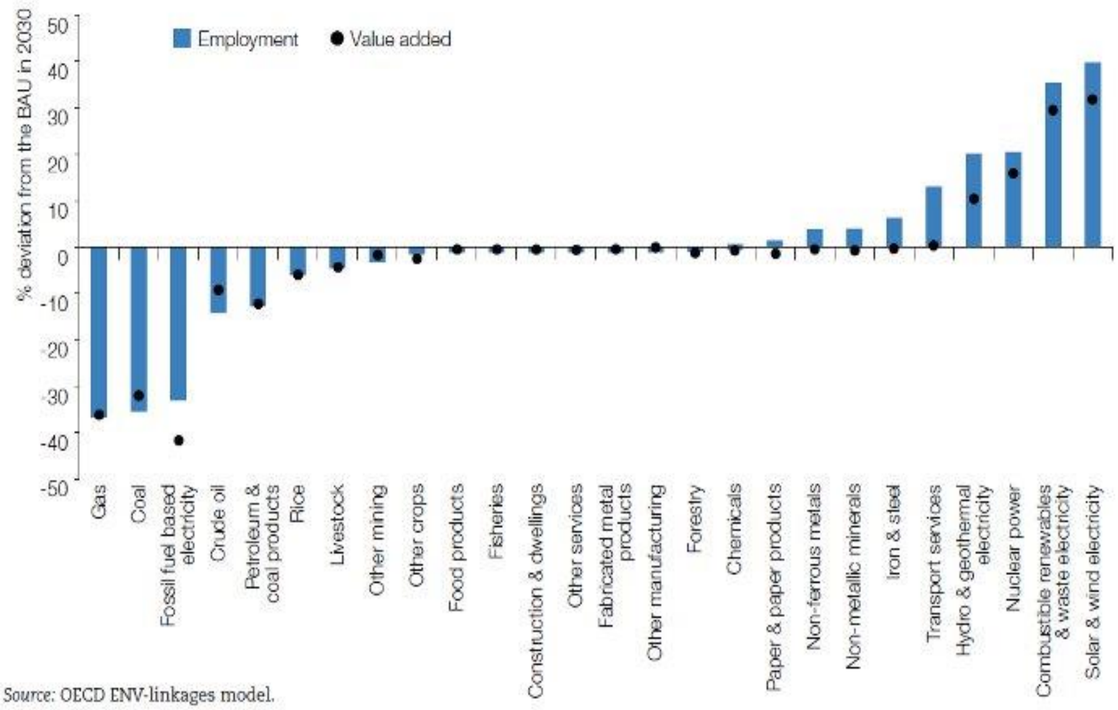


Source Fischer-Kowalski *et al.* (2012, p. 77)

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**).** 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 & 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 OECD Linkages model



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.

2.3 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.

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

2.3.1.1 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 referencing 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 & 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 & 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-routine 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.

2.3.1.2 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 2.3.1.3, 2.3.2 (on classifications) and 2.3.3 (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 policymakers. Hanson & 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 & 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 1-digit occupation. Kambourov & 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 ISCO 88. 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 & 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 & 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 & 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 undereducation) nature. These issues have mostly been investigated from the supply rather than the demand side of the labour market. Theoretical work explains *overeducation* on the basis of a set of

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.

models: the human capital theory (overeducation 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 & van der Velden (2001) put the assignment theory to the test. Educational mismatches do not necessarily imply skill mismatches. Furthermore, 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.

2.3.1.3 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 'specialty' 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 & 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 and 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 & 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 & 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 & 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.

2.3.2 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 2.1).

Table 2.1 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, policymakers, 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 & McKnight (2001) and Levenson & 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 & McKnight (2001), for instance, report that detailed occupational categories are less reliable for skill measurement, because they are prone to coding errors. Levenson & 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).

2.3.2.1 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 subclasses. In the new scheme, occupations were classified on the basis of five main characteristics: (i) skill, talent or intelligence; (ii) tools, instruments, machinery or structures; (iii) materials; (iv) processes; and (v) 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 and 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 & 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 and 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 policymakers. 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.

2.3.2.2 ISCO and ISCED

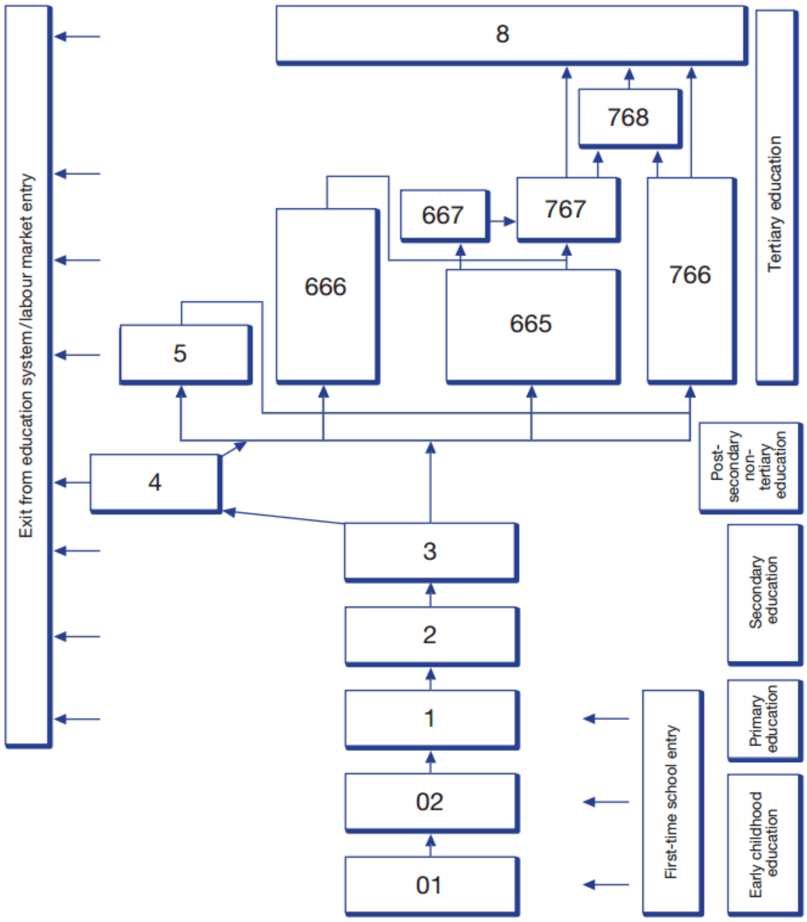
In the 1950s, the United Nations (UN) developed a more structured and internationally comparable occupation taxonomy. This taxonomy was at the root of the *International Standard Classification of Occupations (ISCO)*, which was first published in 1958. The main goal of this classification was to map 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 (1), lower secondary education (2), upper secondary education (3), post-secondary non-tertiary education (4), short-cycle tertiary education (5), Bachelor's or equivalent level (6), Master's or equivalent level (7) and the Doctoral or equivalent level (8). ISCED represents a complex structure of formal education while accounting for the differences between national systems.

This is shown in Figure 2.3, 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 2.3 ISCED 2011 - potential educational pathways



Source ISCED (2011)

2.3.2.3 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: (i) skills and competences (of a transversal, cross-sector, sector-specific and occupation-specific nature), (ii) qualifications (awarded at the (inter-)national level, linked to tasks, technologies, occupations or sectors) and (iii) 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.

2.3.2.4 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 & 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.

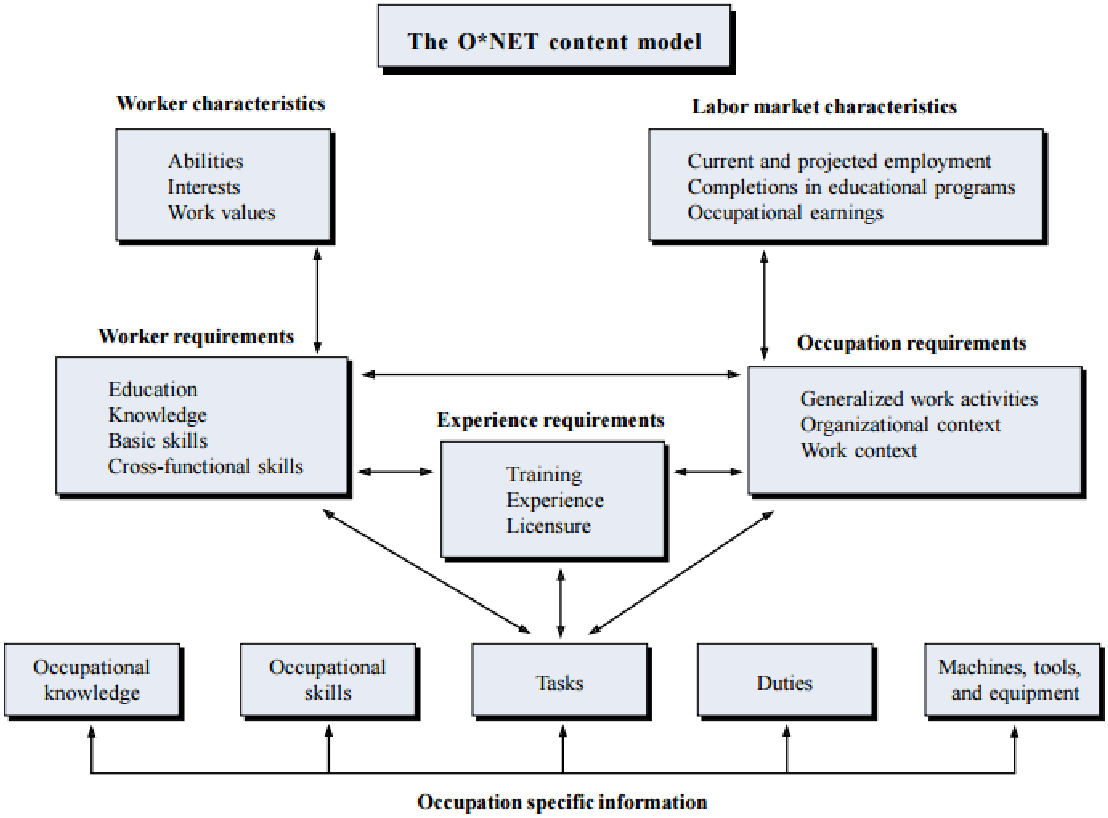
The Dictionary of Occupational Titles appeared for the last time in March 1999. It was regarded as obsolete and replaced by O*NET, an online database (instead of a book). Mariani (1999) describes the transition from the dictionary of occupational titles to the occupational information network. O*NET 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 2.4): 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 2.4 **The O*NET content model**



Source Mariani (1999, p. 5)

2.3.2.5 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, policymakers 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 policymakers 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 detailed. One of the main goals of this report, therefore, is to consider alternative methodologies and

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

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.

2.3.3 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.

2.3.3.1 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 & 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 & 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 & 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, Section 2.3.3.2 'Job Polarisation'). 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 & Katz (2008), who reported that electrification gave rise to skill-biased technological change. Goldin & 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 & 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 & 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 & 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 *et al.* (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).

2.3.3.2 Occupational and skill change in the 21th century

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 2.5 below). Instead, there is a polarisation in favour of both low-skilled and high-skilled jobs. Job polarisation has been found in the US (Autor *et al.*, 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 policymakers. 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 & 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 2.5 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 & 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.

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 and 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 & 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 & 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 & 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.

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 2.3.3.2 'Job Polarisation'. 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 & Manning (2007), who show that routine tasks indeed are concentrated in the centre of the distribution (using data for the UK). Moreover, Acemoglu & 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 and 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 & Dorn (2009). The latter examine employment growth in service occupations.

In an interesting contribution that was published last year, Jung & 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 & 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 & 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 & Osborne (2013) summarise the conclusions of this literature as follows: technological progress has been accompanied by substantial changes in the occupational 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 & 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

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

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 & 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 & 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 & 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 & 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 policymakers 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.

2.3.4 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 policymakers 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.

2.4 Policy discourse and policy applications related to new jobs and skills

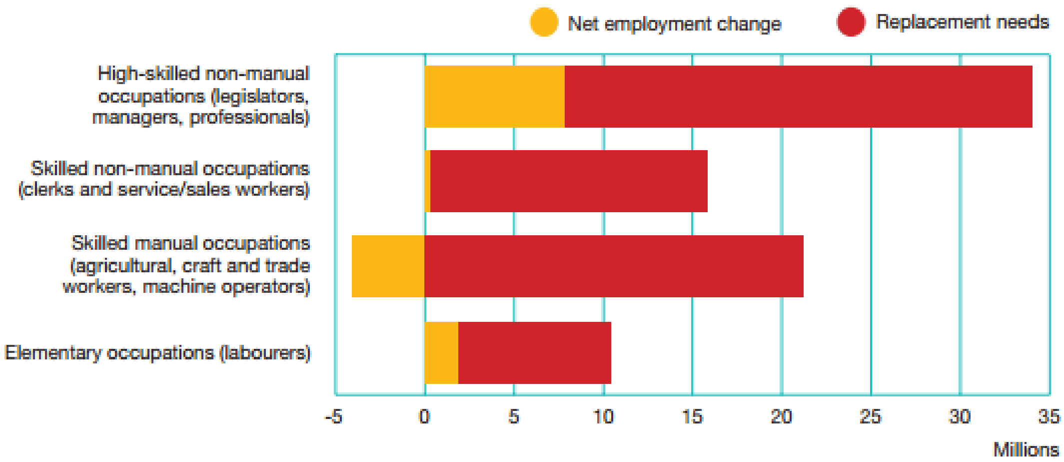
2.4.1 Policy discourse

2.4.1.1 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 2.6).

Figure 2.6 Projected demand in different groups of occupations until 2020



Source European Commission, 2010, based on data from Cedefop

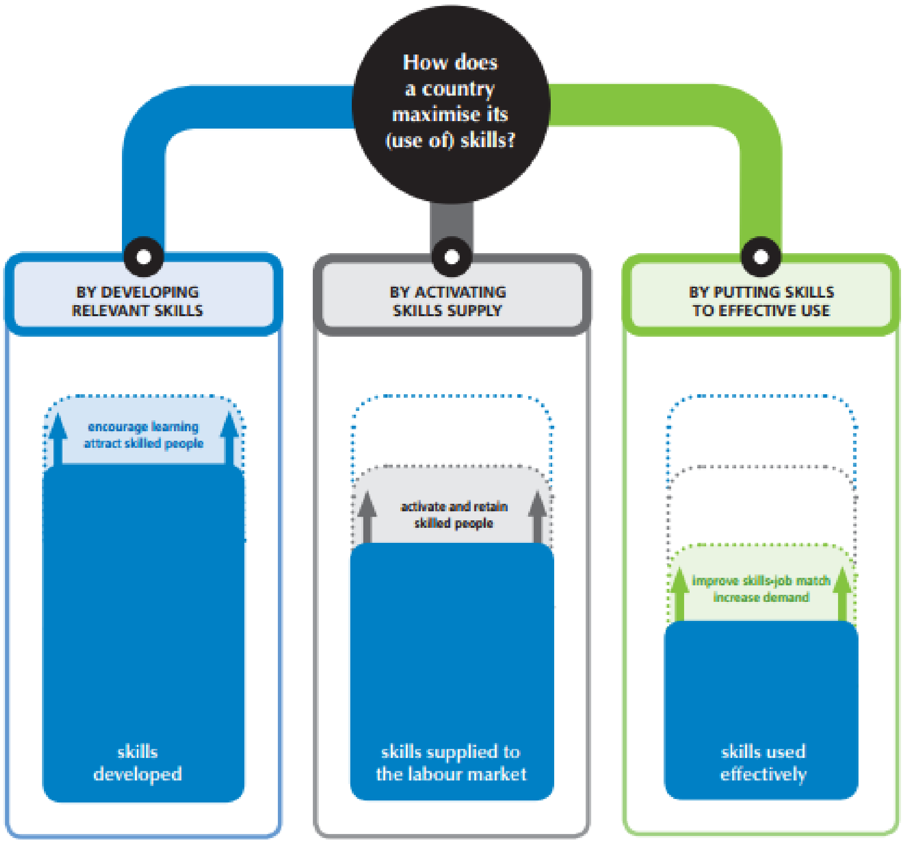
In 2010, the European Commission continued the discussion on new jobs and skills with the '*Agenda for new skills and jobs*', which is part of the Europe 2020 strategy. The aim of this agenda is to reach the EU's employment target of 75% of the working-age population. Other goals of the initiative are 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 policymakers 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, policymakers 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, 2013a). 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 2.7 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 us*e*'. 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 2.7 **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).

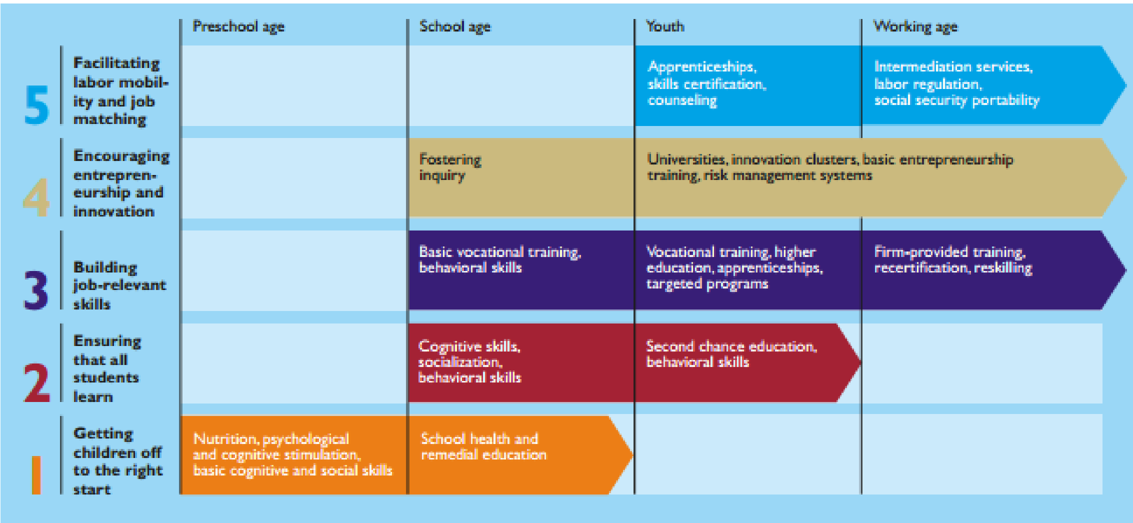
In 2012, *UNESCO* published a report entitled '*Youth and Skills: Putting Education to Work*' in which a more global perspective is taken. In the report, pathways to a better future for young people all around the world are explored. To this end, the 10 most important steps to be taken are summarised.

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 2.8). 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 2.8 STEP strategy through the worker's life cycle



Source World Bank (2010)

2.4.1.2 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 (Italia2020). 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 (Swedisch 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.

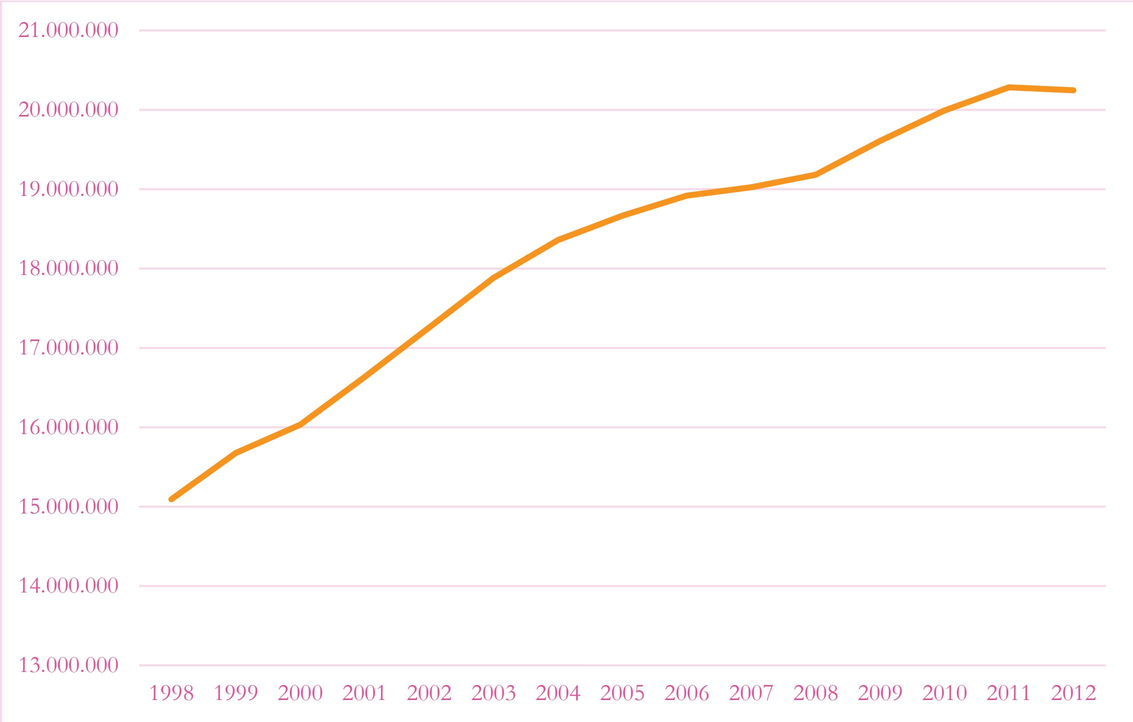
2.4.2 Public policy applications

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 2.5.2.4 '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.

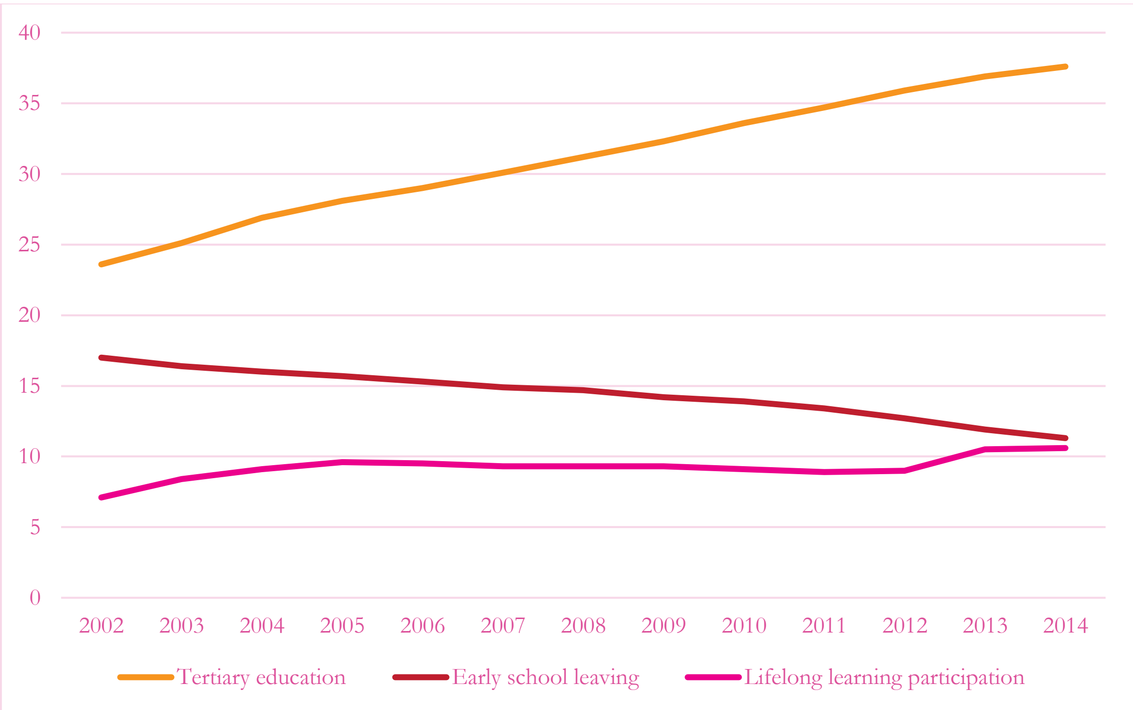
As indicated above, education policies are largely shaped on the national level, despite the prominent role of the EU in some areas. In the past decade, the EU member states have invested heavily in access to higher education. The number of participants in tertiary education in the EU28 has grown from 15 to 20 million between the years 1998 and 2012 (see Figure 2.9). 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 2.10).

Figure 2.9 **Number of tertiary education students in EU28**



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

Figure 2.10 **Developments on European labour markets**



Source Eurostat

2.4.3 Conclusions

From this overview of the policy literature, we conclude that occupations, skills, new occupations and new skills are important subjects to policymakers. 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 policymakers 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. Policymakers 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.

2.5 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 policymakers 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 policymakers). 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 a.o. Askitas & Zimmermann, 2009 and 2015). This section is devoted to the advantages and limitations of traditional and web-based data sources.

2.5.1 Labour market analysis: Traditional methods and data sources

Woods & 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.

2.5.2 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 & 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 & Skuterud (2004), D'Amuri & Marcucci (2010) and Askitas & 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 & Mansour, 2014). Carnevale *et al.* (2014) and Askitas & 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 résumé data are important for workforce agencies and policymakers too (Carnevale *et al.*, 2014).

2.5.2.1 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 & Dalal (2000) and Musch & 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 & 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.

2.5.2.2 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 & 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 & 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, 2015). 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.* (2015a) 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.* (2015a) 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.* (2015a) 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.* (2015a) 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.*, 2015a). 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.

2.5.2.3 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.*, 2014; Pallais, 2014). Maselli & 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, 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 & Baravalle (2010) and Kuhn & 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.*, 2015a). 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.

2.5.2.4 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).

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

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.*, 2015a; 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.* (2015a) 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 & van de Werfhorst (2009) examine the merit selection hypothesis for the case of Australia, on the basis of advertisements published in newspapers between 1985 and 2005. In their work, the field of study is considered too. Importantly, Dörfler & 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 & 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. & 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 & 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 & Lei (2015) consider discrimination based on gender and facial attractiveness in the Chinese labour market, while Maurer-Fazio (2012) looks into ethnic discrimination. Martínek & 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 & 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 & 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 & Parent

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

(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 & Parent (2001) compile a database of job advertisements for webmasters, to which data gathered via a web survey are added. They also apply multivariate regression techniques. Capiluppi & 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 & 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 & 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 & Tijdens (2014). Kureková *et al.* (2015a) 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.*, 2015a). 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.

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 & Tambe (2014) use online resumes to track workers' career paths, focusing on workers previously employed in firms acquired through leveraged buyouts.

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

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

‘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.

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.* (2015a) 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.

2.5.2.5 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 & Levine, 2015). 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.

<u>Empirical applications</u>

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 & 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 & 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 & 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 & Zimmermann (2008) use Google Trends to measure economic and political activities, while Askitas & Zimmermann (2009) and Choi & 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 & 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 & Levine (2015), 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 & Levine (2015) 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.

2.5.2.6 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 & 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.

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 & 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 & 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).

2.5.2.7 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 (i) 50% of the employers used Facebook in the hiring process, (ii) almost 90% of the companies noted that recruiting via Facebook is more cost effective than through other channels and (iii) 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: (i) Who is using Facebook, and what are users doing while on Facebook?, (ii) Why do people use Facebook?, (iii) How are people presenting themselves on Facebook?, (iv) How is Facebook affecting relationships among groups and individuals?, and v) 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 & 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 & Kulkarni (2013) do find that only a small number of members actually use Facebook to look for jobs and networking

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

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.

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 & 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 & Levine (2015) 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.

2.5.2.8 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 & 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).

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 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).

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 & 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 & 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 & Tijdens (2015) on collective bargaining agreements in developing countries and by Guzi & 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.*, 2015a) 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 & Sedlakova, 2015), the value of web data in developing economies (Tijdens & Steinmetz, 2015), among many other topics.

2.5.3 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.

2.6 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.

3. An inquiry into the data generating process concerning new jobs and skills: methodological report

Prepared by Miroslav Beblavý, Mehtap Akgüc, Brian Fabo, Karolien Lenaerts & Félix Paquier

In this paper, we put to the test two innovative approaches, which are both based on web data, to examine occupations and skills. Driven by technological change, new tasks, occupations and skills have emerged whereas others have become redundant. At the same time, existing occupations have substantially transformed. These transformations have been studied from the academic and policy perspectives, often on the basis of data collected from interviews, surveys, trade publications, job advertisements and existing occupational or skill classifications. The traditional methods and data sources, however, have been criticised for several reasons. Many have suggested that they are not suitable to identify new occupations and skills because data are usually lagged. This complicates the identification of new occupations and skills, and makes it very difficult to respond to current trends in a timely manner.

Web data are an interesting tool to overcome these issues and are, therefore, at the heart of our report, which is methodological in nature. More specifically, we test two ways of identifying new occupations and skills in six case studies. The first method is based on a set of *job advertisements published online*. Vacancies are detailed and contain information about education, skill and other requirements. Moreover, by considering for which positions job vacancies are published, we can find new occupations. The second method relies on the *metadata and other information available on online job boards*. By examining the occupational structure and tags used, one can get insights into upcoming or new occupations and skills. In this report, we show that both methodologies can be used to study occupations and skills and explain what their advantages and limitations are. By piloting easy-to-use and up-to-date methodologies to analyse new occupations and skills in real time, we aspire to provide valuable inputs for policymakers, education institutes and other stakeholders.

3.1 Introduction

In the last few decades, the impact of technological change on Europe's labour markets has been widely studied and discussed. Numerous contributions of an academic, policy and popular nature have debated the *future of work*, asking how technological progress affects employment opportunities, working conditions, skill demand, wages and other factors. Technological change shapes occupations, skills and tasks. New occupations and skills emerge while others become obsolete. Yet, these dynamics are not new, nor is the interest in them and the debate about them.

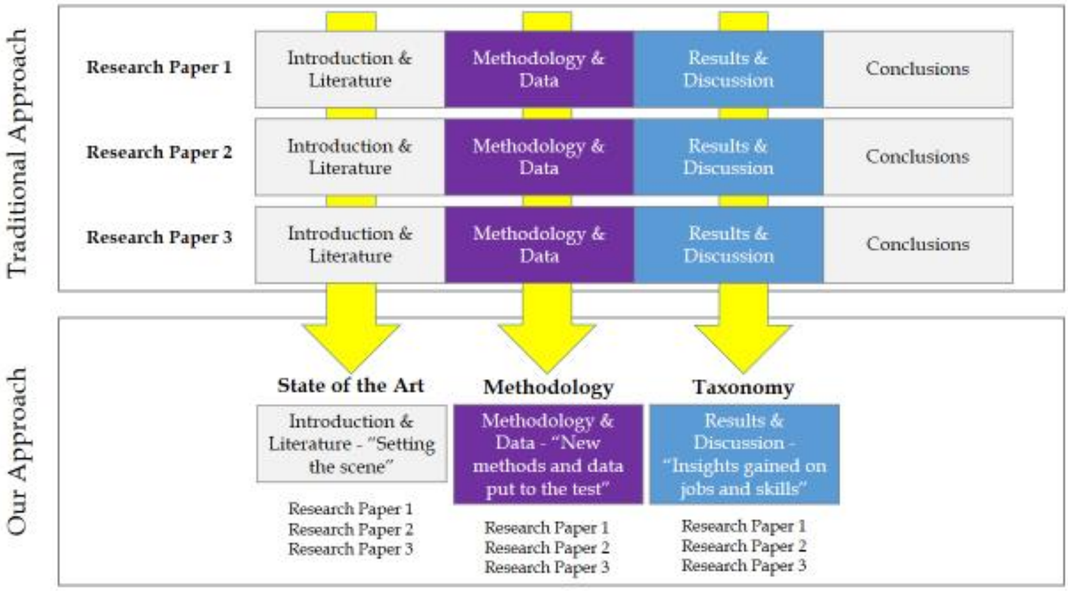
Many efforts in the literature have, therefore, been devoted to the identification of new occupations and skills. Traditionally, new occupations and skills have been identified on the basis of existing classifications, trade publications, employer surveys, interviews and other sources. These traditional sources and methods, however, have been challenged in a number of recent studies (e.g. by Beblavý *et al.*, 2016a). Well-known issues are that the traditional data sources are often lagged, incomplete and of a low quality, making them less suitable for the identification of new occupations and skills, especially in real time.

Internet data can serve as a way to address some of these issues. The use of web data in the social sciences is rapidly advancing and there are many studies that focus specifically on labour-related issues. Nevertheless, only a handful of contributions have examined how Internet data can be used to identify new occupations and skills. Nevertheless, web data have a *great potential* to serve as a data source for this purpose. Some key advantages are the real-time data availability, the large and diverse samples and the straightforward data collection process. Web data can be extracted from many sources, such as online job portals, social networks or surveys. In this report, we focus on *online job boards and their vacancies* and put to the test innovative methods to detect new occupations and skills.

To this end, the report presents a series of *case studies* that are based on *two distinct strategies*. The first strategy is to identify new occupations and skills by analysing the job advertisements published online (through a semantic analysis). A careful analysis of job titles, descriptions, tasks and responsibilities, requirements and other conditions can be very revealing. This strategy provides a great level of detail, but semantic analysis is not always easy to perform. The second strategy involves identifying new occupations and skills on the basis of the metadata available on job boards (i.e. the 'tag' system and the occupational structure that the portals use). New occupations and skills are found when new tags are added to the job portal. This strategy is very easy to carry out but offers less information. In this report, we show that both strategies are viable and facilitate research into new occupations and skills.

The focus of this paper is on the *methodological process* and the *data source used*, and only to a lesser extent on the findings obtained. It is a deliverable for *Work Package 21* of the *InGRID project (Task 21.1.2, MS97*). The findings will be explored in more depth in our taxonomy report, which constitutes another deliverable for the same work package. It is, therefore, important to explain how these reports are linked. Figure 3.1 shows a typical research set-up and illustrates how our approach differs. A research paper is generally composed of an introduction and literature review, a description of the methodology and data set used, a discussion of the results and a conclusions. Our work for Work Package 21 differs from this traditional structure, in the sense that we produce *three reports* (all are based on the same set of underlying research papers that we prepared): a *state-of-the-art report*, which thoroughly reviews the academic and policy literature, a *methodological report*, which zooms in on traditional and more innovative methods and data sources, and a *taxonomy report*, which presents the results obtained by using these methods and data and draws conclusions. We therefore recommend readers to also take a look at these two other reports when going through this methodological paper. We decided to go for this approach as this allows us to better understand each of these three dimensions and to devote to each of them a sufficient discussion.

Figure 3.1 Typical research set-up and how our approach differs



The remainder of this report is, therefore, structured as follows. Section 3.2 briefly recalls the traditional approach that is commonly used to identify new occupations and skills in the academic and policy literature. In Section 3.3, innovative approaches to identify new occupations and skills are introduced. These approaches are embedded in a rapidly advancing field which makes use of Internet data to study labour market-related issues. Section 3.3 further reviews the most recent literature on the topic. Both of these sections build on previous work by Beblavý *et al.* (2016a) and Lenaerts *et al.* (2016). Section 3.4 constitutes the core of this report, as it aims to test some of these innovative methods. To achieve this goal, the section presents a series of case studies that have been performed in light of the InGRID project. Three of these case studies use a dataset of vacancies published online while two case studies use the metadata available on the job portal instead (i.e. the occupational structure that job portals use to cluster job vacancies and the closely related 'tag' system). The final case study is cross-cutting. Some of these case studies are described in more detail in Tijdens *et al.* (2015b), Beblavý *et al.* (2016b), Beblavý *et al.* (2016c) and Beblavý *et al.* (2016d). In Section 3.5, the main findings of the study are summarised.

3.2 Identifying new jobs and skills: the traditional approach in the academic and policy literature

In the academic and policy literature, the impact of technological change on the labour market has been examined from several perspectives. One of those perspectives is that of occupations and skills. As a result of technological progress, existing occupations have radically changed, new occupations have emerged and other occupations have become obsolete. Similarly, new skills have been introduced while other skills are no longer demanded in the labour market. These dynamics have been recorded at different stages all throughout history. An interesting example is presented by Chin *et al.* (2006), who study the impact of the adoption of steam engines in the merchant industry in the 19th century. As ships were equipped with steam engines instead of sails, the occupation of engineer - which was new at the time - became much more important. On the other hand, the occupation of sail-maker became redundant and medium-skilled seamen were replaced by low-skilled engine room operators.

Previous research on the effects of technological progress on occupations and skills has relied on a number of methods and data sources to identify new occupations and skills. Crosby (2002) explains that technological progress affects the tasks that employers want their workers to carry out. At first, these new tasks may become part of occupations that already exist (‘*evolving occupation*’). When this is not possible (e.g. because the task is too different from the other tasks that the worker has) or when the new task dominates the other tasks (e.g. it becomes the worker’s main task), a *new occupation* emerges (which is defined as an occupation that only recently materialised). Crosby (2002) further refers to new occupations with low employment counts that are expected to gain importance as *emerging occupations*. New tasks are typically associated with new skills and changes in the skill demand. In order to identify new occupations and the underlying new tasks and skills, one has to know which occupations already existed before and which did not.

How can this be achieved? According to Crosby (2002), new occupations and skills are generally defined on the basis of surveys (e.g. asking employers to list new occupations), interviews, trade publications, job advertisements, case studies, and occupational/skills classifications (i.e. new occupations are those that have not yet been added to the most recent edition). Often, several of these data sources are combined. The Texas Career Development Resources Office, for example, uses employer surveys, trade publications, vacancies and the 1980 Standard Occupational Classification System (SOC).[8] Similarly, the US Bureau of Labor conducts employer surveys and a census. In the academic literature, most emphasis is on occupational and skill classifications, such as the ILO’s ISCO and ISCED, and the EU’s ESCO (see ILO, 2015). The main issue associated with such classifications, however, is that generally these are updated very rarely.[9] This raises the question whether these classifications are sufficiently up-to-date and whether it is meaningful to identify an occupation as ‘new’ because it is not included in the most recent classification. Especially in sectors and firms that are rapidly progressing, this is problematic.

Traditional data sources[10] generally are well-structured, representative, accurate, and complete. Data, however, often are only available with a lag. In addition, in some cases, data are frequently revised, sample sizes are small, and data quality may be low (Wright, 2012; Shapiro, 2014). For these reasons, traditional data sources prove to be less suitable to identify new occupations and skills (as real-time information is essential, see Damarin (2006)).

In response to these concerns, researchers have strived to develop new methods and find alternative data sources. Many have turned to the Internet, which can serve both as a research platform and a source of real-time labour market data. We also start from the idea of using Internet data and examine how such data can be used to analyse new occupations and skills. There have been several other applications in which web data are used to study economic and social phenomena, but only very few have focused on occupations and skills and on new occupations and skills, in particular. Our contribution is, therefore, innovative, as it puts some of these methods and data sources to the test.

3.3 Innovative methodologies to identify new jobs and skills: previous research

In order to overcome the limitations of traditional datasets, researchers have extended their work to other data sources including web data.[11] Web data have become increasingly widespread in the social sciences in the last two decades, as the Internet developed into a research platform and a data source (Kuhn & Skuterud, 2004; Benfield & Szlemko, 2006; Askitas & Zimmermann, 2009; 2015; and D’Amuri & Marcucci, 2010). Web data are available in real time and, therefore, allow to capture current trends. This is an essential feature if one wants to identify new occupations and skills as they

8 An interesting contribution on occupational classifictions and their revisions is Herman & Abraham (1999).

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

10 Throughout this report, ‘traditional data sources and methods’ refers to (labour force) surveys, census data, interviews, trade publications, etc., i.e.the data sources summed up in this section.

11 Throughout this report, web data and Internet data are used as synonyms.

arise. *Real-time labour market data* can be obtained from job boards, social networks and many other websites (Dorrer *et al.*, 2012). Moreover, the rise of the Internet has considerably affected many labour-related process, such as job search, recruitment and matching with far-reaching consequences for job seekers, employees, employers, recruitment agencies, education institutes and other stakeholders (Dorrer *et al.*, 2012; Carnevale *et al.*, 2014; Kuhn, 2014; Kuhn & Mansour, 2014; Askitas & Zimmermann, 2015).

3.3.1 What web-based data sources are available?

We consider four potential data sources: online job portals and other labour market intermediaries, social networks, web surveys and Google Trends.

Online job portals and other labour market intermediaries

Job portals and labour market intermediaries connect labour demand and supply, which makes them a particularly interesting data source for research (Carnevale *et al.*, 2014; Kuhn, 2014; Kuhn & Mansour, 2014; Kureková *et al.*, 2015a). Detailed data can be derived in several ways: from the vacancies and CVs published on the job board or intermediary platform, from how vacancies and other data are structured on the portal or platform, and from any other information available (e.g. employer reviews, career advice, data on wages and working hours, etc.). Many job boards have developed into career community websites, targeting employers, employees, job seekers and career counsellors. Similarly, online intermediaries often are rich information sources. Both job portals and intermediaries provide a lot of information, which generally also is fairly detailed. Web data are typically combined with data from traditional sources.

Research and Examples: earlier work has mostly used data obtained from private online job boards (see Capiluppi & Baravalle, 2010; Štefánik, 2012a; Kuhn & Shen, 2013). One notable exception is the paper by Kureková *et al.* (2015a), who perform a cross-country analysis of employers' demand for skills in the Czech Republic, Denmark and Ireland using EURES data.

Researchers have studied - on the basis of vacancies or CVs - mobility (Cañibano *et al.*, 2008; Masso *et al.*, 2011; Masso *et al.*, 2013), discrimination (Maurer-Fazio, 2012; Kuhn & Shen, 2013; Maurer-Fazio & Lei, 2015), over-qualification of job applicants (Shen & Kuhn, 2013), job search behaviour (Kudlyak *et al.*, 2012; Faberman & Kudlyak, 2014), mismatch (Capiluppi & Baravalle, 2010; Marinescu, 2015), unemployment insurance (Marinescu & Rathelot, 2015), skill requirements (Kennan *et al.*, 2008; Huang *et al.*, 2009; Kureková *et al.*, 2012; Sasser Modestino *et al.*, 2014; Hershbein & Kahn, 2015) and several other topics. This literature is closely related to studies that use printed job advertisements (Jackson *et al.*, 2005; Jackson, 2007; Dörfler & van de Werfhorst, 2009; Barnichon, 2010).

The bulk of work on online intermediaries has focused on MTurk and UpWork, i.e. very large online platforms. Examples are the studies by Buhrmester *et al.* (2011), Horton (2011), Horton *et al.* (2011), Ghani *et al.* (2014) and Pallais (2014). Other work has investigated smaller platforms, such as CoContest (Maselli & Fabo, 2015) and AlmaLaurea (Bagues & Labini, 2009). Online intermediaries and platforms have also been increasingly used to carry out experiments (see Pallais, 2014; Pallais & Sands, forthcoming, and Horton, forthcoming). Besides intermediaries, TESS (Time-sharing Experiments for the Social Sciences) is an online platform for experiments (using a representative sample of US-based adults).

Job portals:
- Public: EURES (the European Union's mobility portal), websites of public employment services
- Private: Monster, Stepstone, Careerbuilder, Indeed

Intermediaries: UpWork, TaskRabbit, AlmaLaurea, Amazon Mechanical Turk, CoContest

Social networks

Social networks present an interesting but underexploited data source to study the labour market. These networks can play a major role because they can reduce search frictions. Jobs are increasingly advertised on Facebook and Twitter. Job applicants and employees typically have a LinkedIn profile. Social networks have a massive global user base. Profiles often contain very detailed and up-to-date information.

Research and Examples: Acquisti & Fong (2015a; 2015b) study to what extent someone's profile on social networks influences their interview invitation rates.

- LinkedIn: Most work on LinkedIn covers the platform or the company running it (Caers & Castelyns, 2011; Bonsòn & Bednárová, 2013; Rangel, 2014 and Zide *et al.*, 2014). Only a handful of studies use data obtained from LinkedIn to study different phenomena, such as migration (State *et al.*, 2014; Barslund & Busse, 2016) or job applications (Gee, 2015).
- Facebook: There exist many studies on/using Facebook data (see Wilson *et al.* (2012) for a review), but only a small number of them is dedicated to labour market issues. Issues include recruitment (Bohnert & Ross, 2010; Karl *et al.*, 2010a, 2010b; Kluemper & Rosen, 2009), labour supply (Kelkar & Kulkarni, 2013) and other topics (Gee *et al.*, 2015a; 2015b).
- Twitter: Research generally focuses either on the message, the use, the concept or the technology behind Twitter (Williams *et al.*, 2013). Kearney & Levine (2015) use Twitter to study behaviour.

Google Trends

Launched in 2006, Google Trends is a service based on Google Search that enables its users to verify how often search terms, or combinations thereof, are entered relative to the total number of searchers performed (by region, across time). When multiple search terms are entered, their relative popularity is compared. Google Trends also shows a list of 'hot searches' and 'hot topics', both of which capture the fastest growing trends on Google Search and in traditional and social media.

Research and Examples: Google Trends data are used in a wide range of applications, commonly in the context of behavioural analysis (Rode & Shukla, 2014; Kearney & Levine, 2015 and the work of Stephens-Davidowitz),[12] forecasting and nowcasting (Choi & Varian, 2012; Chen *et al.*, 2015), other predictions or measurement exercises (Constant & Zimmermann, 2008; Askitas & Zimmermann, 2009; Choi & Varian, 2009).

Web-based surveys

Data on wages, working conditions, employer reviews, and many other labour-related details are collected through web-based surveys. Web-based surveys were among the first types of research conducted online (Kiesler & Sproull, 1986; Kehoe & Pitkow, 1996). Web surveys are fast, flexible, cheap and easy to set up and analyse, and they allow data collection from a large, diverse sample. For the US, there are two interesting web-based panel surveys that are being increasingly used: RAND's American Life Panel and the Understanding America Study Panel. Both are representative for the US adult population.

Research and Examples: Covers a range of topics, such as employement opportunities (Thiele, 2014), wages and remuneration (Tijdens *et al.*, 2013; Steinmetz *et al.*, 2014; Varkkey *et al.*, 2014; Zofkova & Stroukal, 2014), employer and career branding (Lauby, 2013), working conditions and well-being (Munoz de Bustillo & de Pedraza, 2010; Chandra, 2012); but also topics of a more methodological nature (e.g. de Pedraza *et al.*, 2010; Tijdens, 2014).

- Glassdoor: Glassdoor is a website, hosted on glassdoor.com, which functions as an online job board but also provides other information. More specifically, it allows employers to post vacancies and recruit potential employees through the website. In addition, the website targets job seekers and current employees, who can post their CV, rate their current or former employer and CEO, provide information on their working conditions and wages as well as the recruitment process. Users can interact with current or former employees to ask questions. For employers, Glassdoor provides branding and job advertising solutions. As most of the information on the site comes from former and current employees, it has a clear 'survey' dimension.
- WageIndicator: WageIndicator consists of a series of websites (one for each country), which collect micro data on global labour market trends. Information is collected via online surveys, in which visitors of the WageIndicator websites can participate (i.e. on a voluntary basis). In the survey, respondents are asked about their demographic status, occupation, wage, contributions and other entitlements to social security, working hours and conditions, well-being and job satisfaction, to name just a few topics. WageIndicator is an incredibly rich data sources, as it contains detailed information on minimum and real wages, labour laws and collective agreements, interviews and training advice in a high number of countries and languages.

12 This work can be found here: http://sethsd.com/

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3.3.2 What are the strengths and limitations of web-based data?

3.3.2.1 Strengths

Where traditional data sources, such as (labour force) surveys or census data, and methodologies fall short, an analysis based on web data may be useful to overcome these issues. The first set of benefits relates to the *data collection process* (Wade & Parent, 2001; Benfield & Szlemko, 2006; Kennan *et al.*, 2006; and Mang, 2012). Internet data can be collected in real time. In contrast to traditional sources, there are no lags or revisions. Another advantage is that web data allow researchers to collect large and diverse samples in a fast, flexible, easy and inexpensive way. Web data also make some of the tedious and complicated steps of collecting data from traditional sources redundant (e.g. data entry). Similarly, even though printed vacancies are a rich data source, they are more difficult to manage and manipulate than job advertisements published online.

Secondly, web data can be used to *fill research gaps* (Shapiro, 2014). Internet data are particularly valuable to cover those areas where traditional sources do not exist or are only limited (e.g. low quality or a lot of missing information). In that way, web data can also enable research on topics or concepts that are difficult to grasp or measure with traditional data sources. An important example is self-employment (OECD, 2014). Self-employment is a driver of job creation and entrepreneurship and has, therefore, received much attention from policymakers. Nonetheless, it is not well-represented in traditional data sources according to Fairlie & Robb (2009). More specifically, the traditional data sources on self-employment commonly only provide details on the business or on the owner, and only few datasets appear to combine both. Other issues are that data are lagged and self-employment is defined in different ways in different sources.

Another advantage is that web data often are publicly available and relatively detailed. Moreover, job advertisements, in particular, typically have a clear structure and contain real job titles, descriptions and requirements (Shapiro, 2014). They have clear space and time dimensions and reflect what is demanded in the labour market. As such, vacancies provide an excellent tool to study new occupations and skills as they arise, which is why they are at the heart of our work - along with other data available on the job boards that publish them.

Besides vacancies and job portals, other web-based data sources may be relevant. One way to detect new occupations is by asking survey respondents to select their occupation from a list of options or find it via a search tree (e.g. the WageIndicator survey). These occupations have an ISCO classification code. When a respondent cannot find his or her occupation, he/she can enter it into the survey. In this case, the occupation may be new or just emerging. A similar procedure can be followed for skills.

3.3.2.2 Caveats

Online job portals and labour market intermediaries

Carnevale *et al.* (2014), Kureková *et al.* (2015a) and Kearney & Levine (2015) have drawn attention to the methodological issues related to using data obtained from online job board (vacancies in particular) and intermediaries. Few other studies have discussed the limitations of web data (e.g. Benfield & Szlemko (2006); Shapiro (2014); Beblavý *et al.*, 2016a). The main issue is data representativeness, which takes the following forms:

- Incomplete information: not for every job opening a vacancy is published, not all vacancies are published online, and vacancies may not refer to (new) jobs. It is impossible to collect all vacancies, even if all would be published online. Vacancies only represent a small part of labour demand and are, therefore, often combined with other sources (Dorrer *et al.*, 2012; Wright, 2012; Carnevale *et al.*, 2014).
- Target specific profiles only: vacancies appear to be targeted towards highly-educated white collar workers and STEM jobs in the US (Carnevale *et al.*, 2014).
- Data collection and data processing: data are volatile and may be inconsistent; vacancies may be duplicate and poorly structured; vacancies may not contain all requirements demanded.
- Other issues: ethical and technical issues; adverse selection of job applicants (Autor, 2001); vacancies are typically not standardised or stored (Shapiro, 2014; Kureková *et al.*, 2015a).

Social networks

Despite the fact that web data are generally easier to collect than data from traditional sources, extracting data from social media may prove to be more difficult to obtain when compared with other online sources. Data representativeness is also an issue because social networks may mainly attract certain groups of people:

- Facebook: Wilson *et al.* (2012) note that data crawling is becoming less effective to extract data from Facebook due to stricter privacy settings.
- Twitter: may be difficult to access, and data are limited to the last seven days (see Kwak *et al.*, 2010, for details on how to use crawling techniques). There are no historical data or frequency counts, data come in a format that is hard to manipulate, there is no geographical information.
- Interestingly, in recent years social network platforms have reached out to the academic community, through initiatives such as the Twitter Data Grants or the LinkedIn Economic Graph.

Google Trends

In their recent influential paper, Kearney & Levine (2015) identify two main concerns when using Google Trends data:

- Sample bias: results from the fact that only a sample of searches is fed into the Google Trends analysis.
- Searches with too few observations are excluded.

- Sampling variability issues: related to the first issue, standard error calculations are problematic when data are treated as fixed instead of random.
- Other issues: no data on demographics, potential endogeneity effects which may be hard to control for.

Web-based surveys

Data are not representative because participation is voluntary and response rates can be low (Benfield & Szlemko, 2006): information may be missing, some groups of the population may not be targeted (e.g. individuals without Internet access), literacy of participants matters, credibility and authenticity of the answers provided may be questionable, ethical and technical issues etc. Key methodological issues are sample bias, measurement error, non-response and attrition.

3.3.3 How can these web-based data be accessed?

Generally, there are several ways in which data can be accessed from online sources:
- Data can be made available on the website of interest or that of a partner (e.g. WageIndicator data). In addition, data can be obtained from the site's structure (labelled 'metadata' in the remainder of this report).
- Data can be collected by private companies and offered for sale or free of charge when used for research (e.g. data from Burning Glass). Such data are typically cleaned and coded, but may be aggregated to ensure anonymity.
- Data can be obtained by 'web crawling' or 'web spidering' (see a.o. Capiluppi & Baravalle, 2010; Kuhn & Shen, 2013; Carnevale *et al.*, 2014). This technique is commonly used to extract and process job advertisements. Especially the data processing step can be complicated and is strongly dependent on the content and the structure of the job advertisements collected.

In our work, we have experimented with *data obtained from online job boards and employment websites* in particular. This choice is motivated by our aim to develop and test an innovative method to identify new occupations and skills using Internet data. For this purpose, job portals are an obvious candidate. We acknowledge the potential of other data sources, such as web surveys (e.g. the WageIndicator survey), Google Trends and social networks, but have not exploited these sources so far.

3.4 Putting these innovative methodologies to the test: identifying new jobs and skills using Internet data

Online job boards can be used in two ways, as was already hinted at above: either one uses the *vacancies and CVs* published, or one relies on the structure of the portal and the *metadata* that it offers.

3.4.1 A first approach: Vacancies and CVs

Job vacancies and CVs can be assembled via web crawling or 'spidering' (Capiluppi & Baravalle, 2010; Kuhn & Shen, 2013; Carnevale *et al.*, 2014). With a 'spider' or web bot, a substantial sample of job advertisements can be obtained and stored into a database. The data collection process is relatively easy and fast. Vacancies are typically detailed, and contain crucial information such as 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). By collecting a sample of job 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), a careful analysis of job vacancies is a good start. A comparison of the skill requirements can shed light on these dynamics. Tijdens *et al.* (2012), however, do point out that linking job titles to an occupational structure is not straightforward, especially when they cover multiple countries and languages.

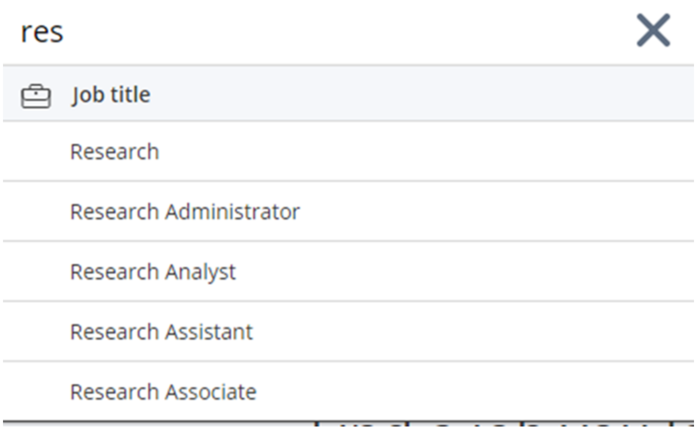
One of the main difficulties of using vacancy data is that data cleaning, processing and management are relatively complicated (Carnevale *et al.*, 2014). Data are assembled in a database, extracted and parsed into smaller fragments. These fragments are then coded and analysed. This process can be straightforward or very difficult, depending on the structure and the content of the job vacancy. To carry out this process, a comprehensive taxonomy of variables and words is essential. In addition, semantic analysis and text mining are often required to support the coding of the data. These issues are difficult to address, but nonetheless have to be overcome when one uses vacancy or CV data.

3.4.2 A second approach: Metadata from job portals

Alternatively, one can simply rely on the *metadata* of the online job portals, rather than the vacancies and CVs published. Job boards are typically structured in such a way that a job seeker is offered a range of similar vacancies (rather than one perfect match) when looking for job offers. This implies that portals arrange their content or advertisements within a clear framework, often based on an occupational classification. Job portals often contain tens of thousands of vacancies, which have to be organised in a structured way in order to keep them manageable.

How does a job board set up an occupational classification? Again, there are several approaches that can be followed. A first approach is to *create an occupational classification on the basis of a system of 'tags'*. Job advertisements can be assigned to specific categories or 'tagged' by the advertiser or the portal. Tags can refer to many things, such as job type, employer type, location, sector, wage bracket, etc. On most, but not all, job portals each vacancy is also assigned one or more occupation tags. Some job boards publish their list of tags online, so that job seekers can select their occupation of interest from the list. Other portals store the list of tags in a library that can be accessed by an application program interface (API) search. In this case, when job seekers start typing into a search box, the system generates options for automatic completion (as illustrated in Figure 3.2).

Figure 3.2 **Example of autocomplete functionality from job board reed.co.uk. The job tags that appear when one types 'res' are displayed**



A second approach is to associate occupations on the basis of keywords that appear in the body of the vacancies that are published. This approach, however, appears to be less reliable. For example, it could occur that a social worker position is offered to a job seeker looking for the keyword 'finance', because the word 'finance' is mentioned in the job advertisement.

One should not think of such an occupational classification as a 'static' list. Instead, in both cases the occupational classification is regularly updated to account for changes in the labour market (e.g.

occupations that appear or disappear, new skills that are being requested, etc.). The Slovak job board profesia.sk is a good example: between 2011 and 2014, the job board added about 10 new occupations each year. Job portals' occupational classification is a good data source to capture the occupational structure in a region at a certain point in time. These classifications can also be compared with those from other sources, such as ISCO and ESCO, to identify new occupations (e.g. what is available on the job portals but missing in the official lists?).

3.4.3 Putting both approaches to the test: empirical evidence from a six case studies

Case studies 1 to 3 are based on vacancies, case studies 4 and 5 on metadata and case study 6 is cross-cutting.

3.4.3.1 Case study 1: 'Do educational requirements in vacancies match the educational attainments of jobholders? An analysis of web-based data for 279 occupations in the Czech Republic'

(Tijdens et al., 2015b)

The first case study that was carried out in light of the InGRID project deals with skill mismatches in the Czech Republic. The study aimed to address the fact that data on skill mismatches are not necessarily available, unlike what one may expect. Allen *et al.* (2013) suggest that only very limited data on the skill requirements of employers are available, which, in addition, may not be comparable to the existing measures on skill supply. Given that especially data on skill demand are problematic, we looked into new methods to obtain such data. In the paper, the concept of 'skills' overlaps with that of 'educational attainment' due to data availability issues. Traditionally, data on skill demand are derived from vacancy monitoring, employer surveys or by asking employees about their current job's requirements, and to a lesser extent from licensing registers and expert surveys.

We combined data from the WageIndicator Internet survey conducted among Czech jobholders with the EURES vacancy data. Data from both sources are aggregated into occupations (i.e. 4-digit ISCO codes) and compared. *WageIndicator data* from the period January 2010 until December 2013 are merged. All visitors of the WageIndicator website are invited to voluntarily complete a survey (which runs continuously). These data are assembled in annual databases. Occupations are coded in ISCO-08, while education is coded in ISCED-97. When WageIndicator data are compared with labour force data from Eurostat, it becomes clear that highly-educated individuals are overrepresented in the survey. The opposite holds for medium- and lower-education individuals.

EURES job vacancy data are composed of the data that the national public employment services supply to the website. The vacancies are coded in ISCO-88 and ISCED-97. Data were collected in December 2013. EURES data for the Czech Republic are fairly complete, as the Czech public employment service requests that all job advertisements are reported to them. These job advertisements are subsequently reported to and published on the EURES website. When compared with the total number of vacancies in Eurostat, the number of vacancies on EURES is very similar for the Czech Republic.

In both datasets, the focus is on *occupations* and *skills*. The skills, captured by ISCED-97 codes for educational attainment in both sets, are already comparable. We distinguish between five education levels, ranging from primary education to higher education. The occupations carry different codes in the EURES and WageIndicator data. In both cases, the categorisation is based on ISCO (the ILO's occupational classification scheme) but the edition differs. The EURES occupations are, therefore, recoded into ISCO-08, using a conversion table provided by the ILO.

We report a substantial variation in labour supply and demand across the occupations examined. For one-third of the occupations, demand is at least five times the supply. For 25% of the occupations, supply is at least five times larger than demand. Furthermore, there is a negative relationship between the demand for an occupation and the educational requirements listed in the vacancies for this occupation, and a negative relationship between the demand for an occupation and the educational attainments of employees working in the occupation, but this conclusion does not hold for the lowest attainment levels. Another important result is that the level of educational attainments of current employees is larger than what is required in the vacancies.

3.4.3.2 Case study 2: 'Skills requirements for the 30 most-frequently advertised occupations in the US: An analysis based on online vacancy data'

(Beblavý et al., 2016c)

For our second case study using job advertisements, we relied on data extracted from Burning Glass Technologies. Burning Glass provides job market analytics, applications and data to inform policymakers, employers, education institutes, recruiters and others about current developments in the labour market. The organisation uses real-time data, extracted from job postings, to this end.

We use data obtained for the 30 most-frequently-advertised occupations in the United States. In total, 1,998,000 vacancies were collected via Burning Glass during the 12-month period September 2013-August 2014. Using a 12-month period prevents that results are driven by seasonal effects. Burning glass data are particularly interesting as the company aggregates vacancies from about 15,000 online job boards and company sites. These job postings are coded and categorised, which implies that occupation and industry codes are commonly available. Job advertisements generally contain information on education, skills and experience requirements is also provided.

Among the 30 most-frequently advertised occupations, we find cooks, security guards, nurses, managers, cashiers, office clerks, labourers and truck drivers. In other words, our data set contains high-skilled, medium-skilled and low-skilled occupations. Following the classification proposed by Kureková *et al.* (2015b), which is based on ISCO, our sample is composed of 2 low-skilled (ISCO 9), 20 medium-skilled (ISCO 4-8), and 8 high-skilled occupations (ISCO 1-3). In the US, the 5 most-frequently advertised occupations are: retail salesperson (233,851 vacancies), customer service representative (CS) (197,232 vacancies), sales worker supervisor (164,298 vacancies), secretary (114,918 vacancies) and sales representative wholesale (111,177 vacancies). The average number of job advertisements available across the 30 occupations is 66,292.

With this set of vacancies, we examined the requirements that US employers have, by analysing the text of the vacancies, identifying crucial keywords and keeping track of the share of job advertisements -in total and for individual occupations- that refer to these keywords. In particular, we focused on six types of qualifications: *education and formal qualifications*, *cognitive skills*, *non-cognitive skills*, *appearance/look*, *experience* and *other requirements* (e.g. having a clean criminal record, being subject to drug testing and being a US citizen). For each type, we use a set of keywords to identify demand (the keywords are listed in Table 3.1). Combinations and variations of these keywords are also used. When at least one of the keywords was present in the vacancy, it was considered to request the requirement of interest. By taking a broad perspective, we are able to identify the skills that are important in the US and focus on new skills if needed.

In our study, *education and formal qualifications* involve requirements for education, specialised training and licenses. *Cognitive skills* are defined as skills 'typically identified with intelligence and the ability to solve abstract problems' (Kureková *et al.*, 2015b, p. 8) and they can be '*specific*' or '*generic*' in nature. In our work, the specific cognitive skills are: computer skills, analytical skills, language skills, and having a driver's license. Among the generic cognitive skills we include the ability to learn. *Non-cognitive skills* are 'personality traits that are to some extent correlated with intelligence measures' (Brunello & Schlotter, 2011). They have a 'characteristics' and an 'attitude' dimension (Anderson & Ruhs, 2008). Following Kureková *et al.* (2015b) we differentiate between '*social*' and '*personal*' non-cognitive skills. The former consists of communication skills, service skills and team-work skills. The latter contains seven types of skills or personality traits: timeliness, independence, reliability, manners, creativity, flexibility and stress-resistance. In recent years, the roles of cognitive and non-cognitive skills in the education and the labour market outcomes of individuals have been debated. Research shows that non-cognitive skills may be particularly important in service jobs.

67% of the vacancies examined include formal education requirements. 49% of these vacancies demand service skills and 38% of them refer to experience. These three factors constitute the main filters that US employers use to select job applicants. Interestingly, other non-cognitive skills are also relevant: 30-40% of the vacancies refer to a pleasant demeanour (manners) and flexibility, while 20-30% contain communication skills, timeliness and creativity. As expected, there are huge differences among the 30 occupations. In general, vacancies in the United States prove to be relatively demanding in terms of the requirements that applicants have to meet, and this also applies to low-skilled and mid-skilled jobs. Nevertheless, employers tend to be more demanding as the level of complexity of an occupation goes up (at least for some requirements).

Table 3.1 Overview of the keywords used to identify six types of qualifications

Education and formal qualifications		
	Formal education	Diploma, GED, bachelor, college, university, degree, high school
	Specialised training and licenses	Apprenticeship, training, card, certificate, certification, certified, CDA, ASE, CPR, AED
Cognitive skills		
Specific	Computer skills	Computer, PC, CRM, Microsoft (Office, Word, Excel, Power Point, Outlook, and Access), Windows, SAP
	Analytical skills	Mathematics, analytical, logic, quantitative
	Language skills	Bilingual, English, Spanish, language
	Driver's license	Driver's license
Generic	Ability to learn	Ability to learn, able to learn
Non-cognitive skills		
Social	Communication skills	Communication, speak, write, articulate, verbal, interact, communicate
	Service skills	Client, customer, guest, needs and attention
	Team-work skills	Team, attitude, focus, leader work, environment, spirit
Personal	Creativity	Creative
	Flexibility	Flexible, stay overnight, travel, shifts, work evenings
	Independence	Self-motivated, initiative, independent
	Pleasant demeanour and manners	Attitude, positive, mature, helpful, confident, enthusiastic, professional
	Reliability	Attention to detail, dependable, reliable
	Stress-resistant	Calm, stress, crisis situation
	Timeliness and punctuality	Timely manner, deadlines, act quickly, punctual, prioritise
Experience		
	Experience	Experience combined with year, month, work, preferred, desirable
Appearance/look		
	Appearance	well-groomed, clean, neat, professional appearance
Other		
	Citizenship	US citizen, citizenship
	Criminal record	No criminal record, clean criminal record
	Drug testing	Drugs, drug testing

3.4.3.3 Case study 3: 'The IT skills pyramid: A study on the demand for digital skills on the US labour market'

As a follow-up to the first study in which we used Burning Glass data, we prepared a second paper in which we focus specifically on *IT skills*. As a starting point for this work, we consider how technological progress affects the US labour market - building on the vast literature that exists on this topic. For many years, researchers have pointed to *skill-biased technological change* to explain growing inequalities (in terms of employment and/or wages) between skilled and unskilled workers (see a.o. Krueger, 1993; Nickell & Bell, 1996; Mendez, 2002; Oesch & Rodriguez, 2011 and Weiss & Garloff, 2011). Also for the US, research has provided evidence of upskilling and skill gaps. Other work has nuanced these claims, arguing that skill-biased technological change only cannot account for *job polarisation* (i.e. when the demand for high-skilled and low-skilled jobs[13] expands at the expense of that for medium-skilled jobs (Autor *et al.*, 2003; Wright & Dwyer, 2003; Goos & Manning, 2007; Jung & Mercenier, 2014)). This phenomenon has been witnessed in many countries, including the US (Autor *et al.*, 2006). Job polarisation can be driven by many factors, with *routinisation-biased technological change* being a major one (Autor *et al.*, 2003). In this scenario, technology can replace labour in routine tasks, which are generally in the middle of the skill distribution but not in non-routine tasks (Goos & Manning, 2007). All these phenomena have important policy consequences. They raise questions such as 'how can society adapt to these transitions' and 'which skills does the labour force need in order to keep up'?

Against this background, our focus is on IT or digital skills and the case of the United States. This focus is motivated by the recent emphasis on the role of the computerisation and the emerging debate on 'digital skill gaps' (see Frey & Osborne, 2013). While basic computer skills are becoming *implicit skills,*[14] and increasingly are considered a prerequisite for most jobs, the computer literacy of the US population seems to lag behind (cf. the results of the PIAAC survey; see OECD, 2013b). The education sector is insufficiently prepared to deal with these technological changes and workers enter the labour market lacking the skills they need. The supply of IT skills is well-documented. Despite the debates, still not much is known about the demand for IT skills in the US. Vacancy data can, therefore, provide us with some relevant insights.

Within the study, a distinction is made between three groups of digital skills: basic, intermediate and advanced (following previous work using similar data sources, see the report by Burning Glass Technologies, 2015). This classification suggests a hierarchy between the skills, which is also reflected in the demand for these skills. The data are obtained from Burning Glass and cover the 30 most-frequently advertised occupations. We calculate the share of vacancies in general and by occupation that make reference to certain keywords used to capture the digital skills. For the *basic digital skills*, we consider the keywords computer skills, software, hardware, e-mail, Internet, web, etc. Basic computer skills are requested in about one-third of the vacancies, closely followed by e-mail and Internet (about 20% in both cases). A positive relation is found between the complexity of an occupation and the demand for these skills.

Secondly, *intermediate digital skills* are skills such as word or text processing (including Microsoft Word, Word, etc.), spreadsheets (including MS Excel), MS PowerPoint, office packages (including MS Office, Open Office, etc.) and SAP. These skills are also labelled 'productivity software skills'. 12% to 15% of the vacancies call for text processing and spreadsheets; about 8% explicitly refers to office packages. As before, the demand for intermediate digital skills rises with the complexity of an occupation.

Finally, a set of *advanced digital skills* is considered. This set combines the most complex and diverse skills that we studied. Job applicants who do not possess these skills, would not at all qualify for a

13 Especially in the service sector, see Maxwell (2006).

14 nterestingly, for the European case, about 550 IT skills are identified by ESCO, which is the European Commission's classification of Education, Skills, Competencies and Occupations. Yet, these IT skills are listed as 'job-specific' skills rather than 'transversal' skills.

position that requires them. We focused on nine classes of skills, each captured with different keywords: CRM (e.g. customer relationship management, etc.), data management and databases (e.g. SQL, MS Access, etc.), data analysis and statistics (e.g. data processing, Stata, Matlab, etc.), programming and programming languages (e.g. C++, Python, JAVA, etc.), digital media and web design (e.g. web development, Photoshop, etc.), desktop publishing (e.g. MS Publish, Visual studio, etc.), CMS (content management system, etc.), social media and blogging (e.g. Twitter, LinkedIn, WordPress, etc.), and SEO (e.g. search engine optimisation, etc.). Of these skills, the category databases and data management is the most highly represented in the vacancies (in about 10% of the job advertisements). In addition, the variation across occupations appears to be substantial. As expected, advanced digital skills show up particularly in vacancies for medium- and high-skilled white collar workers and are often only relevant for a few occupations.

3.4.3.4 Case Study 4: An occupations observatory

(Beblavý et al., 2016d)

For the fourth case study, we opt for a different approach to identify new occupations and skills. This alternative approach is still based on web data and online job boards in particular but, instead of using vacancies, we rely on the *structure of the job portal and the tag system that it uses* to cluster job advertisements. Online job boards use a tag system to structure the large amount of vacancies that they publish. Tags often refer to specific occupations, but can also cover many other factors (e.g. sector, region, company type, etc.). Generally, from the list of tags that the job portal uses, an occupational classification can be derived. This classification is regularly updated, to account for new occupations and skills and remove redundant ones. This means that the occupational classifications are up-to-date, allowing us to capture new occupations as they arise (in contrast to traditional methods where the classifications used are only rarely updated).

We piloted an innovative approach based on changes in the occupational classification of 11 job portals, with the aim to discover whether this approach could be adopted on a larger scale to identify new occupations and to further our understanding of the skills, education and other requirements that new occupations bring. We selected Belgium, the Czech Republic, Denmark, France, Germany, Hungary, Italy, Poland, Slovakia, Spain and the United Kingdom for our pilot (the list of portals can be found in Table 3.2). Given that this is a pilot, we did not set out to cover all EU countries. Instead, we selected a sample of job boards in a subset of countries, covering different regions. The 11 countries chosen represent about 75% of the EU population.

For these countries, we were able to find job boards that cover a substantial part of the labour market and that have a tag system, which we verify by checking whether or not the search box has automatic completion or a publicly available list of tags. Other criteria were that the portal is regularly updated and contains at least 3,000 vacancies. In most cases, the list of occupation tags was not publicly available and had to be recovered via web crawling techniques or through querying the website's autocomplete API (i.e. an application programming interface) (from a repository, see for example Figure 3.3).

Table 3.2 List of pilot countries and job boards selected

Belgium	vacature.com (Dutch-speaking part) (www.vacature.com/vacature/bladeren/functienaam/), references.be (French-speaking part) (www.references.be/job/parcourir/fonction/)
Czech Republic	jobs.cz (www.jobs.cz/)
Denmark	jobsnet.dk (https://job.jobnet.dk/CV)
France	keljob.com (www.keljob.com/emploi/metiers)
Germany	jobs.de (www.jobs.de/regional/taetigkeitssuche)
Hungary	profession.hu (www.profession.hu/)
Italy*	lavoro.corriere.it (http://lavoro.corriere.it/)
Poland	jobs.pl (www.jobs.pl/stanowiska-pracy)
Slovakia	profesia.sk (www.profesia.sk/)
Spain	careerbuilder.es (www.careerbuilder.es/)
United Kingdom	jobsite.co.uk (www.jobsite.co.uk/jobs/all/job-titles/)

* The Italian job board had a public list of tags, but this list did not show all the jobs that appeared when the autocomplete function was used. For this reason, the smaller crawled list of jobs was replaced with a more detailed one from autocomplete API.

Figure 3.3 Example of a repository of a job tags from the Danish portal www.jobnet.dk


```
arbejde","astronom","biokemiker","biolog","mikrobiolog","botaniker","ferskvandsbiolog","fys
ker","geofysiker","geolog","geotekniker","havbiolog","hospitalsfysiker","kemiker","klimatol
g","levnedsmiddelkandidat","bromatolog","levnedsmiddelinspektør","matematiker","meteorolog'
"miljøtekniker","molekylærbiolog","naturgeograf","statistiker","zoolog","organisation,
udvikling og rådgivning","HR-konsulent","uddannelseskonsulent","HR-
medarbejder","personalemedarbejder","personalekonsulent","researcher,
rekruttering","headhunter","rådgivende konsulent","psykologarbejde","psykolog","teologisk
arbejde","præst","sognepræst","teolog","undervisning på gymnasier og
højskoler","gymnasielærer, humaniora og kreative fag","gymnasielærer, naturvidenskab og
idræt","gymnasielærer, samfundsvidenskab","handelsskolelærer","højskolelærer","pædagogisk
kandidat","undervisning på professionshøjskoler","adjunkt, professionshøjskole","lektor,
professionshøjskole","underviser, erhvervsakademi","underviser,
professionshøjskole","seminarielærer","økonomi og
revision","aktuar","businesscontroller","civiløkonom","erhvervsanalytiker","erhvervsøkonom'
"nationaløkonom /
```


In order to use this information to identify new occupations, we developed a method that comprises several steps. First, we obtained from each of the 11 job boards the full list of occupation tags. This occupational classification serves as our *benchmark*. It was cleaned for errors such as duplicates or mistakes, and any tags that did not necessarily refer to occupations were removed (e.g. tags referring to locations, sectors, firms or other items). This cleaning process is fully automated, which means that some errors will not be caught. To alleviate this caveat, the benchmark was fully checked manually (by native speakers). Then, the benchmark list of each country was also translated into English, to facilitate cross-country comparisons. Translations were done using the Google Translate website and again verified by native speakers. This is needed, as not all words are always translated properly. In fact, our first results indicate that there were some severe errors in the translations. Moreover, occupations often have a very specific terminology which may not be translated correctly. These issues are particularly important in light of cross-country comparisons.

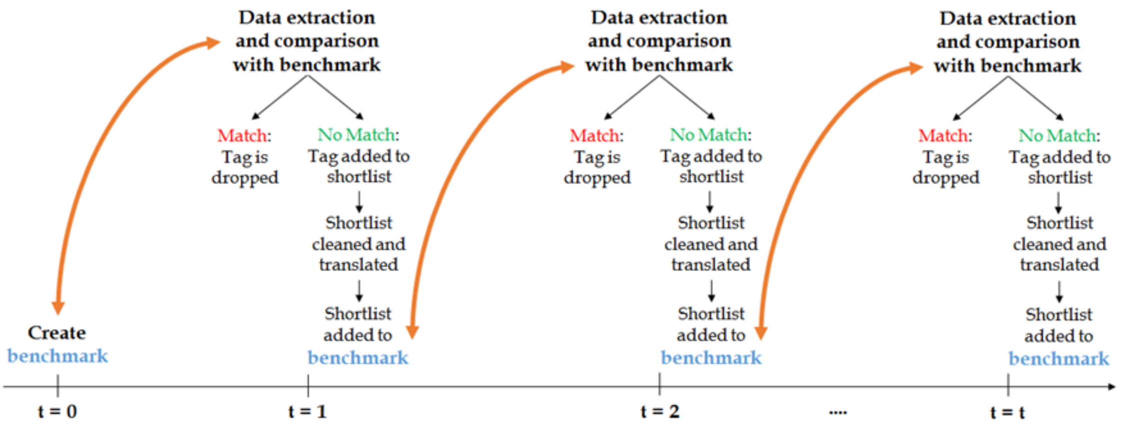
Secondly, this occupational classification was again obtained at the beginning of each month (i.e. early August, September, etc.) over a six-month period.[15] We refer to this step as the '*data collection*'

15 At the end of July, we tested our coding. For some countries, this results in an additional list of new occupations for this period.

step. The occupational classifications extracted are organised in an array and compared to the benchmark. The occupations for which a *match was found* are disregarded. The occupations for which *no match was found in the benchmark* are regarded as potentially new and saved in a database (by country and date) - in each case creating a shortlist of potentially new occupations. This shortlist again is cleaned (first automatically and then manually) and translated into English via Google Translate, after which another manual check is performed. This data cleaning process is identical to that of the benchmark.

With this procedure, we end up with *two outputs*: the benchmark and the shortlist of potentially new occupations on a specific date (by country). Before the data collection process is started again in the next month, the list of new occupations is added to the benchmark. This prevents occupations from being detected as 'new' more than once. The findings from the pilot reveal that for some countries no new occupations were found. There are several possible explanations for this result: for example, it could be that no new occupations emerged or that new occupations emerged but were not picked up by the portal. Alternatively, it could be that potentially new occupations were found but that the manual check of the data revealed that these are not new at all. For instance, on the Belgian job portal an occupation emerged that already exists for decades but for which no vacancies were available before.

Figure 3.4 Illustration of the data collection step



An extensive example for the case of Slovakia - data collection step

A new list of occupation tags was obtained from the Slovak job board on 30 July 2015, 6 August 2015, 2 September 2015 and 4 October 2015. Any occupations that were not already part of the benchmark are potentially new, but could also refer to occupations that have been around for years but for which no vacancies were available or for which no separate tags were used. On 30 July, 21 new tags were found, translated into English and compared to the benchmark. Of the 21 occupations, several pointed to potentially new occupations: e.g. drug safety specialist, sound engineer, spa therapist and development specialists switching network. Although one may argue that some of these occupations are common in specific countries, one must keep in mind that occupations have clear space and time dimensions, which implies that these may very well be new on the Slovak labour market. Other occupations were refuted for not being really new: e.g. police officer, soldier and wigmaker. All new tags were added to the benchmark and the data collection process was restarted on August 6. Then, 3 new tags were retrieved: photographer, warder, forest engineer, of which especially the latter could refer to a new occupation. A new list was obtained on September 2 and October 4, both of which resulted in another set of 3 new tags: geologist, revision pharmacist and specialist OSS/BSS and forester, forest technician and head of post. We used our list of candidates that potentially capture new occupations - such as spa therapist, drug safety specialist or OSS/BSS specialist in the above example - for a more in-depth analysis which is explained in further detail below.

Thirdly, there is the '*data analysis*' step. In this step, the shortlist of potentially new occupations - which has been cleaned as explained above and reduced to only those occupations that could be new - is further processed. Occupations that obviously are not new are dropped from the shortlist of new occupations, but they are nevertheless added to the benchmark for future reference. Furthermore, any mistakes that are due to the data collection or matching procedures are taken care of as well. In Table 3.3, we report the number of tags or occupations in the benchmark, the total number of new tags detected and the number of new tags that actually referred to (potentially) new occupations (i.e. 'valid' tags). There is a lot of heterogeneity across job boards, both in terms of the number of tags in the benchmark and the number of new tags. This finding, however, should be interpreted with caution. It does not necessarily imply that new occupations only and/or mostly emerged in a subset of the countries. In fact, the Belgian portal has a very high number of new tags, but these tags generally referred to general concepts rather than new occupations. On 9 March 2016, 42 job advertisements were assigned the tag 'wood', covering different occupations such as 'CNC machine operator in the wood processing industry' and 'salesperson of wood products' on the Belgian portal. Therefore, careful manual inspections of potential new occupation tags are essential to prevent false positives. As is evidenced by Table 3.3 below, only a small percentage of the new tags correspond to potentially new occupations. The remaining tags generally appeared to refer to traditional occupations, which were not advertised online or for which no vacancies were available when the benchmark was created. Another reason might be that some tags are associated with seasonal jobs, which are only advertised during a specific time of the year. More details on the number of tags and the type of tags detected can be found in Appendix 1.

Table 3.3 Number of tags in the benchmark and on the shortlist for each country

Country	Number of tags in benchmark	Number of new tags	Number of valid new tags
BE	415	714	NA
CZ	424	0	0
DE	1,507	0	0
DK	2,163	0	0
ES	233	2	1
FR	1,087	32	11
HU	369	91	11
IT	962	0	0
PL	795	15	7
SK	468	30	16
UK	6,063	0	0

Note: The number of valid tags for Belgium is missing, because of the peculiar way in which the job portal adds new tags (which, as explained, not only refer to actual occupations but also to other items and words). Therefore, there were many tags that carried valuable information, but a manual inspection of these tags was required to discover which ones captured new or emerging occupations.

In order to discover whether an occupation is indeed new, in a specific sector or the global economy/in the country or elsewhere, an in-depth analysis is carried out. To this end, we create an occupation card for each potentially new occupation. All occupation cards are combined into an occupations observatory. An occupation card has six parts, in which more information on the occupation are provided. By putting all this information together, we verify whether the occupation is indeed new. The first section deals with the identification of the occupation, presenting details on the vacancy that introduced the tag. The second section discuss the responsibilities and tasks associated with the new occupation. In the third section, the requirements and qualifications demanded (e.g. education, skills and experience) are studied. These first sections give some first insights into whether the occupation is completely new or already emerging, new in a specific sector or in the economy as a whole, etc. The fourth section extends the analysis to other countries while the fifth section aims to discover whether the occupation is present in the most recent occupational classifications. The latter is important since the literature defines a new occupation as an occupation that has not yet been included in the latest occupational classification (Crosby, 2002). The sixth section summarises the card. The template of the occupation cards is presented in Appendix 2.

In general, we find that it is feasible to identify new occupations on the basis of this innovative methodology, which relies on metadata of job boards instead of vacancies, although one can consider a lower frequency (given that new occupations do not emerge very often - as is clear from our case study).

3.4.3.5 Case Study 5: 'The importance of foreign language skills in the labour markets of Central and Eastern Europe: an assessment based on data from online job portals'

(Beblavý et al., 2016b)

For our second case study based on data derived from online job portals - i.e. their structure and tag system rather than the vacancies - we empirically examine how important knowledge of foreign languages is on labour markets in Central and Eastern Europe. More specifically, we focus on the countries in the Visegrad region: the Czech Republic, Hungary, Poland and Slovakia. This case study is motivated by the fact that in a globalised world, knowledge of foreign languages is a very important skill. Especially in Europe, with its 24 official languages and countless regional and minority languages, foreign language skills are a key asset. Yet, while many Europeans are able to speak at least one foreign language, the cross-country variation is considerable (according to the results of the 2012 Eurobarometer).

Our case study is devoted to the Visegrad region, which is relatively open to foreign direct investment and international trade. Because English has developed into the global language of business, knowledge of the language may be relevant skill on the Visegrad labour markets. Furthermore, the Visegrad countries have strong historical, cultural and economic ties with Germany and Austria (making German potentially relevant as well), and have shared a border with the former Soviet Union. In addition, the main national language of none of the four countries is widely spoken in other countries across Europe. While it is not very easy to predict which foreign language skills are the most demanded in the Visegrad region, it is clear that the population's language skills may not be as well-developed as in some other European countries (according to Eurobarometer results).

How do we investigate these research questions? As a first step, we identified for each of the four countries a 'representative' online job portal, which means that these portals were chosen after a thorough analysis of their content and market coverage. For each job board, we assessed their coverage in terms of occupations, sectors, regions, skill levels, etc. In addition to these criteria, job portals also had to use a 'tag system' to organise the vacancies that can be accessed either directly or by search API. With these conditions in mind, the following websites were selected for analysis: www.jobs.cz (*Czech Republic*), www.profession.hu (*Hungary*), www.pracuj.pl (*Poland*) and www.profesia.sk (*Slovakia*). Only the Slovak job portal publishes a list of tags online (i.e. an overview table presenting all tags and the number of associated job vacancies). To obtain this list for the other job boards, tags were crawled from the autocomplete function of the search box that job seekers use to indicate what type of vacancy they are interested in (i.e. API query). Often, a list of tags corresponds to a list of occupations but, as stated above, many job portals use a range of other tags as well (e.g. related to sector, type of organisation, specific skills, etc.). All lists were collected on 17 July 2015. To rule out that our results are affected by seasonal dynamics, we contacted each of the job boards to inquire about the statistics for the entire year 2015. The Slovak job board informed us that 46% of the vacancies required English, while 14% was tagged 'German'. On the Hungarian portal, 55% of the vacancies demanded English or German, 10% English (specifically) and 2% German. The Czech job board confirmed that 10% of the job advertisements called for German, but the share for English varied between 28% and 59%, depending on whether the job advertisements were supplied by public employment agencies or employers. We, unfortunately, did not receive any additional information from the Polish job board. Below, we further discuss the results of our initial work.

For each country, we first extracted the total number of vacancies available. This number amounted to 15,269 vacancies on the Czech job board, 11,231 vacancies on the Hungarian job board, 36,079 vacancies on the Polish job board and 11,344 vacancies on the Slovak job board (or about 74,000 advertisements in total across the countries and considering all occupations). Then, we counted how many of these vacancies carried tags referring to foreign language skills.[16] We kept track of the number of job advertisements tagged 'English', 'German', 'Russian', 'French', 'Spanish', etc. and then examined which of these foreign languages was demanded the most (or, in other words, for which tag do we find the highest number of vacancies). In the study, we include the main European languages, languages spoken in the neighbouring countries, languages that may be relevant due to historical, cultural or economic reasons, etc. No distinction is made between reading, writing, listening and speaking skills. One, however, has to be aware that tags are not disjunctive groups: a single job vacancy could request the knowledge of multiple foreign languages.

In the case study, we first look at the total number of vacancies and the share that demands foreign language skills. We then repeat this exercise for a set of occupations for which we can find at least 30 vacancies in all four countries. To perform the occupation-level analysis, occupations had to be matched across the Visegrad countries. To this end, occupation titles had to be translated into English and then compared. Occupations that were not represented in all four countries were dropped from the sample. The remaining occupations were mapped into each other. This was relatively straightforward when there was only one potential match. More commonly, multiple matches were possible. One example is that an individual occupation or tag can be represented by several tags on other job portals. For instance, the tag 'teacher' - which is a single tag in the Czech Republic, Hungary and Slovakia - is divided into two tags, 'teacher' (Nauczyciel) and 'instructor' (Wykładowca), in Poland. Another example is the tag 'programmer', which can be represented by multiple tags (e.g. JAVA, Python and other programmers). When multiple matches were possible, a weighted average was computed (weights equal to the number of vacancies by occupation). As a consequence, in some cases the matching is not 'exact' but instead based on whether or not occupations were 'relatively comparable'. Despite this caveat, the language requirements of the occupations that were mapped into a single occupation are very comparable (considering the share of vacancies that refer to foreign languages). Altogether, 59 occupations were identified in the four countries for which the total number of job advertisements and the number of vacancies that demand foreign languages (i.e. that carry specific foreign language tags) are obtained and used to calculate shares. In the hypothetical example that a job board would contain 500 vacancies for teachers, of which 150 would be tagged 'English', the share would be 0.3. Among the 59 occupations, 2 are low-skilled, 20 are medium-skilled and 35 are high-skilled.

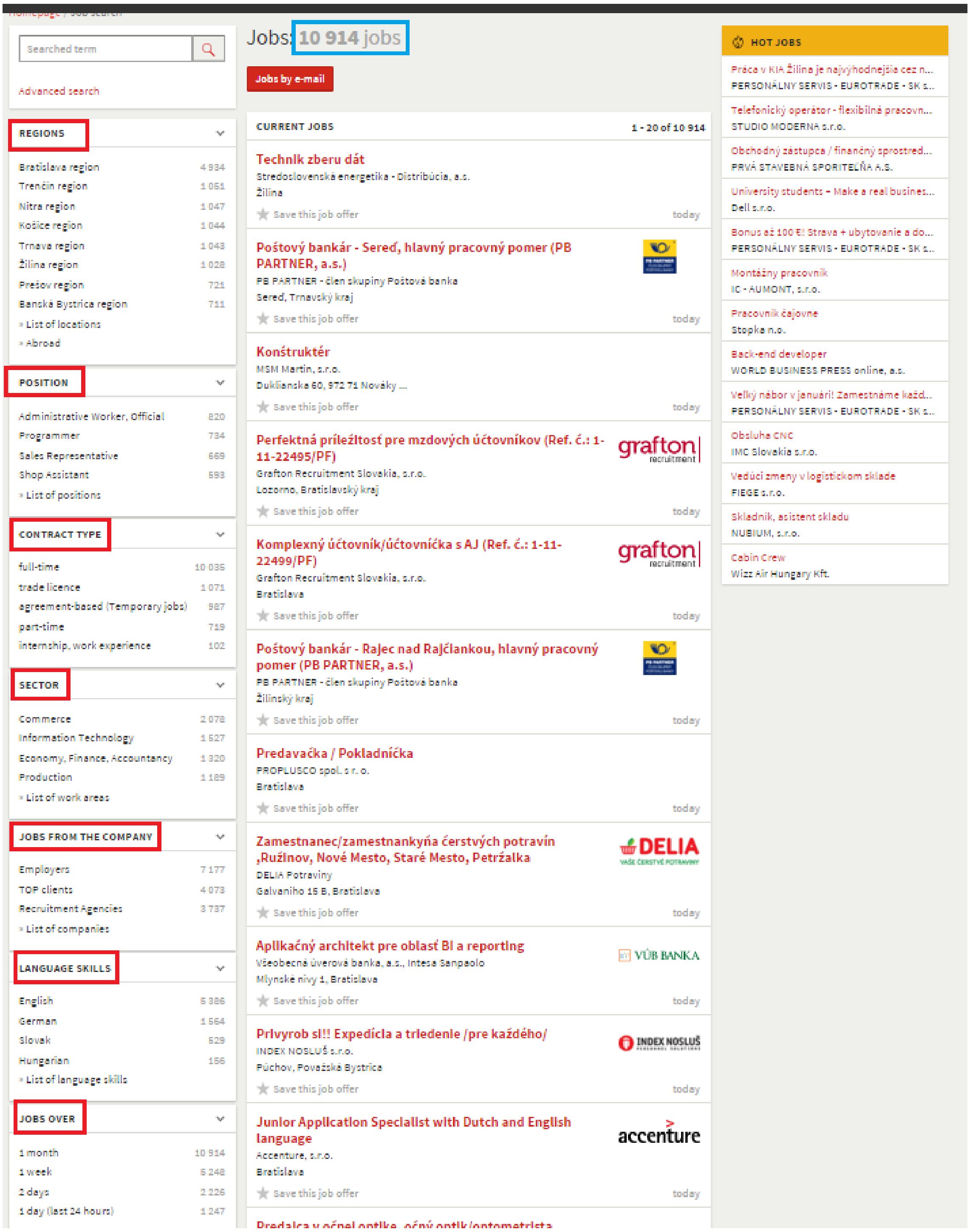
16 In practice, job seekers can indicate on the website that they are looking for a position where 'English' is a requirement, filtering out jobs for which this is not needed.

Illustration for profesia.sk on how to obtain the number of available vacancies in general and by occupation, and the percentage of those that request language skills

On 14 January 2016, there were 10,914 vacancies on www.profesia.sk (blue square in Figure 3.5). Of these vacancies, 5,386 demand English (49%) and 1,564 require German (14%). Other criteria that one can select to filter occupations are region and sector (red squares - left side of Figure 3.5). This exercise can also be done for individual occupations (labelled 'positions' on the site). First, one has to select an occupation for the list of positions. In the example in Figure 3.6, we selected 'accountant'. On www.profesia.sk, we found 471 vacancies for accountants (indicated by the blue square on top of the page in Figure 3.6, where we are looking at vacancies 1-20 of this list). Again, we have the option to use other filters, such as sector, company or language skills. In terms of foreign language skills, we see that of the 471 job advertisements for accountants, 372 demand English (79%) and 81 require German (17%) (red square - left side).

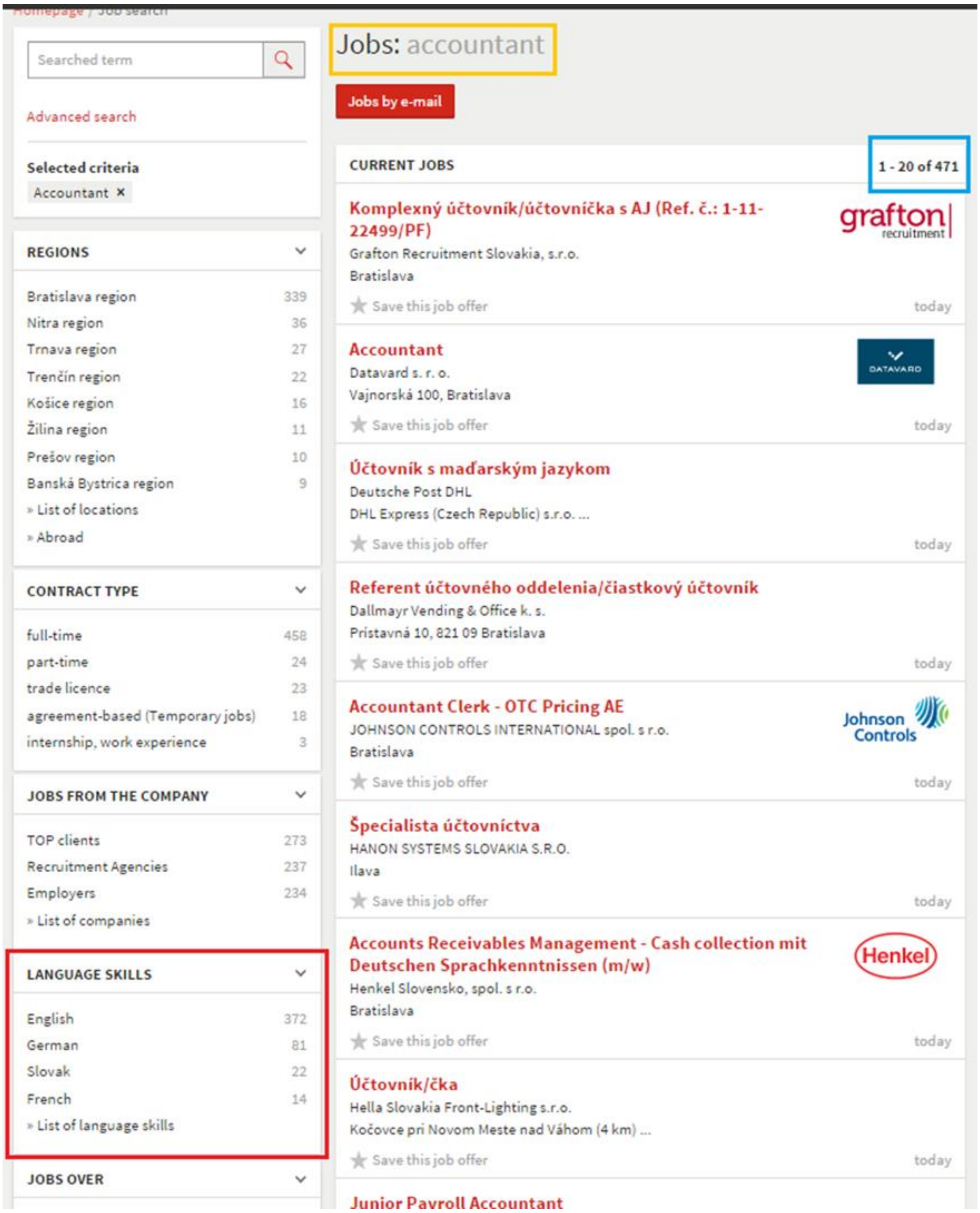
Our findings suggest that one-third to three-fourths of the vacancies studied demands foreign language skills. English is the most frequently requested foreign language in the Visegrad group. 52% of the job advertisements calls for English language skills but less than one-third of the population is able to have a conversation in the language (according to the 2012 Eurobarometer). The demand for English is higher for occupations that are more complex than for those that are less complex. German, which is found in 12% of the vacancies, is the second-most-in-demand foreign language in the Visegrad region. Interestingly, the 2012 Eurobarometer results reveal that between 15% and 22% of the Visegrad population has sufficient German language skills to hold a conversation in the language. For German, there is no link between the demand for language skills and the complexity of an occupation. Other languages, such as French, Italian, Spanish and Russian, are only requested in a small minority of the vacancies.

Figure 3.5 **Illustration of how to derive the total number of vacancies and the number of vacancies that request specific language skills using the Slovak job board www.profesia.sk**



Note: The total number of vacancies is indicated by the blue square (on top of the web page - 10,914 jobs), the red squares indicate all selection criteria that can be used to filter vacancies (region, position, contract type, sector, company, language skills and publication time) (on the left side of the web page).

Figure 3.6 **Illustration of how to derive the number of vacancies for a specific occupation and the share of vacancies that request specific language skills from www.profesia.sk**



Note: The orange square indicates the occupation of interest (accountant), the blue square shows the number of vacancies available for this occupation (right side, top of page), i.e. 471, and the red square indicates the number of available vacancies that also request certain language skills (left side, bottom of page) (372 out of the 471 accountant positions demand English, 81 out of the 471 require German, etc.).

3.4.3.6 Case study 6: 'Cross-cutting work on non-cognitive skills'

As a final case study, we focus on the identification of *non-cognitive skills (or soft skills)*. This case study is cross-cutting, as it combines insights from a series of research papers that use vacancy data and other information obtained from online sources. Throughout our work, we focus on cognitive as well as non-cognitive skills, arguing that both could be important determinants of social and economic outcomes (e.g. educational attainment or earnings). In the field of economics, the academic literature on non-cognitive skills is fairly recent. The literature started to advance towards the end of the 1990s, fuelled by several seminal contributions from James Heckman. Before that time, academic studies were mainly concerned with *cognitive skills*, and how they affect labour market and social outcomes. In other disciplines, such as psychology and sociology, research into non-cognitive skills is much more developed.

Non-cognitive skills are typically understood as personality traits, which are relevant for human capital outcomes (next to intelligence and cognitive abilities) (Heckman & Rubinstein, 2001; Thiel & Thomsen, 2013). Examples are self-discipline, trustworthiness and tenacity. Similarly, Kautz *et al.* (2014) describe non-cognitive skills as 'attributes that cannot be measured by IQ or achievement test' (p. 13). In psychology, personality traits are classified into five groups (also known as the 'Big Five' or under the acronym 'OCEAN'): openness to experiences, conscientiousness, extraversion, agreeableness and neuroticism.

Recent research confirms that non-cognitive skills influence labour market, social and other outcomes. Heckman (1999), for example, finds that a one-side focus on cognitive skills overlooks the fact that non-cognitive skills crucially determine success in later life. Heckman *et al.* (2006) conclude that non-cognitive skills increase wages directly and indirectly, by their impact on productivity and through schooling and work experience. Lindqvist & Vestman (2011) analyse the impact of cognitive and non-cognitive skills on the labour market outcomes in the Swedish army. For men with poor labour market outcomes, i.e. unemployed or low earnings, a lack of non-cognitive skills appears to be the main driver.

Despite this recent upsurge of studies, little is known about the role of non-cognitive skills in the labour market. Heckman & Rubinstein (2001) argue that researchers neglect non-cognitive skills mostly due to *data availability and measurement issues*. While there exist several methods to capture cognitive abilities, it is much more difficult to measure concepts related to personality or motivation (e.g. persistence, trustworthiness, etc.), and often these concepts are lumped together (Heckman & Rubinstein, 2001). In their recent paper, Thiel & Thomsen (2013) conclude that the commonly used measures for non-cognitive skills are ambiguous and often do not manage to strike a good balance between being too broad and too specific. There is also a longstanding debate on whether non-cognitive skills are stable. Kautz *et al.* (2014) show that such skills are stable at any age but can change across the life cycle.

In our work, we aspire to contribute to this literature by capturing non-cognitive skills on the basis of web data (including vacancies, metadata from the job portals and other information sources). We distinguish between two sets of non-cognitive skills: *personal skills and social skills (*Kureková *et al.*, 2015b*)*. The former captures personal traits that determine how one approaches a task, including reliability, timeliness, independence, creativity, flexibility, manners, and stress-resistance. The latter captures personal traits that determine how one interacts and communicates with others. This set of skills comprises communication skills, team-working skills and service skills.

In our study, we set out to discover how frequently personal and social non-cognitive skills are demanded by employers in Europe and the US on the basis of vacancies via semantic analysis) and other data sources (e.g. our strategy to identify new occupations could also be used to find tags that refer to non-cognitive skills). As explained in other sections of this report, we mainly analyse the demand for non-cognitive skills on the basis of job postings. More specifically, we prepared a list of keywords that refer to non-cognitive skills (one list for each case study, which overlap to a large extent) and then compare the list with the text of each vacancy. Examples of keywords that were used are: client, customer, needs and attention (service skills), team, attitude, environment (team-working skills), flexible, stay overnight, travel, shifts (flexibility) and clams, stress, crisis situation (stress-resistant). Alternatively, one can identify non-cognitive skills on the basis of the tag system that job boards use to organise their advertisements. We did not explore this approach any further. Our work corroborates earlier studies that did similar analyses, such as Brunello & Schlotter (2011).

3.4.4 A comparison of the two approaches: advantages and limitations

Both approaches to identify new jobs and skills have their advantages and limitations. A brief overview of these advantages and limitations is presented in the table below.

Table 3.4 Overview of the advantages and limitations of using vacancies and job portal metadata to identify new occupations and skills

	Vacancies	Metadata
+	Detailed information, clear structure (job title, job description, requirements, etc.), easy to collect large and diverse sample	Easy and fast to collect, manage, process and analyse data due to smaller samples, and to use and interpret
-	Data processing, coding and analysis is complicated and may be challenging	Depending on the job board, data may not be very detailed or complete, more limited potential for research

3.5 Conclusions

On the basis of six case studies, we demonstrate that online data, and data extracted from *online vacancies* and *job boards* in particular, are valuable in the analysis of (new) occupations and skills, and the impact of technological progress on the labour market. Web data have become more widely used for labour market research in the last decade, but only few contributions have specifically focused on the topic of new occupations and skills. Nevertheless, this is a key topic for policymakers, who aim to tackle issues such as skill mismatch and unemployment. Research suggests that traditional methodologies and data sources fall short to identify new occupations and skills. Web data, however, can overcome many of the issues associated with them (e.g. real time data availability). As this research field is now rapidly advancing, we decided to assess some of these new data sources and methods.

To this end, we carried out a number of case studies. *Three of the case studies* are based on a sample of job advertisements published online, such as Burning Glass and other job sites. By keeping track of vacancies, one can study the jobs that arise, the qualifications that they require, and many other details. This allows researchers to use vacancies to identify new occupations and skills. With this methodology, we examined to what extent there are skill mismatches in the Czech Republic, what US employers expect from job applicants for the 30 most-frequently advertised occupations and how important IT skills are on the US labour market. *Two case studies* instead rely on metadata, i.e. the occupational structure and the tag system that job portals use to cluster their vacancies. By keeping track of the tags that are added or disappear, one can understand what occupations and skills are demanded. We tested this methodology to detect new occupations in an 'occupations observatory' and the role of foreign language skills on Central and Eastern European labour markets. The final case study concentrates on non-cognitive skills and is cross-cutting, as such skills can be examined on the basis of job advertisements as well as metadata.

In this report, we provide evidence for the potential of web data as a source for labour market analysis. Our research focused on occupations and skills in particular and demonstrated that innovative methods are an important step forward in this field.

4. An inquiry into the data generating process concerning new jobs and skills: taxonomy report

Prepared by Miroslav Beblavý, Mehtap Akgüc, Brian Fabo, Karolien Lenaerts & Félix Paquier

This paper presents the findings of six case studies, each of which makes use of web data, to carry out research on occupations and skills. The idea behind the case studies is to put into test a series of methodologies and assess what one can learn. Four case studies are based on job advertisements, one case study is based on metadata, and one case study is based on a combination of both data sources. By analysing these data, we are able to better understand what types of occupations and skills are high in demand, how these differ across countries and sectors and related topics. More specifically, our case studies cover mismatches between the educational requirements in vacancies and educational attainments of jobholders in the Czech Republic, the requirements listed in job vacancies for the 30 most-frequently-advertised occupations in the US in general and IT skills in particular, foreign language skills requirements in the Visegrad region and the demand for non-cognitive skills. One of the case studies is devoted to a pilot of a new method to detect new and emerging occupations. This paper summarises the main findings of each of these case studies. It shows that web data are a highly valuable data source for labour market research and research concerning occupations and skills in particular.

4.1 Introduction

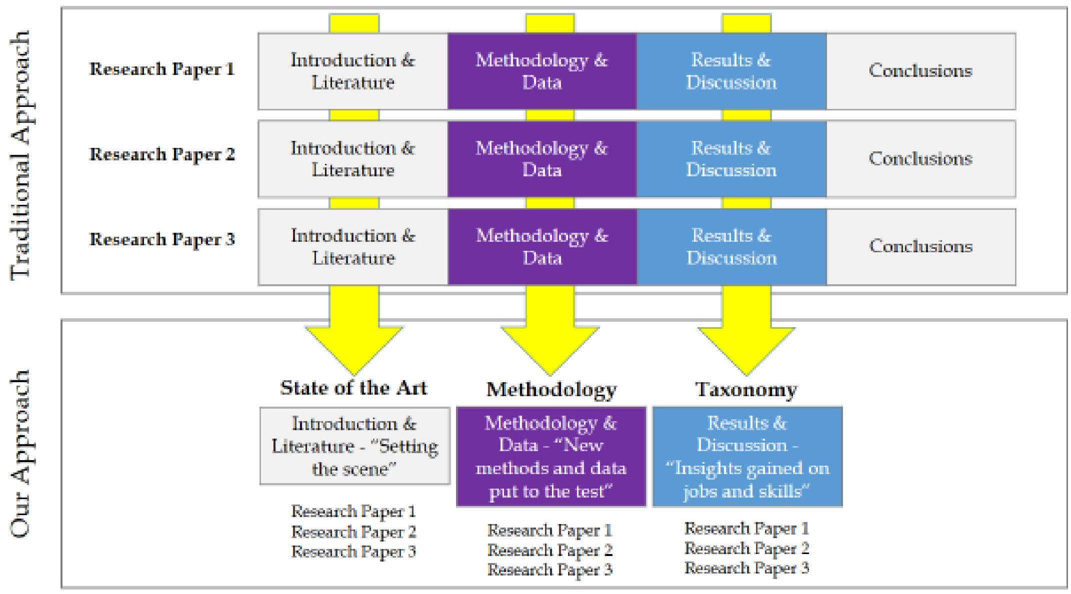
In recent years, web data have increasingly been used for labour market research. We contribute to this rapidly advancing field by focusing on how such data can be used to do research on new occupations and skills. In order to assess the potential of web data in this area, we carried out *six case studies*. These case studies cover a range of topics, from the mismatch between the educational requirements listed in job advertisements and the educational attainment of jobholders, over foreign language skills or IT skills requirements, to a new method to capture new and emerging occupations.

In this paper, we present our *taxonomy report*, which outlines the findings of these six case studies. Four of these case studies are based on a sample of *vacancies*, collected from online job portals. For one case study, we only used the *metadata* available on such job boards (e.g. the occupational classification and its corresponding tags). In the remaining case study, we combine both methods (e.g. new and emerging occupations are identified on the basis of metadata, subsequently more information on them is gathered from job advertisements). For the case studies that rely on data extracted from vacancies, we use web crawling to collect the data. As a second step, we perform a semantic analysis to derive information from the vacancy text (e.g. tasks and responsibilities). This procedure is explained in a number of recent papers by Capiluppi & Baravalle (2010), Kuhn & Shen (2013) and Carnevale *et al.* (2014), who also discuss the advantages and limitations of this approach. While data collection is relatively easy and fast, data processing - such as the semantic analysis - is less straightforward. Given the high level of detail that job listings offer, they are an interesting data source to study occupations and skills. Metadata, on the other hand, are easier to obtain and analyse than vacancies, but contain less information. Those data do, nevertheless, allow us to study occupations and skills, as we demonstrate in our work.

This paper is the counterpart of the methodological report that we present along with this report as a deliverable for *Work Package 21* of the *InGRID FP7 project (Task 21.1.2, MS97)*. While the methodological report introduces the methodology and data that we used in our work, the current paper is a *taxonomy report*. Its aim is to present the results of six case studies that we carried out to assess the potential role of web data for labour market research (with a focus on occupations and skills in particular). In the taxonomy report, we explain what our research question was for each of these case studies, why it is interesting and what we have learned from our analyses. The methodology and data used to obtain these findings are only briefly recalled. We refer readers who would like to know more about these steps to the methodology report.

Given that both the methodology and the taxonomy are deliverables of the same work package and closely related to each other, we illustrate in Figure 4.1 below precisely how these reports are linked. In Figure4.1, we compare the traditional research approach with our approach. Traditionally, a research paper describes all phases of a research project: the framework in which the researcher operates, previous literature on the topic, the data and methodology used, and the results and conclusions. In our work, we also cover these different dimensions but we have separated them into three distinct papers. Each of these papers serves as a deliverable for Work Package 21 of the project. More specifically, we prepared a *state-of-the-art report* (which reviews the academic and policy literature) (Beblavý *et al.*, 2016a), a *methodology report* (which discusses methodology and data) and a *taxonomy report* (which is dedicated to the results and conclusions). In this way, we can carefully assess each of the different dimensions. In addition, this allows us to easily compare the results and methodologies of the different case studies. As all papers are closely linked to each other, we advise readers to consider them together and to also take a look at the other two reports when going through one of them.

Figure 4.1 Typical research set-up and how our approach differs



In the remainder of this taxonomy report, we present the six case studies. Each time, we briefly recall the scope of the case study as well as the methodology and data used, and then discuss the main findings obtained. Table 4.1 below summarises the case studies. It describes their scope, data and main results. For a subset of the case studies, further details are presented in Tijdens *et al.* (2015), Beblavý *et al.* (2016b), Beblavý *et al.* (2016c) and Beblavý *et al.* (2016d). Section 3 concludes the report.

Table 4.1 Overview of the six case studies

Case	Type	Timing	Source	Country	Occupations	Focus	Main results
1	Vacancies	December 2013	EURES for the vacancies	CZ	279 occupations, all skill levels	Mismatches between labour demand and supply	Substantial mismatch for most occupations, link between demand and educational requirements
2	Vacancies	September 2013-August 2014	Burning Glass Technologies	US	30 most-frequently advertised occupations, all skill levels	All requirements (education, experience, cognitive skills, non-cognitive skills and other requirements)	US employers are fairly demanding even for low-skilled occupations, especially education, experience and service skills matter, also high demand for other soft skills
3	Vacancies	September 2013-August 2014	Burning Glass Technologies	US	30 most-frequently advertised occupations, all skill levels	IT skills, sub-divided into basic/general skills, intermediate skills, advanced skills	Basic IT skills are rather widespread, intermediate level especially in office jobs, clear pattern in terms of demand across the skill levels of occupations
4	Metadata from job boards (also vacancies in second stage)	July 2015 - December 2015	11 online job boards	BE, CZ, DE, DK, ES, FR, HU, IT, PL, SK, UK	All occupations are considered, new occupation tags are captured	All requirements, not only in a single country but also cross-country	Occupation tags are an easy and fast way to identify potentially new or emerging occupations, though a lot of variation depending on the portal and country
5	Metadata from job boards	17 July 2015	4 online job boards	Visegrad: CZ, HU, PL, SK	All occupations in a first stage, in second stage 59 occupations were retained	Foreign language skills (English, German and Russian in particular)	English language skills are widely demanded and come with a wage premium, no such a relation for German
6	Vacancies	Several time frames	Several data sources	CZ, DK, IE, SK, US	Wide range of occupations, of different skills levels	Non-cognitive or soft skills	Non-cognitive skills prevalent in occupations of every skill level, difference across the countries are notable

4.2 Case Study 1: 'Do educational requirements in vacancies match the educational attainments of jobholders? An analysis of web-based data for 279 occupations in the Czech Republic'

(Tijdens et al., 2015b)

As a first case study, we focused on the Czech Republic and examined whether there is a *mismatch between the educational requirements that employers demand and the educational attainment that jobholders have.* Data on the educational requirements of employers were derived from a sample of job advertisements published on EURES (4-digit ISCO). Data on the educational attainment of jobholders are extracted from WageIndicator (also 4-digit ISCO). As the results of this case study are presented in detail in another deliverable of the InGRID project (see Tijdens *et al.*, 2015), we here recall only the key findings of the paper.

4.2.1 Results on supply and demand by occupation (ratios)

A comparison of labour demand and supply for 279 occupations reveals that there is a mismatch between labour demand and supply for the vast majority of these occupations. In 32% of the cases, demand is at least five times the supply, whereas the opposite holds in 25% of the cases. Only for very few occupations, demand and supply are balanced. In other words, there is a substantial variation in demand and supply across occupations.

We further find that the relationship between the demand for an occupation and the educational requirements in the job advertisements is negative: as the amount of unfilled vacancies rises, the educational requirements become less important. A similar negative relation is detected between the demand for an occupation and jobholders' educational attainments, though only for medium and high education levels.

4.2.2 Results on educational requirements and attainments by occupation

As the mean level of education requested in the job advertisements across the different occupations does not correspond to the mean level of educational attainments of the jobholders working in the occupation, a further analysis was carried out. In general, the educational attainments of jobholders appeared to exceed the requirements listed in the vacancies. This finding is confirmed regardless of whether the lowest, mean or highest education levels are used. The range of educational requirements is wide in medium- and high-skilled occupations and limited in low-skilled occupations, while the opposite applies when educational attainments are considered (broad range in low-skilled, but condensed in medium- and high-skilled).

4.2.3 Summary

- There is a mismatch in the number of vacancies available and the number of jobholders on the labour market: in most occupations there is a substantial difference between these two (and for a considerable share of occupations, the difference could be regarded as excessive).
- In terms of educational attainments and requirements, it becomes clear that the attainments of the jobholders surpass the requirements in the vacancies.
- There is a negative correlation between demand for an occupation and the educational requirements.

4.3 Case Study 2: 'Skills requirements for the 30 most-frequently advertised occupations in the US: An analysis based on online vacancy data'

(Beblavý et al., 2016c)

In the second case study, we focused our attention on *labour demand* and again used a sample of job advertisements that were published online to get some more insight into the requirements that employers have. Our analysis was based on a sample of about two million vacancies for the 30 most-frequently advertised occupations in the United States. This sample was obtained from Burning Glass Technologies, a US-based company that provides job market analytics and vacancy data. The job advertisements on which our analysis is based were collected over the 12-month period between September 2013 and August 2014. As explained in more depth in our methodological report, Burning Glass data are highly structured, coded, categorised, and ready-for-use.

The list of the 30 most-frequently-advertised occupations is represented in Appendix 3. It covers *low-skilled, medium-skilled and high-skilled occupations*, including cooks, office clerks, truck drivers, managers and nurses. To determine the skill level of an occupation, we follow Kureková *et al.* (2015b) and consider occupations with ISCO code 9 as low-skilled, occupations with ISCO codes 4-8 as medium-skilled and occupations with ISCO codes 1-3 as high-skilled. Out of the 30 occupations in our sample, 2 are low-skilled, 20 are medium-skilled and 8 are high-skilled according to this definition. In our sample, we find occupations of all ISCO classes, with the exception of ISCO class 6. This implies that our sample covers occupations of different complexities and with different education and skills requirements. While some of these occupations are specific to certain sectors, others can be found throughout the economy.

For these 30 occupations, we analysed the requirements that US employers specify in their job advertisements. We started our work by identifying six types of qualifications, *education and formal qualifications*, *cognitive skills*, *non-cognitive skills*, *experience*, *appearance* and *other requirements*, which we aim to capture in the vacancies using a set of keywords - or combinations thereof (listed in Table 4.2). Each of these types can be subdivided into sub-types, such as 'formal education' and 'specialised training and licenses' for the first type, 'generic cognitive skills' and 'specific cognitive skills' for the second type or 'social non-cognitive skills' and 'personal non-cognitive skills' for the third type. In each case, we compare our list of keywords with the vacancy text and keep track of the number and share of job advertisements - in total and by occupation - that contain one or more of these keywords.

Our focus on these six categories is motivated by earlier work such as Kureková *et al.* (2015b). In addition, by taking a broad perspective, we aspire to better understand what requirements are particularly important to employers and how this differs across the 30 occupations. We devote special attention to the *role of cognitive and non-cognitive skills*, as there is an ongoing debate on whether cognitive or non-cognitive skills are the most relevant on the labour market (see Maxwell, 2006; Kureková *et al.*, 2015b). In our case study, cognitive skills are defined as 'skills that are typically identified with intelligence and the ability to solve abstract problems (Kureková *et al.*, 2015b, p.8)'. Cognitive skills can be 'generic' (e.g. problem-solving) or 'specific' (e.g. ICT skills). Non-cognitive skills are defined as 'personality traits that are to some extent correlated with intelligence measures' (Brunello & Schottler, 2011). These skills can be 'social' or 'personal' in nature. Results for the non-cognitive skills are presented in case study six below.

Table 4.2 Overview of the keywords used to identify six types of qualifications

Qualification		Sub-type	Keywords used for identification
Education & formal qualifications		Formal education	Diploma, GED, bachelor, college, university, degree, high school
		Specialised training & licenses	Apprenticeship, training, card, certificate, certification, certified, CDA, ASE, CPR, AED
Cognitive skills	Specific	Computer skills	Computer, PC, CRM, Microsoft (Office, Word, Excel, Power Point, Outlook, and Access), Windows, SAP
		Analytical skills	Mathematics, analytical, logic, quantitative
		Language skills	Bilingual, English, Spanish, language
		Driver's license	Driver's license
	Generic	Ability to learn	Ability to learn, able to learn
Non-cognitive skills	Social	Communication skills	Communication, speak, write, articulate, verbal, interact, communicate
		Service skills	Client, customer, guest, needs, attention
		Team-work skills	Team, attitude, focus, leader work, spirit, environment
	Personal	Creativity	Creative
		Flexibility	Flexible, stay overnight, travel, shifts, work evenings
		Independence	Self-motivated, initiative, independent
		Pleasant demeanour & manners	Attitude, positive, mature, helpful, confident, enthusiastic, professional
		Reliability	Attention to detail, dependable, reliable
		Stress-resistant	Calm, stress, crisis situation
		Timeliness & punctuality	Timely manner, deadlines, act quickly, punctual, prioritise
Experience		Experience	Experience combined with year, month, work, preferred, desirable
Appearance/look		Appearance	Well-groomed, clean, neat, professional
Other		Citizenship	US citizen, citizenship
		Criminal record	No criminal record, clean criminal record
		Drug testing	Drugs, drug testing

4.3.1 The sum of skills and the sum of all requirements

As a first step in the analysis, we calculated two measures that allow us to capture how much structure employers put into their vacancies and what qualifications are listed the most (in general and across occupations) (Kureková *et al.*, 2012; Kureková *et al.*, 2015b). The first measure that we use is the *'sum of skills'*. This measure captures requirements for education, cognitive skills and non-cognitive skills from the vacancies. It is equal to the sum of the percentage of vacancies that refer to education and formal qualifications, cognitive skills and non-cognitive skills. For this measure, we take 17 qualifications and skills into account, which are listed in Table 4.2. In addition to the sum of skills, we use a second measure to capture the *'sum of all requirements'*. This measure is calculated as the sum of the percentage of vacancies that refer to education and formal qualifications, cognitive skills, non-cognitive skills, experience, appearance and other factors. In other words, it captures each of the six types of requirements that are presented in Table 4.2 (17 skills and 5 additional aspects, based on the 'sum of skills' measure). For both measures, it is not their precise value that matters. Instead, the idea is that these measures can be used to rank occupations so as to better understand for which occupations vacancies are rich in terms of the requirements mentioned and how this changes with their complexity. In other words, the sum of skills and the sum of all requirements cannot be interpreted in absolute terms; it is the relative interpretation of the measures that counts.

An example of how the sum of skills and the sum of all requirements are calculated is presented in Table 4.3 for the 'general and operations managers'. The sum of skills is equal to the sum of the percentage of vacancies listing requirements related to education and formal qualifications (75%+13%), cognitive skills (32%+14%+17% for the specific cognitive skills; +2%+6% for the generic cognitive skills) and non-cognitive skills (27%+48%+ 48% for the social non-cognitive skills; +40%+25%+1%+7%+38%+33%+5% for the personal non-cognitive skills). The sum of all these percentages is 431%. The sum of all requirements is based on the sum of skills, but also includes other information. More specifically, for the general and operations managers, it is equal to 431% (sum of skills)+1% (percentage of vacancies with requirements in terms of appearance)+40% (experience)+16% (other factors: criminal record 7%, drug testing 7%, citizenship 2%). This results in a total of 488%.

Table 4.3 Example of the calculation of the sum of skills and the sum of all requirements for the occupation 'general and operations managers' (based on 30,641 vacancies)

Education & Formal Qualifications	**Cognitive Skills**	**Non-Cognitive Skills**	
- Education: 75% - Specialised training & licenses: 13% **Sum = 88%**	*Specific Cognitive Skills* - Computer skills: 32% - Analytical skills: 14% - Language skills: 17% *Generic Cognitive Skills* - Driving license: 2% - Ability to learn: 6% **Sum = 71%**	*Social Non-Cognitive Skills:* - Communication skills: 27% - Service skills: 48% - Team-working skills: 48% *Personal Non-Cognitive Skills:* - Timeliness: 40% - Independence: 25% - Reliability: 1% - Demeanour: 7% - Creativity: 38% - Flexibility: 33% - Stress-resistant: 5% **Sum = 272%**	*Sum of skills = 431%* *= 88% + 71% + 272%*
Appearance	**Experience**	**Other**	
Pleasant physical appearance: 1% **Sum = 1%**	Experience: 40% **Sum = 40%**	- Criminal record: 7% - Drug testing: 7% - Citizenship: 2% **Sum = 16%**	*Sum of all = 488%* *= 431% + 1% + 40% 16%*

Table 4.4 presents the sum of skills and the sum of all requirements for each of the 30 most-frequently advertised occupations. The *sum of skills* across all occupations is equal to 377% (when all vacancies are considered at once). For individual occupations, this number ranges from 225% to 525%. Hence, there clearly is a lot of variation across the 30 occupations. For four occupations the sum of skills does not reach 300%: 'janitors and cleaners', 'labourers', 'personal care aides' and 'maintenance workers'. For 16 occupations, the sum of skills falls between 300% and 400%. The five highest-

ranking occupations are security guards (525%), tellers (477%), meeting, convention and event planners (453%), general and operations managers (431%) and first-line office supervisors (430%).

The *sum of all requirements* is also reported in Table 4.4. It is strongly and positively correlated with the sum of skills. The sum of all requirements is equal to 445% when all vacancies are considered at once. This value varies between 289% and 650% across the 30 occupations.

From Table 4.4, it is clear that employers are relatively demanding in the vacancies that they post, even for low-skilled jobs. This result has also been documented in other work, such as Maxwell (2006), Kureková *et al.* (2012) and Kureková *et al.* (2015b). Another key conclusion is that there is substantial variation in the requirements demanded across the 30 occupations. This variation is related to the complexity of the occupations (captured by the ISCO codes), at least to some extent.

Table 4.4 Sum of skills and sum of all requirements in total and by occupation

ISCO	Occupation	Sum of skills (%)	Sum of all requirements (%)
1	General and Operations Managers	431	488
2	Computer Support Specialists	405	467
2	HR Specialists	375	460
3	Bookkeeping, Accounting, Auditing Clerks	358	425
3	First-Line Office Supervisors	430	500
3	Medical Assistants	340	418
3	Meeting, Convention, Event Planners	453	607
3	Nursing Assistant	321	382
4	Cashiers	357	410
4	CS Representatives	420	484
4	Medical Secretaries	341	399
4	Office Clerks	333	399
4	Secretaries	373	442
4	Tellers	477	542
5	Combined Food Preparation Workers	318	384
5	Cooks, Restaurant	300	370
5	Merchandise Displayers	422	501
5	Personal Care Aides	269	326
5	Retail Salesperson	386	430
5	Sale Worker Supervisors	419	466
5	Sales Agents, Financial Services	415	479
5	Sales Representative Wholesale	380	447
5	Security Guards	525	650
5	Supervisors of Food Preparation, Serving Workers	364	415
7	Installation, Maintenance, Repair Workers	376	472
7	Maintenance Worker	298	379
8	Heavy Truck And Tractor Drivers	316	400
8	Light Truck, Delivery Service Drivers	349	440
9	Janitors And Cleaners	225	289
9	Labourers	255	331
	Across occupations (all vacancies considered at once)	**377**	**445**

The link between the sum of skills/the sum of all requirements and the complexity of a group of occupations is further explored in Table 4.5, which presents the averages of the measures by ISCO category. These results, in combination with those presented above, show that the employers are rather demanding: for the 17 skill demands, the average is 360%. When the other factors are introduced as well, the average is 440%. This conclusion also applies to low-skilled and medium-skilled jobs (even though scores are decreasing, the averages remain relatively high and are stable in the middle of the distribution). The correlation between the ISCO coding and the sum of skills is -0.51 (as occupations become more complex, requirements tend to increase, as one would expect). The correlation between the ISCO classification and the sum of all requirements is -0.42.

Table 4.5 Average sum of skills and sum of all requirements by ISCO class (in %)

ISCO	Average sum of skills	Average sum of all requirements
1	431	488
2	390	464
3	380	466
4	384	446
5	380	447
7	337	426
8	333	420
9	240	310

4.3.2 Specific results on education, training and experience

When we focus on the extent to which vacancies refer to education and experience in Table 4.6, we notice that these requirements are made explicit in the majority of the advertisements. More specifically, 67% of the job vacancies examined request formal education gained through full time study (i.e. having at least a high school degree in our study). Across the 30 occupations, this percentage ranges from 45 to 83% (see Table 4.6). On average, 52 (ISCO group 8) to 75% (ISCO group 1) of vacancies refer to formal education. These results suggest that education is an important filter for most employers. In fact, for 28 out of the 30 occupations - including labourers - more than half of the vacancies demands at least some level or form of formal education. For 19 occupations, at least two-thirds of the advertisements comprise formal education requirements.

In contrast, only 16% of all job advertisements requires specialised training or licenses. In this case, there is a lot more variation across occupations, as shown in Table 4.6. For 10 occupations, the percentage of vacancies that refer to specialised training or licenses is below 10%, whereas for three occupations it is higher than 30%. These three occupations are meeting, convention, event planners (37%), medical assistants (64%) and nursing assistants (77%). Across ISCO groups, the average percentages of job advertisements that refers to specialised training or licenses are 13% (ISCO 1), 15% (ISCO 2), 40% (ISCO 3), 12% (ISCO 4), 14% (ISCO 5), 20% (ISCO 7), 10% (ISCO 8) and 22% (ISCO 9). This suggests that specialised training/licenses are relevant for certain occupations in particular. More specifically, of the six occupations for which the number is 25% or higher, four are health-related professions.

Like formal education, experience is one of the most common requirements: it appears in about 38% of the job advertisements. The share of vacancies that refer to experience ranges from 21 to 51% across the 30 occupations. With the exception of 13 occupations, at least 40% of the job advertisements include experience. The largest shares of vacancies that demand experience are found for HR specialists (51%), computer support specialists (49%), medical assistants, bookkeeping, accounting, auditing clerks, secretaries and medical secretaries (47% in each case). There is a small negative correlation of -0.24 between the ISCO classification and the percentage of vacancies that request experience. As occupations become more and more complex, they thus tend to require experience more frequently. Although one can expect that the experience required for a job depends on the position to be filled in within a company, it is clear that experience is an important filter in the selection and recruitment process. Moreover, for many occupations it is a qualification that workers need in order to be able to perform the work.

Table 4.6 Share of vacancies referring to education, training and experience

ISCO	Occupation	Share with education requirements (%)	Share with specialised training/licenses (%)	Share with experience (%)
1	General and Operations Managers	75	13	40
2	Computer Support Specialists	73	16	49
2	HR Specialists	69	14	51
3	Bookkeeping, Accounting, Auditing Clerks	65	9	47
3	First-Line Office Supervisors	72	14	44
3	Medical Assistants	59	64	47
3	Meeting, Convention, Event Planners	60	37	31
3	Nursing Assistant	64	77	36
4	Cashiers	81	5	32
4	CS Representatives	66	8	40
4	Medical Secretaries	56	25	47
4	Office Clerks	66	16	43
4	Secretaries	70	13	47
4	Tellers	83	4	43
5	Combined Food Preparation Workers	63	13	33
5	Cooks, Restaurant	67	23	46
5	Merchandise Displayers	66	6	37
5	Personal Care Aides	78	26	31
5	Retail Salesperson	67	3	24
5	Sale Worker Supervisors	73	9	32
5	Sales Agents, Financial Services	72	8	41
5	Sales Representative Wholesale	68	9	42
5	Security Guards	80	27	21
5	Supervisors Of Food Preparation, Serving Workers	72	12	35
7	Installation, Maintenance, Repair Workers	69	21	44
7	Maintenance Worker	62	20	46
8	Heavy Truck And Tractor Drivers	45	9	31
8	Light Truck, Delivery Service Drivers	59	11	39
9	Janitors and Cleaners	49	13	36
9	Labourers	58	11	42
	Across occupations (all vacancies considered at once)	**67**	**16**	**38**

4.3.3 Specific results on cognitive skills

In this study, we considered five categories of cognitive skills (four 'specific' and one 'generic'): computer skills, analytical skills, language skills, having a driving license and ability to learn. In contrast to education requirements, which were found in many job advertisements, cognitive skills appeared in less than one fourth of the vacancies across occupations. Nevertheless, there is a lot of variation - both across occupations and across the different cognitive skills examined. This confirms previous work of Kureková *et al.* (2012) and Kureková *et al.* (2015b).

A closer look at the five sets of cognitive skills reveals that between 12% and 25% of the vacancies studied list computer skills, analytical skills or language skills (as is shown in Table 4.7). More specifically, 25% of the job advertisements refer to computer skills, 12% to analytical skills and 16% to language skills. Across the occupations, between 3% and 62% of the vacancies request computer skills, between 1% and 29% request analytical skills, and from 7% and 53% request language skills. Having a driving license and ability to learn are only mentioned in a very small share of vacancies.

The five occupations with the highest share of vacancies that refer to computer skills are the computer support specialists (62%), meeting, convention, event planners (57%), secretaries (53%), bookkeeping, accounting, auditing clerks (45%) and office clerks (44%) The occupations with the lowest percentages are cooks (3%), janitors and cleaners (5%), heavy truck and tractor drivers (5%), and light truck and delivery service drives (6%). These percentages, and the differences detected across occupations, are in line with the expectations of what the positions entail (in terms of tasks and responsibilities). As a result of technological progress, many 'office jobs' nowadays do require at least some level of computer skills. Over time, some of these skills may even become '*implicit skills*' that will no longer be mentioned in a vacancy. There is a strong negative correlation of -0.63 between the ISCO code and the extent to which vacancies demand computer skills. This correlation implies that as jobs become more complicated and reach higher levels in the occupational hierarchy (a lower ISCO code), computer skills are more often listed.

When we turn to the analytical skills, we find that overall these skills are not so high in demand. There does appear to be some variation across the 30 occupations as depicted in Table 4.7, with the highest percentages reported for the tellers (29%), the sales agents - financial services (21%) and the bookkeeping, accounting, auditing clerks (20%).

Table 4.7 Share of vacancies referring to computer skills, analytical skills and language skills

ISCO	Occupation	Share with computer skills (%)	Share with analytical skills (%)	Share with language skills (%)
1	General and Operations Managers	32	14	17
2	Computer Support Specialists	62	16	9
2	HR Specialists	39	12	13
3	Bookkeeping, Accounting, Auditing Clerks	45	19	10
3	First-Line Office Supervisors	38	13	12
3	Medical Assistants	19	10	22
3	Meeting, Convention, Event Planners	57	1	53
3	Nursing Assistant	24	7	16
4	Cashiers	11	15	8
4	CS Representatives	35	8	18
4	Medical Secretaries	38	12	20
4	Office Clerks	44	12	15
4	Secretaries	53	13	15
4	Tellers	25	29	20
5	Combined Food Preparation Workers	8	4	14
5	Cooks, Restaurant	3	4	29
5	Merchandise Displayers	22	14	13
5	Personal Care Aides	9	8	13
5	Retail Salesperson	20	17	11
5	Sale Worker Supervisors	14	18	7
5	Sales Agents, Financial Services	22	21	16
5	Sales Representative Wholesale	26	7	16
5	Security Guards	11	15	38
5	Supervisors Of Food Preparation, Serving Workers	11	5	16
7	Installation, Maintenance, Repair Workers	23	12	9
7	Maintenance Worker	24	13	11
8	Heavy Truck And Tractor Drivers	5	5	10
8	Light Truck, Delivery Service Drivers	6	5	23
9	Janitors and Cleaners	5	5	17
9	Labourers	13	9	15
	Across occupations (all vacancies)	**25**	**12**	**16**

Table 4.7 further presents the percentage of vacancies that refer to language skills across the 30 occupations. For 27 occupations, less than 25% of all job advertisements has language requirements. The percentage of advertisements that comprise language skills is higher for cooks (29%), security guards (38%) and meeting, convention and event planners (53%). Given that the US has English as its main language, we expect that the language requirements in the vacancies mainly refer to the ability to speak and understand English (perhaps with the exception of the meeting, convention and event planners). In that sense, the results reported above are not very surprising.

Table 4.7 Share of vacancies referring to computer skills, analytical skills and language skills

ISCO	Occupation	Share with computer skills (%)	Share with analytical skills (%)	Share with language skills (%)
1	General and Operations Managers	32	14	17
2	Computer Support Specialists	62	16	9
2	HR Specialists	39	12	13
3	Bookkeeping, Accounting, Auditing Clerks	45	19	10
3	First-Line Office Supervisors	38	13	12
3	Medical Assistants	19	10	22
3	Meeting, Convention, Event Planners	57	1	53
3	Nursing Assistant	24	7	16
4	Cashiers	11	15	8
4	CS Representatives	35	8	18
4	Medical Secretaries	38	12	20
4	Office Clerks	44	12	15
4	Secretaries	53	13	15
4	Tellers	25	29	20
5	Combined Food Preparation Workers	8	4	14
5	Cooks, Restaurant	3	4	29
5	Merchandise Displayers	22	14	13
5	Personal Care Aides	9	8	13
5	Retail Salesperson	20	17	11
5	Sale Worker Supervisors	14	18	7
5	Sales Agents, Financial Services	22	21	16
5	Sales Representative Wholesale	26	7	16
5	Security Guards	11	15	38
5	Supervisors Of Food Preparation, Serving Workers	11	5	16
7	Installation, Maintenance, Repair Workers	23	12	9
7	Maintenance Worker	24	13	11
8	Heavy Truck And Tractor Drivers	5	5	10
8	Light Truck, Delivery Service Drivers	6	5	23
9	Janitors and Cleaners	5	5	17
9	Labourers	13	9	15
	Across occupations (all vacancies)	**25**	**12**	**16**

4.3.4 Summary

- US employers mention many qualifications in their job advertisements for the 30 most-frequently-advertised occupations, even for low- and medium-skilled positions. Yet, there is a positive relationship between the requirements listed and the complexity of the occupation: vacancies for more complex occupations contain more qualifications, as expected.
- The three qualifications that are found the most are: formal education (67% of the advertisements refer to it), service skills (49%) and experience (38%). There is some variation across the occupations examined but this does not affect this conclusion.
- Cognitive skills appear to be less important when all vacancies are considered at once (e.g. the most commonly found cognitive skill is 'computer skills', as mentioned in 20-30% of the vacancies), but are more relevant for a subset of occupations.
- Other requirements, such as having a driving license, are mentioned much less frequently.

4.4 Case Study 3: 'The IT skills pyramid: a study on the demand for digital skills on the US labour market'

For our third case study, we use the same data as in the second case study but this time the focus is on *IT or digital skills*. Our interest in digital skills is motivated by the ongoing computerisation and its impact on the labour market. Our work is further inspired by a recent report produced by Burning Glass Technologies (BGT, 2015), which investigated the demand for digital skills for middle-skill jobs in the United States. In the report, three sets of digital skills were distinguished: *productivity software skills*, *advanced digital skills* and *occupation-specific digital skills* (which are skills that are specific to an occupation, e.g. nurses have to know how to use certain medical equipment). This distinction suggests a hierarchy between these categories, in which having acquired the productivity software skills is a prerequisite for acquiring the advanced digital skills. This hierarchy may also be reflected in the demand for these skills.

In our study, we further explore the idea of a hierarchy but we use a different approach to categorise digital skills. More specifically, we consider basic, intermediate and advanced digital skills and assess for each set how prevalent it is using a sample of 2 million vacancies for the 30 most-frequently-advertised occupations.[17] In comparison to the Burning Glass report (BGT, 2015), we add another layer of skills and broaden each of the different skills sets examined. *Basic digital skills* are not discussed in the Burning Glass report but we add them to our analysis because we also want to have a better understanding of how important basic IT skills such as computer, internet and email skills actually are. Moreover, adding this layer also allows us to look into general concepts, such as software and hardware. The second layer, the *intermediate digital skills*, corresponds to what the Burning Glass report labels 'productivity software skills'. In BGT (2015), the focus is on spreadsheets, word processing programmes and keywords such as MS Office and SAP. We consider word processing, spreadsheets, PowerPoint, office packages and SAP in this category, also examining different programmes that are associated with them (e.g. Microsoft Word, MS Excel). The top layer of the pyramid represents the *advanced digital skills*. In the Burning Glass study, these skills can be seen as higher-end computer networking skills. Jobs that call for such skills are not accessible to workers who do not possess them. Among the advanced digital skills in BGT (2015), there are four categories: customer relationship management (CRM), computer and network support (e.g. SQL, Linux), digital media and design (e.g. Adobe Acrobat), and social media tools and search engine analysis (e.g. blogs). In our work, we distinguish between 9 categories (CRM, databases and data management, data analysis and statistics, programming and programming languages, digital media and web design, desktop publishing, CMS (content management system), social media and blogging, and SEO (search engine optimisation)) and further examined buzz words like big data, cloud computing, etc.

As explained in more depth in the methodology report, we first create a list of *keywords* to capture each of the skills mentioned above and calculate - in total and by occupation - the share of job

17 Occupation-specific digital skills are not considered, as our interest lies in transversal IT skills.

advertisements that contain these keywords. Our list of keywords is inspired by other academic and policy-relevant publications on the topic, as well as trade publications, information from specialised job portals, newspaper articles, blog posts and a variety of other sources. This list is not exhaustive but should nevertheless give us a better understanding of the demand for IT skills on the US labour market.

4.4.1 A comparison of the Burning Glass vacancies with the occupation tasks

As a first step in our analysis, we take a broad perspective and compare the tasks and skills described in the Burning Glass job advertisements with the tasks that are typically associated with the occupations they refer to. This information is extracted from existing occupational classifications, like ISCO and O*NET. In Figure 4.2, we present an example of this comparison for three occupations (one low-skilled, one medium-skilled, one high-skilled). In the figure, the *'word cloud'* is created on the basis of all vacancies available for the occupation. A word cloud is based on the 100 most-frequently mentioned words, corrected for punctuations, stop words (commonly used words in the English language), stemming, etc. By generating word clouds, we can shed some light on how important digital skills are - do they actually show up in the work clouds?

For the *low-skilled occupation*, janitors and cleaners, we notice that the list of tasks does not include any reference to IT-related skills. A similar picture emerges from the word clouds: the word cloud reflects the list of common tasks very well. Common words are experience, cleaning, clean, wipe, sweep, mop, sanitation etc. No IT skills are found. We then turn our attention to a *medium-skilled occupation*, medical secretary. This occupation was selected because it is a middle-skill jobs that does require IT skills. When we look at the list of tasks of a medical secretary, we notice that text processing is among the tasks mentioned (e.g. compiling reports, documents and correspondence, completing forms, maintaining files). Many of these tasks likely also involve spreadsheets (e.g. preparing financial statements, billing, drafting budgets). Other tasks that can be expected to be performed on a computer are scheduling and confirming appointments, communication with patients and staff (which could entail using scheduling software and email). Tasks related to data management and data entry seem likely as well. All the aforementioned tasks are reflected in the word cloud: the emphasis on the medical dimension is clear, with words such as health, medical, patient, care, hospital, etc. A second dimension that stands out is secretarial work, with words including clerical, administrative, scheduling, billing, communication, forms and office. The computer-related skills are reflected in computer, systems, data and programs. Finally, we consider a *high-skilled occupation,* the computer support specialists. This occupation is a typical IT-job and could have the highest demand for IT skills of all occupations in our sample. Moreover, it is likely that any specialised IT skills (or advanced digital skills) will also show up here. Among the list of tasks, we indeed spot several advanced digital skills, including management of operating systems and programming. We also find a number of general concepts, like hardware and software. The list of tasks is rather general and does not include specific programming languages or software. When we look at the word cloud, we find words such as computer, electronics, online, equipment, systems, software, access, technology, etc. We also find a number of words that highlight the customer-related dimension of this job, with client, support, and services as examples.

Figure 4.2 Comparison of the list of tasks and the most frequent keywords in the vacancies

Janitor & Cleaner (low-skilled)

List of tasks

• Sweeping or vacuum-cleaning, washing and polishing floors, furniture and other fixtures in buildings, coaches, buses, trams, trains and aircraft
• Making beds, cleaning bathrooms, supplying towels, soap and related items
• Cleaning kitchens and generally helping with kitchen work, including dishwashing
• Picking up rubbish, emptying garbage containers and taking contents to waste areas to removal

Medical Secretary (medium-skilled)

List of tasks

• Scheduling and confirming medical appointments and communicating messages for medical staff and patients
• Compiling, recording and reviewing medical charts, reports, documents and correspondence
• Interviewing patients to complete forms, documents and case histories
• Completing insurance and other claims forms
• Maintaining medical files and records and technical library
• Preparing financial statements and billing procedures
• Assisting in the preparation of budgets, drafting of contracts and purchasing or acquisition orders
• Supervising the work of office support workers and other office staff

Computer Support Specialist (high-skilled)

List of tasks

• Answering user inquiries regarding software or hardware operation to resolve problems
• Entering commands and observing system functioning to detect errors
• Installing and performing minor repairs to hardware, software, or peripheral equipment, following design or installation specifications
• Overseeing the daily performance of communications and computer systems
• Setting up equipment for employee use, performing or ensuring proper installation of cables, operating systems, or appropriate software
• Maintaining records of daily data communication transactions, problems and remedial actions taken, or installation activities
• Reproducing technical problems encountered by users
• Consulting user guides, technical manuals and other documents to research and implement solutions

In addition to the word clouds, we have coded all tasks defined for the occupation (in ISCO and O*NET) as follows: for each task, we determined whether it *clearly requires IT skills*, *could require IT skills* (the task does not imply IT skills but it could be performed in such a way that IT skills could be used to carry it out), or *clearly does not require IT skills*. This coding exercise was carried out by two individual coders. Table 4.8 summarises the share of tasks requiring IT skills and compares it with the prevalence of IT skills in the vacancies (the correlation between these two measures is 0.6).

Table 4.8 Share of vacancies requiring IT skills and share of tasks associated that require IT skills

Occupation	IT skill requirement in vacancies (%)	Task may require IT skills (%)	Task certainly requires IT skills (%)
General and Operations Managers	32	58.620	0.000
HR Specialists	39	63.330	16.670
Meeting, Convention, Event Planners	57	82.140	0.000
Computer Support Specialists	62	25.000	75.000
Merch Displayers	22	10.000	3.330
Nursing Assistant	24	7.690	0.000
Medical Assistants	19	21.430	25.000
Security Guards	11	16.670	0.000
Supervisors of Food Prep, Serving Workers	11	22.220	0.000
Cooks, Restaurant	3	15.380	0.000
Combined Food Prep Workers	8	14.290	0.000
Janitors And Cleaners	5	7.410	0.000
Personal Care Aides	9	30.000	0.000
Sale Worker Supervisors	14	53.570	3.570
Cashiers	11	40.000	2.860
Retail Salesperson	20	48.280	0.000
Sales Agents, Financial Services	22	78.570	0.000
Sales Representative Wholesale	26	62.960	0.000
First-Line Office Supervisors	38	51.430	2.860
Bookkeeping, Accounting, Auditing Clerks	45	62.860	31.430
Tellers	25	61.760	20.590
CS Representatives	35	55.000	5.000
Medical Secretaries	38	62.500	16.670
Secretaries	53	52.500	30.000
Office Clerks	44	52.000	32.000
Maintenance Worker	24	16.220	0.000
Installation, Maintenance, Repair Workers	23	22.500	2.500
Heavy Truck And Tractor Drivers	5	2.700	5.410
Light Truck, Delivery Service Drivers	6	22.730	0.000
Labourers	13	0.000	0.000
Correlation with skill requirement		**0.594**	**0.656**

4.4.2 Basic and general digital skills

As a first step in the analysis, we focus on the prevalence of general IT-related concepts. In Table 4.9, we list the number and the percentage of vacancies in which these concepts are mentioned. In 690,922 of the 1,988,768 job advertisements in our sample, computer skills are requested (this is captured by the keyword 'computer'). This corresponds to 34.74% of the vacancies. Across the occupations, this number ranges from 5% (personal care aides) to 92% (meeting, convention, event planners). Other occupations with a high demand for such skills are computer support specialists (65.02%), medical secretaries (58.29%) and merchandise displayers and office clerks (about 54%). Besides computer skills, we consider how many advertisements include general concepts such as software or hardware. 9.45% of the vacancies mentions the keyword software, while 2.75% refers to the keyword hardware. When it comes to internet, we find that 19% of the vacancies refers to internet skills. This share ranges from 6% to 60%. For email, the corresponding percentages are 22%, 7% and 93%.

Table 4.9 Number and share of vacancies in which general IT-related concepts such as computer, software, hardware, internet and email are demanded

	Number of vacancies	Percentage of vacancies	Max. across occupations (%)	Min. across occupations (%)
Computer	690,922	34.74	92.34	4.99
Software	187,850	9.45	37.46	1.51
Hardware	54,607	2.75	36.72	0.04
Internet/Web	379,021	19.06	59.55	6.02
Email/MS Outlook	434,975	21.87	93.05	7.07
* Email/Email	344,147	17.30	40.56	6.27
* MS Outlook	119,513	6.01	52.86	0.46

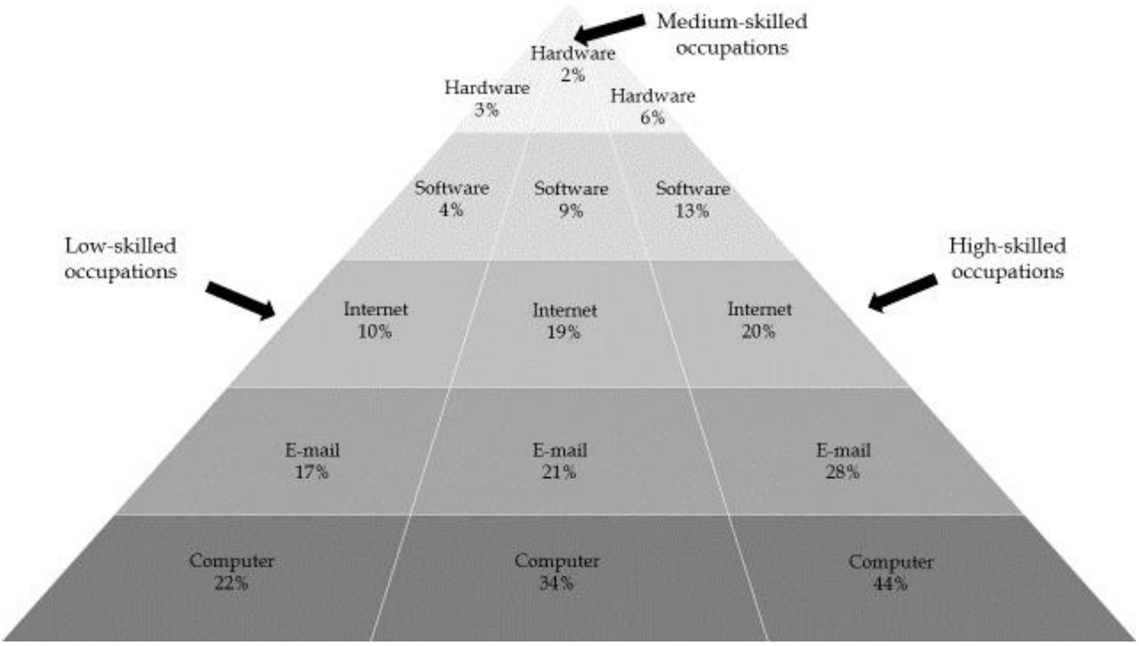
Table 4.10 lists the five occupations with the highest demand for the basic or general computer skills examined. In the table, the percentage of job advertisements for a specific occupation that refers to these skills are mentioned. There is a lot of variation, both across occupations for individual skills and across skills. Interestingly, some of the occupations appear in the top 5 for multiple skills. More precisely, computer support specialists, office clerks, secretaries and combined food preparation workers each appear three times. Cooks, janitors and cleaners, and customer service representatives appear twice.

Table 4.10 The five occupations with the highest demand for computer, software, hardware, internet and email knowledge or skills

	Computer	Software	Hardware	Internet	Email
1	Meeting, Convention, Event Planners (92%)	Secretaries (37%)	Combined Food Preparation Workers (37%)	CS Representatives (60%)	Combined Food Preparation Workers (93%)
2	Computer Support Specialists (65%)	Cooks, Restaurant (30%)	Secretaries (23%)	Combined Food Preparation Workers (45%)	Cooks, Restaurant (41%)
3	Medical Secretaries (58%)	Computer Support Specialists (24%)	CS Representatives (8%)	Secretaries (44%)	Office Clerks (33%)
4	Office Clerks (54%)	Office Clerks (21%)	Retail Salesperson (7%)	Tellers (29%)	Computer Support Specialists (31%)
5	Merchandise Displayers (54%)	Janitors And Cleaners (17%)	Installation, Maintenance, Repair Workers (6%)	Personal Care Aides (28%)	Janitors And Cleaners (28%)

In Figure 4.3, we compare our findings for low-skilled, medium-skilled and high-skilled in an IT skills pyramid. The pyramid has five horizontal slices, reflecting different skills, and three vertical slices, reflecting different sets of occupations (low-skilled on the left, medium-skilled in the middle, and high-skilled on the right). Horizontal slices show the percentage of vacancies that demand a certain skill or a set of skills, such as email and MS Outlook in the second slice. Regardless of the complexity of the occupations, the same skills appear in the same order: in all cases general computer skills are demanded the most, while software and hardware are only referred to in a handful of vacancies. In addition, a clear pattern emerges across occupations: the number of job advertisements that refer to basic or general computer skills is lower for the low- than for the medium-skilled occupations and lower for the medium- than for the high-skilled occupations.

Figure 4.3 The basic IT skills pyramid for occupations of different levels of complexity



4.4.3 Intermediate digital skills

When we focus on the intermediate digital skills, we devote special attention to word or text processing and spreadsheets - which were found to be particularly important in the Burning Glass study (BGT, 2015). The results of our analysis of the percentage of job advertisements that refer to intermediate digital skills are reported in Table 4.11. Almost 13% of the vacancies refer explicitly to word or text processing (this ranges between 1% and more than 50% across occupations), while spreadsheets appear in 14% (<1%-55%). About 3% of the job advertisements call for Microsoft PowerPoint, MS PowerPoint, etc. (here, we did not search for words such as present, presenting or presentations, because these very likely appear in nearly all vacancies). For individual occupations, this number varies between <1% and 20%. All of the aforementioned skills are typically included in standard office packages, and therefore we extend our search to also capture keywords such as MS Office, Open Office, Libre Office and so on. In 170,747 of the vacancies or 9%, an explicit reference to office packages is made. This number is as high as 31% for some occupations, and less than 1% for others. Note that 428,594 vacancies or 21.55% refers to at least one of the following keywords (but could include more than one as well): Text Processing, Spreadsheets, MS PowerPoint, or Office. To avoid double counting, we do not simply add the individual counts but instead go through all vacancies and include them when at least one of the keywords is found. 68% of the job listings comprises at least one of the keywords mentioned so far. Finally, a last type of intermediate digital skills that we examine is SAP, which is found in 1% of the vacancies when all job advertisements are considered at once (0%-<5%).

Table 4.11 Overview of the intermediate digital skills

	Number of vacancies	Percentage of vacancies	Max. across occupations (%)	Min. across occupations (%)
Word/Text Processing	255,660	12.86	54.3054.30	1.021.02
* Word Processing/Text/Processing	47,794	2.40	16.37	0.11
* MS Word/Word	255,638	12.85	54.30	1.02
Spreadsheet/MS Excel	287,848	14.47	54.53	0.47
* Spreadsheet	52,995	2.66	18.07	0.04
* MS Excel/Excel	256,906	12.92	54.27	0.44
MS PowerPoint	53,540	2.69	19.88	0.03
MS Office/Open Office/Libre Office	170,747	8.59	31.39	0.38
SAP	20,171	1.01	5.39	0.01

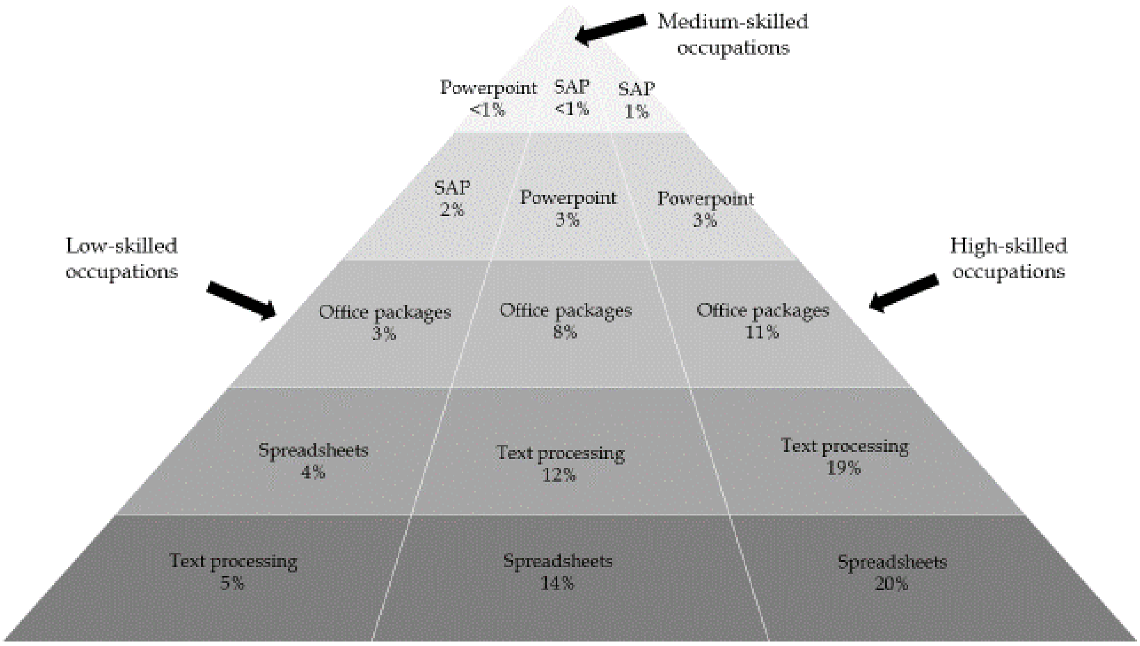
Table 4.12 presents for each of the intermediate digital skills the five occupations with the highest demand, i.e. the five occupations with the highest shares of advertisements that call for these skills. As before, there are several occupations that appear to be rather demanding when it comes to intermediate digital skills. Computer support specialists and office clerks, for example, appear in four out of the five cases (for the former PowerPoint is missing, for the latter SAP is missing).

Table 4.12 The five occupations with the highest demand for different intermediate digital skills

	Text Processing	Spreadsheets	PowerPoint	Office	SAP
1	Combined Food Preparation Workers (54%)	Combined Food Preparation Workers (55%)	Cooks, Restaurant (20%)	Cooks, Restaurant (32%)	Computer Support Specialists (5%)
2	Cooks, Restaurant (51%)	Cooks, Restaurant (51%)	Janitors And Cleaners (8%)	Office Clerks (22%)	Labourers (3%)
3	Office Clerks (37%)	Computer Support Specialists (47%)	Office Clerks (7%)	Janitors And Cleaners (21%)	Cooks, Restaurant (2%)
4	Computer Support Specialists (33%)	Office Clerks (34%)	Bookkeeping, Accounting, Auditing Clerks (5%)	Computer Support Specialists (21%)	Janitors And Cleaners (2%)
5	Janitors And Cleaners (26%)	Janitors And Cleaners (28%)	General and Operations Managers (5%)	Cashiers (19%)	Medical Secretaries (2%)

We then distinguish low-, medium- and high-skilled occupations to verify whether any differences can be detected in terms of intermediate digital skills. This comparison is presented in a skill pyramid (Figure 4.4). There is a similar pattern as before: the share of vacancies that request specific intermediate digital skills is the largest for high-skilled occupations and the lowest for low-skilled ones, while medium-skilled occupations are found in the middle. This pattern is found for text processing, spreadsheets and office packages. On the other hand, SAP is mentioned the most often among the low-skilled occupations - though the differences with the other groups are minor. For PowerPoint, the differences are also minor but here we detect the highest share for the medium-skilled occupations. For low-skilled occupations, text processing seems more relevant than spreadsheets while the opposite holds for medium- and high-skilled occupations. Also, SAP and PowerPoint have changed positions with regards to the medium- and high-skilled occupations.

Figure 4.4 The intermediate IT skills pyramid for occupations of different levels of complexity



4.4.4 Advanced digital skills

In our study, we investigate nine classes of advanced digital skills: CRM (customer relationship management), databases and data management, data analysis and statistics, programming and programming languages, digital media and web design, desktop publishing, CMS (content management system), social media and blogging, and SEO (search engine optimisation.) The list of keywords that is used to identify each of these categories is presented in Figure 4.5. For each category, we search for the general concepts (e.g. social networks) and specific programs that are commonly used (e.g. Twitter).

Figure 4.5 List of keywords used to identify advanced digital skills*

CRM	•CRM •customer relationship manangement
Databases & data management	•Database, data base, database management, data base management, data management, data entry, data warehouse •SQL, Microsoft Acces, MS Access, Access
Data analysis & statistics	•Data analysis, data processing, statstics •Stata, EViews, SAS, SPSS, Matlab
Programming & programming languages	•Programming, programming language •C++, C+, C++ program, C+ program, Python, Java, Ruby, Perl, PhP, Fortran, Visual Basic, VBA.net, Javascript
Digital media & web design	•Digital media, digital design, web design, web page design, web development •Illustrator, InDesign, Photoshop, CSS
Desktop publishing	•Desktop publishing •Microsoft Publish, MS Publish, Visual Studio
CMS	•CMS, content management system, client mangament system, customer relationship management, contact management system •Drupal, Plone, Joomla
Social media & blogging	•Social media, social network, Facebook, Twitter, LinkedIn •Blog, WordPress
SEO	•SEO, search engine optimisation •Google Analytics

* On the left, the name of the aggregated category is mentioned. On the right, the keywords associated with the category are shown

Table 4.13 reports for each of the advanced digital skills the number and percentage of job advertisements that list them, as well as the minimum and maximum shares across occupations. One of the most striking results presented in the table is that very few vacancies refer to advanced digital skills: for five of the categories, less than 1% of the vacancies refer to any of the keywords. For three other categories, the share is below 3%. Only for one category, which is databases and data management, over 10% of the job advertisements make reference to any of the keywords examined (12% to be precise). By listing both the counts for the aggregated categories and for individual keywords, we get more insight into the composition of these categories. Aggregated categories are constructed by counting all job advertisements that refer to at least one of the keywords mentioned in the subgroups.

Another important result is that for some of the advanced digital skills, the variation across occupations is huge. This applies particularly to databases and data management (the minimum value is 1%, the maximum is equal to 39%) and programming and programming languages (the minimum is 1%, the maximum is 21%). For the remaining advanced digital skills, smaller divergences are detected. Examples are data analysis and statistics (0.15%-8.94%), social media and blogging (0.41%-6.71%).

Table 4.13 Advanced digital skills, the keywords in bold refer to aggregated categories

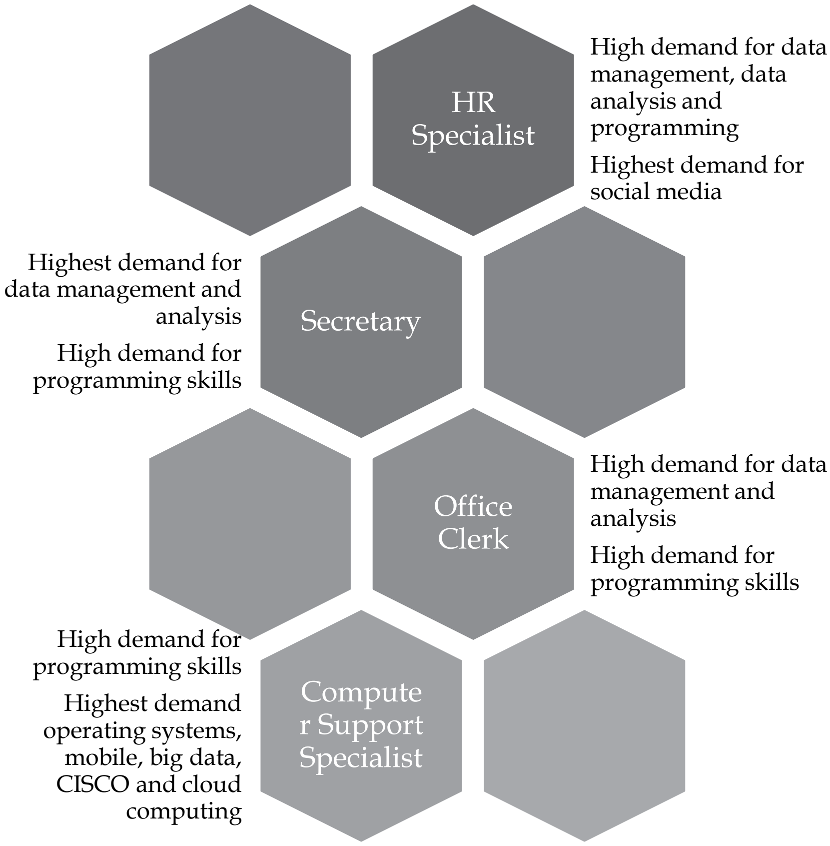
Advanced digital skills	Number of vacancies	Percentage of vacancies	Max. across occupations (%)	Min. across occupations (%)
CRM	**17,639**	**0.89**	**4.08**	**0.03**
Databases & data management	**232,160**	**11.67**	**38.63**	**1.25**
* Database, data base, data/database/ data base management, data entry, data warehouse	173,315	8.71	34.25	0.32
* MS Access	70,504	3.55	36.21	0.11
* SQL	2,405	0,12	3,30	0,01
Data analysis & statistics	**39,662**	**1.99**	**8.94**	**0.15**
* Data analytics/processing, statistics	39,242	1.97	8.86	0.14
* EViews	2	0.00	0.00	0.00
* Stata	a	0.00	0.01	0.00
* SAS	423	0.02	0.11	0.00
* Matlab	20	0.00	0.01	0.00
* SPSS	117	0.01	0.06	0.00
Programming & programming languages	**31,127**	**1.57**	**21.19**	**0.17**
* Programming language, programmer	679	0.03	0.47	0.00
* Programming	18,272	0.92	5.76	0.00
* Python	282	0.01	0.28	0.00
* Ruby	250	0.01	0.11	0.00
* Fortran	8	0.00	0.01	0.00
* Visual Basic, VBA.NET	407	0.02	0.52	0.00
* Java	974	0.05	0.94	0.00
* PhP	5,747	0.29	0.69	0.09
* C+/C++ program	23,411	1.18	20.86	0.01
* Perl	289	0.01	0.31	0.00
* JavaScript	370	0.02	0.26	0.00
Digital media & web design	**7,293**	**0.37**	**1.91**	**0.02**
* Digital media/design	506	0.03	0.12	0.00
* Web/web page design, web development	1,827	0.09	1.01	0.01
* Illustrator	569	0.03	0.13	0.00
* InDesign	553	0.03	0.23	0.00
* Photoshop	1,219	0.06	0.40	0.00
* CSS	3,642	0.18	0.93	0.01
Desktop publishing	**2,188**	**0.11**	**1.13**	**0.00**
* Desktop publishing	1,678	0.08	0.91	0.00
* MS Publish	482	0.02	0.25	0.00
* Visual Studio	61	0.00	0.10	0.00
CMS	**11,574**	**0.58**	**4.64**	**0.01**
* Content/client/customer/contact management system	11,354	0.57	4.64	0.01
* Drupal	133	0.01	0.05	0.00
* Joomla	141	0.01	0.05	0.00
* Plone	8	0.00	0.00	0.00
Social media & blogging	**53,569**	**2.69**	**6.71**	**0.41**
* Social media, social network	13,439	0.68	3.64	0.07
* Facebook	27,021	1.36	3.54	0.23
* LinkedIn	21,045	1.06	3.69	0.17
* Twitter	20,769	1.04	2.39	0.21
* Blog	5,716	0.29	3.06	0.01
* Word Press	468	0.02	0.23	0.00
SEO	**429**	**0.02**	**0.20**	**0.00**
* SEO, search engine, optimisation	406	0.02	0.20	0.00
* Google Analytics	39	0.00	0.03	0.00

We then investigate in which occupations the advanced digital skills that appear in at least 1% of the job advertisements are the most highly requested (i.e. the most frequently mentioned). Results are reported in Table 4.14. Many of the occupations that show up in the table are typical medium- to high-skilled white-collar office jobs. In Table 4.14, we find four occupations that appear more than once: HR specialist (four times), secretary (three times), office clerk (two times) and bookkeeping, accounting, auditing clerks (two times). General concepts typically receive much more counts than the individual programs listed. Then, we zoom in on four occupations that have relatively high demands for the advanced digital skills: secretaries, HR specialists, computer support specialists and office clerks. Figure 4.6 presents a brief overview of which advanced digital skills matter most for these occupations.

Table 4.14 The five occupations with the highest demand for different advanced digital skills. Only skills that appear in at least 1% of total vacancies are listed

	Databases & data management	**Data analysis & statistics**	**Programming & programming languages**	**Social media & blogging**
1	Secretary (39%)	Secretary (9%)	Security Guard (21%)	HR Specialist (7%)
2	Meeting, Convention, Event Planner (37%)	Office Clerk (7%)	Computer Support Specialist (3%)	Sales Representative Wholesale (5%)
3	Office Clerk (36%)	Bookkeeping, Accounting, Auditing Clerk (6%)	HR Specialist (3%)	Nursing Assistant (5%)
4	HR Specialist (33%)	HR Specialist (6%)	Secretary (2%)	Personal Care Aide (4%)
5	Bookkeeping, Accounting, Auditing Clerk (31%)	First-Line Office Supervisor (5%)	Maintenance Worker (2%)	Sales Agent, Financial Services (4%)

Figure 4.6 Focus on the advanced digital skills demanded in four occupations



4.4.5 Skills mismatches

We concluded our analysis by going back to the list of tasks that we coded to further our understanding of skill mismatch. More specifically, for each of the tasks that could or does require IT skills, we examined which precise IT skills are implied (e.g. instead of thinking about 'computer skills', we looked into 'text processing' or 'data management'). This revised list of tasks was then compared with the share of advertisements requiring those specific IT skills to identify potential mismatches. A mismatch was *defined as a situation in which either the share of vacancies that call for a specific skill is very high but this is not clear from the list of tasks, or vice versa*. On the basis of this approach, we identified 16 occupations with a mismatch (see Table 4.15 and 4.16). In ten cases, the mismatch was of the latter category. For example, bank tellers' tasks heavily involve working with databases but there does not seem to be much explicit demand for data skills in the job advertisements for this occupation. Five occupations had relatively high requirement of a specific IT skill, which does not seem to be related to any of the tasks for that occupation.

Interestingly, the mismatch where the skill was required according to the task but not mentioned explicitly in the job advertisements is linked to basic IT skills, such as email, which suggests that those are sometimes assumed implicitly. The opposite case relates to advanced digital skills, such as computer programming, which potentially point to a technologically-driven up-skilling of occupations.

Table 4.15 Comparison of density of IT skills requirement in vacancies and IT skills requirements associated with tasks relevant for specific occupations. Mismatches are indicated in grey. Results for internet, social media and blogging, email and software

Occupation	Internet		Social media & blogging		Email		Software	
Bookkeeping, Accounting, Auditing Clerks	1	17.34	0	2.42	1	31.43	1	24.21
Cashiers	1	12.67	0	0.41	1	7.07	1	2.46
Combined Food Prep Workers	0	6.02	0	1.07	1	11.52	1	1.95
Computer Support Specialists	1	43.98	0	2.89	1	27.16	1	37.46
Cooks, Restaurant	0	8.32	0	1.48	1	16.77	0	1.81
CS Representatives	1	19.2	0	2.24	1	26.11	1	12.13
First-Line Office Supervisors	1	17.11	1	3.34	1	26.26	1	13.74
General and Operations Managers	1	14.3	1	3.14	1	24.14	1	11.64
Heavy Truck And Tractor Drivers	1	10.2	0	1.5	1	15.23	1	2.06
HR Specialists	1	23.75	1	6.71	1	28.47	1	17.04
Janitors And Cleaners	0	12.12	0	3.67	1	16.71	0	1.99
Labourers	0	8.81	0	1.58	0	17.19	0	4.48
Light Truck, Delivery Service Drivers	0	9.49	0	1.84	1	13.58	1	2.76
Maintenance Worker	1	13.89	0	2.1	1	20.24	1	9.36
Medical Assistants	0	14.76	0	2.57	1	15.17	1	9.34
Medical Secretaries	1	10.08	0	2.9	1	20.61	1	15.71
Meeting, Convention, Event Planners	1	45.41	1	0.88	1	93.05	0	1.51
Merch Displayers	0	59.55	0	1.11	0	27.65	1	12.33
Nursing Assistant	0	8.49	0	4.89	1	12.28	1	3.28
Office Clerks	1	21.56	0	2.97	1	33.05	1	21.2
Personal Care Aides	0	11.27	0	4.11	1	15.12	1	3.59
Retail Salesperson	1	27.99	0	2.81	1	14.19	1	3.37
Sale Worker Supervisors	1	10.81	0	2.06	1	16.8	1	4.03
Sales Agents, Financial Services	1	12.3	0	3.91	1	13.49	1	12.21
Sales Representative Wholesale	1	23.98	0	5	1	27.91	1	9.08
Secretaries	1	22.89	1	3.42	1	41.41	1	29.59
Security Guards	0	29.47	0	0.98	1	11.32	0	2.59
Supervisors Of Food Prep, Serving Workers	1	8.66	0	2.63	0	15.2	1	5.62
Tellers	1	9.81	0	1.73	1	20.96	1	5.54

Table 4.16 **Comparison of density of IT skills requirement in vacancies and IT skills requirements associated with tasks relevant for specific occupations. Mismatches are indicated in grey. Results for word processing, spreadsheets, databases and data management, and programming and programming languages**

Occupation	Word processing		Spreadsheets		Databases & data management		Programming & program. Languages	
Bookkeeping, Accounting, Auditing Clerks	1	32.75	1	47.23	1	31.45	0	1.01
Cashiers	1	3.11	1	2.69	1	2.49	0	0.34
Combined Food Prep Workers	1	2.63	1	2.41	0	2.21	0	0.60
Computer Support Specialists	1	13.72	1	13.5	1	19.47	1	3.11
Cooks, Restaurant	1	2.94	1	3.4	1	2.17	0	0.60
CS Representatives	1	15.01	1	15.59	1	17.31	0	0.68
First-Line Office Supervisors	1	21.97	1	24.47	1	14.3	0	1.40
General and Operations Managers	1	18.03	1	19.76	1	6.05	0	0.90
Heavy Truck And Tractor Drivers	0	2.35	0	1.13	0	1.73	0	0.54
HR Specialists	1	26.35	1	27.97	1	33.46	0	2.93
Janitors And Cleaners	0	4.07	0	1.79	0	1.25	0	0.60
Labourers	0	4.78	0	5.28	0	7.04	0	0.33
Light Truck, Delivery Service Drivers	1	2.87	1	1.63	0	3.13	0	0.37
Maintenance Worker	1	10.42	1	9.46	1	5.37	0	2.10
Medical Assistants	1	7.33	1	5.11	1	11.79	0	1.18
Medical Secretaries	1	19.79	1	15.04	1	22.5	0	1.30
Meeting, Convention, Event Planners	1	54.3	1	54.53	0	37.47	0	0.22
Merch Displayers	1	8.34	1	20.9	1	15.23	0	0.17
Nursing Assistant	1	2.96	1	1.08	1	3.69	0	0.64
Office Clerks	1	36.8	1	33.83	1	35.51	0	1.54
Personal Care Aides	1	1.02	1	0.47	1	6.14	0	1.26
Retail Salesperson	1	5.19	1	14.51	1	3.73	0	0.51
Sale Worker Supervisors	1	7.12	1	6.75	1	4.29	0	0.52
Sales Agents, Financial Services	1	7.67	1	8.68	1	6.85	0	0.56
Sales Representative Wholesale	1	13.68	1	16.47	1	13.66	0	0.47
Secretaries	1	50.51	1	50.77	1	38.63	0	2.13
Security Guards	1	3.85	0	2.65	0	7.81	0	21.19
Supervisors Of Food Prep, Serving Workers	1	9.3	1	5.95	1	3.14	0	0.40
Tellers	1	3.65	1	3.62	1	1.42	0	0.44

4.4.6 Summary

- About 35% of the job advertisements of a sample of close to two million vacancies for the 30 most-frequently-advertised occupations in the US calls for computer skills. This number is particularly interesting, as it implies that there are jobs for which computer skills are not a prerequisite to carry out the work (despite the computerisation of many occupations), while at the same time for other jobs computer skills have already developed into implicit skills. Interestingly, when looking into specific occupations, there is a lot of variation (meaning that requests for computer skills range from 'rare' to 'universal').
- The analysis also points to a clear hierarchy: basic digital skills are relatively widespread across the occupations, while advanced digital skills are rare. For intermediate digital skills, the conclusion is reached that these can be found for many occupations, especially white-collar office jobs. Regardless of the types of IT skills, a clear pattern emerges: IT skills are much more requested in vacancies for high-skilled than for medium- and low-skilled occupations, and similarly more for medium- than for low-skilled occupations.
- Within the basic digital skills, especially 'computer skills', 'internet' and 'email' are particularly relevant. These skills are widespread among low-skilled occupations as well as the other two categories. Even for high- and medium-skilled occupations, these skills are mentioned in the vacancies.
- For the intermediate digital skills, text/word processing and spreadsheets are most relevant. Having these skills can be regarded as an 'entry ticket' to medium- and high-skilled jobs.
- When it comes to the advanced digital skills, especially databases are relevant. Even for high-skilled jobs, these skills are mentioned fairly infrequently.

4.5 Case Study 4: 'An occupations observatory'

(Beblavý et al., 2016d)

In the fourth case study, we piloted a new methodology to identify new and emerging occupations, which is based on the metadata available on job portals and the tag system that portals use to structure their vacancies, in particular. For 11 countries,[18] we selected a job board and kept track of the new occupation tags that were added over a six-month period. Online job portals use occupation tags to organise job advertisements so that job seekers can easily navigate the website and find similar vacancies. Occupation tags often are stored in a database. Few portals publish their list of tags online.

As explained in detail in the methodological report, our proposed approach to identify new and emerging occupations involves searching for new tags that are added to the job portal's occupational classification. For each country, it delivers a list of tags that can be compared over time. Our approach consists of three steps: establishing the benchmark (by collecting an initial list of occupation tags), collecting data (i.e. newly added tags were extracted, cleaned and translated - on a monthly basis) and analysing the data. The underlying idea is to extract newly added occupation tags, evaluate whether they indeed refer to a new or emerging occupation, add them to the benchmark, and then repeat the process. If an occupation tag clearly does not refer to a new or emerging occupation, it is added to the benchmark but no further steps are taken. If, in contrast, the tag could refer to a new or emerging occupation, it is examined in more depth (e.g. by checking available vacancies on other job boards, presence in occupational classification). For this examination, we also rely on job vacancies to complete any missing information.

The results of our approach are summarised in an *occupation card*. For each potentially new or emerging occupation, we produce an occupation card that combines information from different sources: the vacancy that accompanies the newly added tag, the portal on which it was found, similar job advertisements on other online job boards, the existing occupational classifications, Google Trends, etc. By filling in an occupation card, one has a very clear idea of whether an occupation indeed is new or emerging, as it that provide details on the identification process, tasks, requirements and prevalence, link with the existing occupational classifications and so on. All occupation cards will be assembled in an '*Occupations Observatory*'.

18 The 11 countries are: Belgium, the Czech Republic, Denmark, France, Germany, Hungary, Italy, Poland, Slovakia, Spain and the UK.

4.5.1 Structure of an occupation card

Each occupation card has *six main sections*, which deal with different topics. Section 4.5.1 A deals with '*identification'*. It describes where the occupation, its corresponding vacancy and tag, were found. To this end, information is provided on when the job advertisement was published, on which job board, for which country and sector, etc. As a second step, the card provides more details on the vacancy, by listing the job description and profile, and any other tags that were linked to the vacancy. Section 4.5.1 A captures the time and space dimensions of an occupation, which are relevant to be able to evaluate whether it truly is new or emerging. Section 4.5.1 A also briefly recalls the aim of the occupation card and the methodology used to compile it.

> For example, Section 4.5.1 A could mention that a tag for OSS/BSS specialist was found on profesia.sk on 2 September 2015. We would also go back to the advertisement that triggered the new tag and look at the information available in the vacancy (type of employer, industry, job description, profile, portal tags).

The second section of an occupation card is Section 4.5.1 B, which covers '*definition'* as well as *'tasks and responsibilities'*. For example, one of the tags that was added to the Slovak job board in our pilot was 'OSS/BSS'. In Section 4.5.1 B, an explanation would then be offered on what OSS/BSS means and whether it is related to any existing occupations. The latter is important because new or emerging occupations typically evolve out of existing ones. Section 4.5.1 B also discusses the prevalence of the occupation in the country on whose job board it was found and presents details on the responsibilities and tasks involved (using information from other job portals).

> For example, Section 4.5.1 B would provide a definition of OSS/BSS, explain whether this occupation is related to any existing occupations, and consider its prevalence in Slovakia (are there similar vacancies on the same/other job portals or via a web search). It also comprises an overview of the tasks and responsibilities of an OSS/BSS specialist, e.g. validate and write code.

Section 4.5.1 C is devoted to the '*requirements'* that come with the occupation, with a focus on formal education, cognitive and non-cognitive skills and experience in particular. In our pilot, this information was derived from the vacancies available for the occupation. By assessing requirements for an occupation, we can get more insight into whether it is linked to other occupations (e.g. as their requirements are relatively similar) and how different it actually is.

> For example, in Slovakia, an OSS/BSS specialist is expected to tertiary education, previous experience with IT, JAVA, SQL, C++ and other programs, knowledge of telecommunications, communication skills, and so on. Many vacancies also list non-cognitive skills, such as detail-oriented, self-motivated, ambitious and other skills.

In the fourth section, Section 4.5.1 D, the analysis carried out to complete 4.5.1 B and C is *extended to other countries (within and outside of Europe)*. The aim of this exercise is to determine whether the occupation is new and emerging in one country only, whether it already exists elsewhere, and what differences there are across the countries. This comparison is further complemented with a Google Trends analysis of whether the occupation is on the rise or in decline, and in which countries.

> For example, is the position of an OSS/BSS specialist is only new in Slovakia or does it also exist in other countries? For Belgium, on the basis of a search on Google and job portals, we find occupations similar to that of the online marketing coordinator in Europe and the US. We also consider whether the tasks and requirements are similar in these countries.

Section 4.5.1 E bridges the gap between our methodology and the traditional approach to capture new and emerging occupations by verifying whether the occupation is present in the existing *occupational classifications* (both national and international).

> For example, for Belgium, we aimed to find the occupation of an online marketing coordinator in different occupational classifications. We could not find it in ISCO and ESCO, nor in the classification of many European countries. However, a similar occupation was found in the national classification of Italy, Poland and Germany, and the United States.

The final section, Section 4.5.1 F, *summarises the conclusions of our analysis*. It discusses whether the occupation is indeed new or emerging and what its impact on education and training could be. Section 4.5.1 F covers the country where the occupation was found, the European level and the global level.

As a further illustration, we present occupation cards for two potentially new or emerging occupations (online marketing coordinator and drug safety specialist). Other examples can be found in Beblavý *et al.* (2016d).

4.5.2 First example of an occupation card: 'Online Marketing Coordinator'

4.5.2.1 Occupation Card 1: Online Marketing Coordinator

Date: 30 September 2015

A. Identification

The identification of new occupations, such as the Online Marketing Coordinator presented in the current document, is based on an innovative methodology that we are piloting here. This methodology is embedded in the rapidly growing strand of the literature that relies on web-based data sources to conduct labour market research (see Askitas & Zimmermann, 2015). The main idea behind our methodology is to identify new occupations via the *occupational classification* that online job portals use to guide job seekers on their website. Typically, such occupational classifications have - at their core - a *tag system*, i.e. a list of tags that is used to assign vacancies to specific job categories. This list of tags can be published online or stored in a library accessed by an API search when a job seeker enters a word in the search box. Earlier research suggests that job portals tend to regularly update their list of tags to account for the emergence of new occupations and the disappearance of redundant ones.

In our pilot study, we focus on 11 countries for which we keep track of one of their main online job portals. For these countries, we created a *benchmark*, which is composed of their occupational classification (their list of tags) on 30 June 2015. Our goal is to determine whether this tag system could also be used to identify new occupations, by comparing the benchmark classification with the *current occupational classification* of the portal at regularly intervals, i.e. every month. The *tags that are not yet included* in the benchmark, i.e. missing from the list of tags when the benchmark and the new list of tags are compared, could point to new or emerging occupations. For more details on our methodology, we refer to the *Methodological Note* that is available on the website in the Occupations Observatory.

In the beginning of *August 2015*, a new tag was added to the *Belgian* online job board in our pilot. This tag was picked up (either via the API or via a web crawling technique that extracts the list of tags - this depends on the portal) and stored in a database. We then searched for an actual vacancy for an *online marketing coordinator* on this portal (to discover what triggered the new tag). More details on this tag/vacancy can be found below; these details cover (i) the portal to which the tag was added and on which the vacancy was found, and (ii) the content of the sample vacancy that we study in more depth (to identify tasks and responsibilities - skills and other requirements).

Details on the tag and the job advertisement	
When did the tag/vacancy appear online?	July 2015
On which online job board was the tag/vacancy published?	vacature.com
Which country is covered by this job portal?	Belgium (Flanders)
In which industry is the employer active?	Broad (no specific industry listed)
What type of employer has posted the vacancy?	Private company

Sample job advertisement	
Job description (responsibilities and tasks of the job)	- Responsible for (co-)planning, implementation, monitoring and online publication of online digital marketing communication - Responsible for various online tools such as websites, email, apps and social pages - Detect the needs of sales force, come up with inspiring new ideas, present company's message in a simple and attractive way - Work smoothly together with colleagues and external partners - Report to the senior marketing coordinator
Job profile (education, skills and other requirements for the job)	- At least a bachelor's/master's degree or equivalent by experience - Digital native bitten by the online microbe; always following the latest trends - Can use CMS systems and WordPress, understands the basics of HTML and has good knowledge of SEO, SEA, Google Analytics - Has good writing skills (NL/EN) and communicates fluently - Stress-resistant, result-oriented, enjoys working on many projects at once
Job portal tags (tags attached to the vacancy on the job board)	- Function group: web application developer, database marketing - Function: online marketing coordinator; marketing; online marketing; eMarketing; eMarketing; marketer; eMarketeer; digital marketing; digital marketer; online marketer; social media; social - Sector: general industry - Employment type: fixed position, working time 36-40 hours per week - Education level: Professional Bachelor - Experience: 1-2 years of experience

B. Definition, responsibilities and tasks

Definition

What is 'Online Marketing'?
Online marketing is a form of marketing and advertising that relies on the Internet to deliver promotional marketing messages to consumers. The concept includes email marketing, search engine marketing (SEM), social media marketing, mobile advertising and display advertising, e.g. web banner advertising. The concept of online marketing is also known as *Internet advertising* or *online advertising*. Online advertising is widely used across virtually all sectors.

Similarly to other forms of marketing, online marketing commonly involves a *publisher* (who integrates ads into its online content) and an *advertiser* (who provides ads to be displayed with the publisher's content). Other agents that could be involved are *advertising agencies* (who generate and place the ad copy), an *ad server* (who technologically delivers the ad and tracks statistics), and *advertising affiliates* (who are responsible for independent promotional work for the advertiser).

Some examples of related job titles: 'online marketing experts/assistants', 'online marketers', 'eMarketing specialist', 'online marketing and sales support'

More information on the occupation can be found on the Wikipedia pages:
- covering *online advertising* (https://en.wikipedia.org/wiki/Online_advertising);
- covering *digital marketing* (https://en.wikipedia.org/wiki/Digital_marketing).

Is this position related to any existing occupations?
At first sight, the position of an online marketing coordinator appears to **combine** some of the tasks and responsibilities of other *marketing, advertising, sales or communication occupations* and those of occupations in the field of *information and communication technologies*.

Note that the concept of online marketing is closely related to that of *digital marketing*. Digital marketing is the 'targeted, measureable and interactive marketing of products or services using digital technologies to reach and convert leads into customers. Its objective is to promote brands, build preference and increase sales through various digital marketing techniques, mainly using the Internet as a core promotional medium.' The term emerged in the 1990s, but the concept only started to grow in 2000-10. Digital marketing includes, but is not limited to, email direct marketing, social media marketing, search engine optimisation or marketing, e-commerce marketing, content marketing/automation, influencer marketing, and mobile marketing. Online and digital marketing seem to overlap to some extent.

How prevalent is the occupation of an Online Marketing Coordinator in Belgium?
We looked for similar occupations on several job portals and did a Google search. Results of this exercise:

Job portals
- vacature.com: offers 11 vacancies for 'online marketing' and 9 for 'digital marketing'.
- jobat.be: offers about 30 job ads for 'online marketing' and 'digital marketing'.
- bloovi.be: offers about 35 related job advertisements.
- monster.be: offers about 16 job advertisements for 'online marketer'.
- creativeskills.be: about 5 job advertisements published during the summer.
- careerjet.be: about 67 job advertisements for 'digital marketing'.

Google Search (limited to .be websites):
- 'online marketing vacature': about 110,000 results.
- 'online marketing job': about 165,000 results.
- 'internet marketing vacature': about 63,700 results.
- 'internet marketing job': about 189,000 results.
- 'digital marketing vacature': about 23,300 results.
- 'digital marketing job': about 81,200 results.

What are the responsibilities and tasks of an online marketing coordinator?

This information is obtained from a sample of job vacancies, extracted from job portals (for Belgium).
- Responsibilities and tasks are generally *closely related to those of other marketing occupations*, i.e. other marketing, advertising, sales or communication occupations, such as initiation and implementation of offline and online campaigns and initiatives, but there is a lot more emphasis on the 'online' dimension here.
- Some vacancies focus on '*online marketing'* and only include tasks and responsibilities related to marketing; other vacancies are looking for a *broader profile* and list tasks and responsibilities that are related to offline marketing, sales, web design, and other tasks.
- Development of an *online marketing, advertising and sales* strategy, which involves online branding, marketing activities and campaigns, generate traffic to websites, sending out newsletters.
- Implementation of *applications* (mobile, SMS), attract new followers, generate traffic to applications.

- Development of a *social media strategy*, which involves online branding, advertising activities, attracting new followers, organic search optimisation (via creating content, communication strategy), running a blog.

C. Education, skills and other requirements

This information is obtained from a sample of vacancies, extracted from job portals (for Belgium)

Formal education required	
Is formal education required?	Yes
Level of education	Tertiary education: bachelor's or master's degree
Field of education	Some vacancies require training in marketing, new media communications; other vacancies do not specify a field of education

Skills required	
Communication skills	Writing and communication skills, language skills (e.g. Dutch, French, English, German), copywriting
Computer skills	SEM, SEO, SEA, HTML, MS Office, Google Analytics, social media, web design, Web2.0, Photoshop, Dreamweaver, InDesign
Non-cognitive skills	Analytical thinking, self-motivated, takes initiative, entrepreneurial mind-set, problem-solving, result-oriented, team player, organised, customer friendly, flexible, dynamic
Occupation-specific skills	Understanding online marketing (content, campaigns), knowledge of online customer behaviour, planning, conception and optimisation of campaigns, eMarketing techniques, communication strategy, interest in what is happening online

Experience required	
Is experience required?	This depends on the level of the position in the firm (executive, assistant, ...): e.g. 1-2 years, 3-5 years, 5+ years
Is job-related experience required?	Yes, in some vacancies: - experience in online marketing activities and campaigns, sales-driven organisations, e-commerce - experience in the sector, e.g. tourism

D. Geographical prevalence

European perspective

Results from job portals and Google search for countries in different parts of Europe:

Some of the job portals consulted: Indeed, Monster, Stepstone, ...

Similar vacancies in Western Europe	
France	*Chargé de mission commercial et marketing, Chargé de Marketing Digital, Responsable Web Marketing, E-marketeur*
Germany	*Onlinemarketing-Manager/in, Mitarbeiter (m/w) im Onlinemarketing (SEA) für den Webshop, Junior Marketing Manager im Online-Bereich, Trainee Kreation Onlinemarketing (m/w, Vollzeit, E-Commerce)*
The Netherlands	*Online Marketeer, Marketing Assistant, Digital Marketing & e-Commerce Consultant, Marketeer/SEO specialist*
UK	*Digital Marketing Manager, Digital Marketing Analyst, Online Marketing Executive, Web and Digital Marketing Apprentice, Online Marketing Coordinator*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Belgium? YES	Tasks/Responsibilities: developing and implementing a marketing or sales strategy, branding, web design, online promotion, email marketing, content creation and management for website, social media platforms, newsletters, create statistics and reports, keeping up-to-date with technological advancements, proofreading, target group identification, budget planning, graphic design Requirements: - bachelor's degree, previous experience in similar roles - knowledge of digital marketing, SEO, SEM, HTML, CSS, PHP, Adobe Photoshop or Illustrator, OM tools (Google Analytics, Adwords certificates required, Facebook), reporting results, able to develop a strategy, community management, written, verbal communication and presentation skills, English and other languages, data analysis, affinity with Internet/technology/IT - independent, dynamic, responsible, interested in the field, timeliness, creativity, enthusiastic, open-minded, focused, well-organised, commercial awareness, eager to learn, goal-oriented

Similar vacancies in Southern Europe	
Italy	*Responsabile Marketing e Web Marketing, Web Marketing Specialist, Online marketing manager, Impiegato web marketing, Addetto web marketing, Web Marketing Assistant*
Spain	*Especialista en Marketing Digital/E-commerce, Digital Marketing & SEM Executive, e-Commerce Marketing Manager, Responsable de Marketing Digital, Digital Marketing & Communication Support*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Belgium? YES	Tasks/Responsibilities: development and execution of marketing strategies, creation of advertising campaigns, branding, email marketing, management of and content creation for website, social media, newsletters, creation of all business graphics and materials (also offline), attract traffic to platforms, data analysis and reporting, copywriting, coordinate communication/sales strategy Requirements: - bachelor's degree, experience in related field or position - knowledge of marketing, social media, database management and CRM, marketing tools, analytical skills, computer skills (including programming, SEO/SEM, PHP, HTML, Facebook, MS Office, Adobe Photoshop or Illustrator, GIMP, Adwords, Retargeting, Premiere, Dreamweaver, Google Analytics), language skills, written and verbal communication skills, project management, a driving license is needed - organised, independent, results-oriented, stress-resistant, dynamic, business-minded, energetic, detail-oriented, proactive, team work, interest in company activities and sector, problem-solving

Similar vacancies in Northern Europe	
Denmark	*Online marketingspecialist, Social Media Marketing Manager, Online marketingkonsulent, Web og marketingkoordinator*
Sweden	*Online Marketing Coordinator Global Media, Online marketing manager, Juniorkonsult Digital Markadsföring, Digital Marketing Specialist*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Belgium? YES	Tasks/Responsibilities: development and implementation of online marketing strategy, email marketing, branding, report preparation, data analysis, management and optimisation of campaigns, budget planning, set up a digital marketing toolbox, launch new campaigns via social media, monitoring, measurement and analysis of marketing plans Requirements: - tertiary education in a related field (bachelor's, master's), experience in a related position, field or company - knowledge of online marketing, market analysis, web experience, experience with SEO, InDesign, Illustrator, Adobe Photoshop, Salesforce, Hubspot, Google Adwords, DoubleClick, social media (Facebook, LinkedIn, YouTube), a good understanding of online marketing and the web, web design skills, language skills, written and verbal communication skills - committed, passionate, creativity, independent, responsible, team-working skills, interested, proactive, ambitious, well-organised, adaptable, analytical mindset

Similar vacancies in Central and Eastern Europe	
Czech Republic	*E-Commerce Marketing Manager, Online Marketing Expert, Online marketing specialist, Online marketing manager*
Hungary	*Online Marketing munkatárs, Értékesítési/Marketing asszisztens, Online marketing specialist, Online marketing manager, Online marketing és kommunikációs specialist*
Poland	*Online Marketing Manager, Specjalista ds. marketingu online, E-Commerce Marketing Manager - branża sportowa*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Belgium? YES	Tasks/Responsibilities: preparation and implementation of online marketing campaigns or strategies, market research, copywriting, email marketing, drawing traffic to website, overseeing social media strategy, keeping track of emerging technologies, set up web, mobile or digital campaigns, measure and report performance of strategies, newsletter, content creation, branding, web design, search engine marketing Requirements: - high school education, vocational training, graduate professional degree, university degree, experience in similar role, firm, sector - knowledge of digital marketing, reporting, copywriting skills, MS Office, SEO/SEM, internet analytics and tools (Google Adwords, Display Ads, Mixpanel, Colibri, Crazy Egg, Brand24, Facebook-Ads), Photoshop, PPC, language skills, written and verbal communication skills, graphic skills, data analysis and reporting skills, market knowledge - customer-oriented, creative, loyal, independent, proactive, team player, positive, self-motivated, passion for marketing, flexibility

A global perspective

Results from job portals and Google search for countries in different parts of the world: we focus mainly on the United States, for which we find vacancies for *Online Marketing Specialist, Online Marketing Consultant, Integrated Digital Marketing Manager, Web Marketing Manager*.

Some of the job portals consulted: Indeed, Monster, Stepstone, ...

Do these vacancies involve similar tasks and have similar requirements as the vacancies for Belgium? *YES*

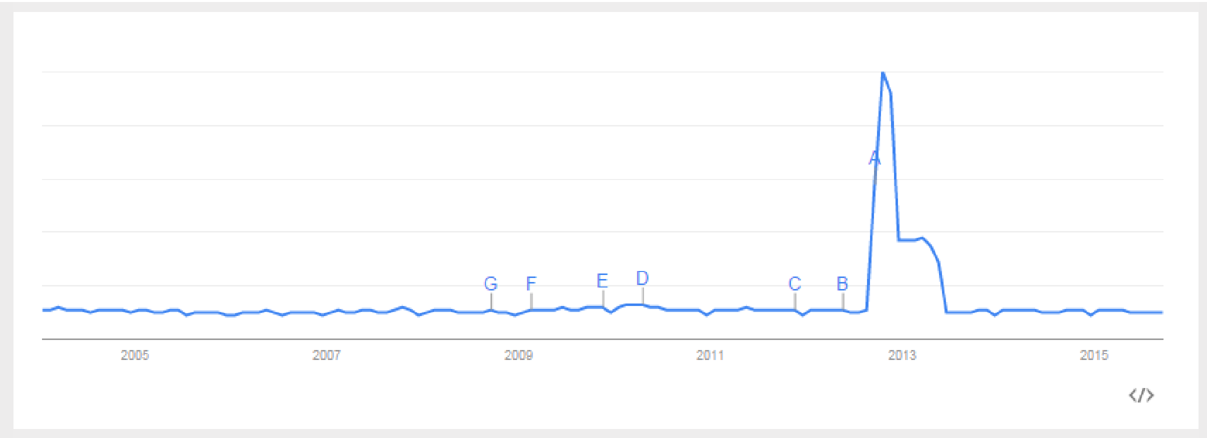
- *Tasks/Responsibilities* are relatively similar to those for Belgium. Again, tasks commonly involve marketing (e.g. e-commerce, implementation of campaigns and strategies, promotions, content creation for websites, social media, email marketing, paid advertising, branding, budget planning), sales and communications. In addition, some vacancies also refer to web design, copywriting and editing, as was the case for Belgium. Other tasks involve data analysis and database management, reporting on performance indicators, search for new technologies to use in daily tasks, continuous training and participation in workshops, conferences and industry events. These tasks seem to appear less in the Belgian vacancies (either not needed for position or assumed implicitly).

- *Requirements* are rather similar as well. Almost all vacancies require experience in a similar role and sector. Education and cognitive skills: at least a bachelor's degree in a related field, knowledge of online marketing techniques and strategies, web technology, organic search, search engine spiders and ranking factors, web design, MS Office, Google Analytics, HTML, CSS, written and communication skills, project management. Non-cognitive skills: teamwork, leadership skills, creativity, goal-oriented, positive, stress-resistant, problem-solving skills, self-motivated, able to do many tasks at once. Rather similar requirements, again a strong emphasis on the non-cognitive skills. We did find some differences in terms of the platforms and tools that are used, e.g. Google Adwords, SEOMoz, CrazyEg, Movable Ink, HubSpot.

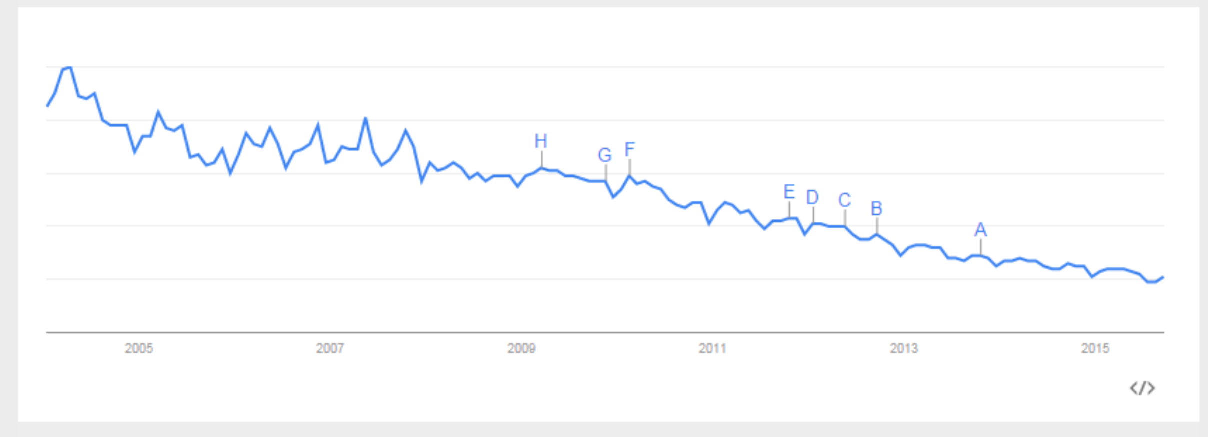
A Google Trends Analysis

An analysis on the basis of Google Trends reveals the following patterns (see graphs, global): especially 'digital marketing' is on the rise, Internet marketing has declined over time and online marketing has been popular during the last five years (with a peak in 2013). These findings indicate that the Internet has become so widespread that the term and concept are relatively common nowadays. Nevertheless, the interest in occupations related to web-based marketing appears to grow. These patterns are found in Belgium, many European countries (France, Germany, the Netherlands, the UK, Italy, Finland, Sweden, Hungary, and Poland, among others) and the United States. Some differences are detected for online marketing (after the peak in 2013, the interest appears to remain somewhat higher in Denmark and Romania, and there is a slight upward trend for Spain) and internet marketing (high peaks and then a drop to nearly zero for Poland and Sweden).

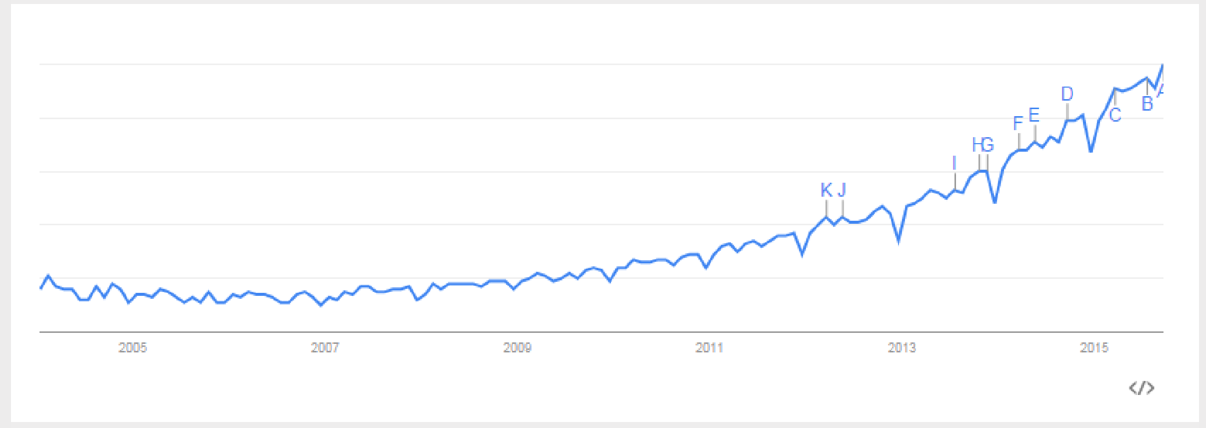
Google Trends: online marketing worldwide (30/09/2015)



Google Trends: internet marketing worldwide (30/09/2015)



Google Trends: digital marketing worldwide (30/09/2015)



E. Occupational classification

International classifications

ISCO-08:the term 'online' does not appear in combination with 'marketing'; nor do 'digital' and 'internet'; the term 'internet' does appear in combination with 'salesperson' (occupation 5244: service & sales workers => sales workers => other sales workers => contact centre sales persons).

Where could this occupation fit in the ISCO08 classification?
- 1221 'Sales and marketing managers'.
- 1222 'Advertising and public relations managers'.
- 2431 'Advertising and marketing professionals'.

ESCO: it does not appear to exist at this point ('marketing' does exist)

Where could this occupation fit in the ESCO classification?
- 579 'Advertising and marketing professionals'.
- 563 'Sales, marketing and development managers'.
- 361 'Other sales workers'.

National classifications

Belgium: based on ISCO (from 2011 onwards).

In Europe:

- *France*: PCS and PCS-ESE, but occupation is not included there (different translations were checked; it might be due to the fact that the last update was in 2003).
- *Germany*: Klassifikation der Berufe (KB) (most recent version is 2010), occupation is included: *92113 Komplexe Spezialistentätigkeiten* (includes *Online-Marketingmanager/in*) as part of the category *Werbung, Marketing, kaufmännische und redaktionelle Medienberufe*.
- *The Netherlands*: based on ISCO (Central Bureau for Statistics, from 2013 onwards).
- *UK*: SOC (most recent version is 2010), but occupation is not included there.
- *Italy*: has the Classificazione delle professioni (CP, most recent version 2011, an update of CP2001 and adapted to ISCO08), in this classification there is an occupation named *tecnici del marketing* (code 3.3.3.5.0, in which an example job title is *tecnico del web marketing*), that is part of the professioni tecniche nell'organizzazione, amministrazione e nelle attività finanziarie e commerciali/tecnici dei rapporti con i mercati/tecnici del marketing.
- *Spain*: has the Clasificación Nacional de Ocupaciones 2011 (CNO-11), includes marketing professionals (Profesionales de la publicidad y la comercialización) but it is not clear whether this covers online marketing professionals.
- *Denmark*: DISCO, Danish national classification based on ISCO, most recent version is DISCO 2008, not found.
- *Sweden*: has the Standard för svensk yrkesklassificering (SSYK) (most recent version is SSYK2012), based on ISCO08. Includes many marketing professions, but it does not seem to include online or web marketing.
- *Czech Republic***:** Klasifikace zaměstnání (CZ-ISCO), based on ISCO08. Few marketing occupations, few web-related professions (not found in the list).
- *Hungary***:** has HCSO/FEOR (edition 2008), but this does not include the occupation.
- *Poland***:** has the Klasyfikacja zawodów i specjalności (KZiS 2014), based on ISCO08 (but it is updated more recently, 2014). In an alphabetical list, a similar occupation was found: *122104 Kierownik do spraw marketingu internetowego* (Director of Marketing online). This is likely the result of the recent update.

In the rest of the world (US):

- *US* has SOC (last version is 2010), occupation is included: 11-2021 Marketing Managers lists 'Internet Marketing Managers' as an example job title (part of 11-2000 Advertising, Marketing, Promotions, Public Relations, and Sales Managers).
- *US* also has the *O*NET* classification**:** the occupation exists as part of 'Online Merchants' (13-1199.06 - Online Merchants www.onetonline.org/link/summary/13-1199.06).

  This occupation is labelled as a '*Bright Outlook*' occupation (in the category 'new and emerging'), i.e. occupations expected to grow rapidly in the next several years, will have large numbers of job openings, or are new and emerging occupations.

  O*NET summary of online merchants: Conduct retail activities of businesses operating exclusively online; may perform duties such as preparing business strategies, buying merchandise, managing inventory, implementing marketing activities, fulfilling and shipping online orders, and balancing financial records.

  Examples of job titles**:** Marketing Director; Marketing Specialist; Online Marketing Manager; Online Services Manager; Social Media Director.

Other O*NET occupations that are related to 'Online marketing':
- Search Marketing Strategists: www.onetonline.org/link/summary/15-1199.10
- Marketing Managers: www.onetonline.org/link/summary/11-2021.00
- Market Research Analysts and Marketing Specialists: www.onetonline.org/link/summary/13-1161.00

F. Conclusions

Is Online Marketing Coordinator a new or emerging occupation?	
In Belgium?	Given its limited prevalence and the relative novelty of some of the tools and technologies that the worker has to use, the occupation is relatively new and emerging in Belgium. The tasks and duties that are involved in the job are highly specialised, but there still is a clear link with other existing jobs (among others, in marketing, sales, communication). The occupation seems to combine different aspects of these jobs (marketing, social media, IT). Its importance is likely to grow in the future, as the Internet is increasingly used in everyday life. In some industries and firms, the occupation is likely to be completely new, while in other industries and companies, it is emerging. Interestingly, one of the vacancies mentioned that the position is new within the organisation. Does this occupation have a future? Undoubtedly yes. What is the impact on training? What are the skills implications? Educational institutes will have to keep in mind that the marketing professions of the future will also have a strong web-based dimension. This means that students will need to learn how to work with these programs, tools and platforms (Google Analytics, SEO, email marketing, social media) and how to reach their target audience in this way. They also have to acquire some programming skills, web and graphic design skills, etc. Marketing jobs are likely to develop into broader professions, and students will thus have to develop a wider range of skills as well. Another important dimension that should not be overlooked is data and analytics. Strong analytical skills are essential (data collection, result interpretation, reporting, drawing conclusions to adjust strategies and develop new campaigns). Finally, training programmes should focus extensively on communication skills, because these are requested in nearly all vacancies. Moreover, firms that want to remain competitive should make sure that their employees receive on-the-job- training or have other training opportunities, to keep up with technological changes and changes in the market. Similarly, for the workers that hold a marketing position, it could be interesting to engage in life-long-learning and to keep up to date with current developments (to keep their job or transfer to other positions).
In Europe?	A similar conclusion is reached for Europe. In many countries, the classification is not present in the most recent national occupational classification. In some countries, i.e. Germany, Italy and Poland, the occupation is part of the most recent national occupational classification (there it could be regarded as emerging rather than new). There are a lot of vacancies for similar positions across Europe, especially in the west, north and south, less so in the east. Given that the tasks and responsibilities and the requirements are comparable in other European countries, the conclusions formulated above apply here. Education should focus on new technologies, communication skills and data analysis. Companies can benefit from providing on-the-job- training to their staff, to keep up with recent developments. Marketing professionals should be aware of these developments and engage in training activities too.
Worldwide?	For the US, the occupation appears to be relatively new or emerging as well, depending on the industry and firm. The occupation is included in SOC and O*NET. Similar conclusions are reached for the educational institutes, firms and individuals.

4.5.3 Second example of an occupation card: 'Drug Safety Specialist'

4.5.3.1 Occupation Card 2: Drug Safety Specialist

Date: 3 November 2015.

A. Identification

The identification of new occupations, such as the drug safety specialist presented in the current document, is based on an innovative methodology that we are piloting here. This methodology is embedded in the rapidly growing strand of the literature that relies on web-based data sources to conduct labour market research (see Askitas & Zimmermann, 2015). The main idea behind our methodology is to identify new occupations via the *occupational classification* that online job portals use to guide job seekers on their website. Typically, such occupational classifications have - at their core - a *tag system*, i.e. a list of tags that is used to assign vacancies to specific job categories. This list of tags can be published online or stored in a library accessed by an API search when a job seeker enters a word in the search box. Earlier research suggests that job portals tend to regularly update their list of tags, to account for the emergence of new occupations and the disappearance of redundant ones.

In our pilot study, we focus on 11 countries for which we keep track of one of their main online job portals. For these countries, we created a *benchmark*, which is composed of their occupational classification (their list of tags) on 30 June 2015. Our goal is to determine whether this tag system could also be used to identify new occupations, by comparing the benchmark classification with the *current occupational classification* of the portal at regularly intervals, i.e. every month. The *tags that are not yet included* in the benchmark, i.e. missing from the list of tags when the benchmark and the new list of tags are compared, could point to new or emerging occupations. For more details on our methodology, we refer to the *Methodological Note* that is available on the website in the New Occupations Observatory.

In July 2015, a new tag was added to the *Slovakian* online job board in our pilot. This tag was picked up (either via the API or via a web crawling technique that extracts the list of tags - this depends on the portal) and stored in a database. We then searched for an actual vacancy for a *drug safety specialist* on this portal (to discover what triggered the new tag). More details on this tag/vacancy can be found below; these details cover (i) the portal to which the tag was added and on which the vacancy was found, and (ii) the content of the sample vacancy that we study in more depth (to identify tasks and responsibilities - skills and other requirements).

Details on the tag and the job advertisement	
When did the tag/vacancy appear online?	October 2015
On which online job board was the tag/vacancy published?	profesia.sk
Which country is covered by this job portal?	Slovakia
In which industry is the employer active?	Pharmaceuticals
What type of employer has posted the vacancy?	Private company

We found overall three job vacancies on the Slovakian job portal under the searched category of drug safety specialist. Only one of these jobs consisted only of this one category (Safety Manager); the other two consisted of more categories (Quality Manager/Responsible Pharma and Pharmacist). Consequently, we will be primarily referring to the found job vacancy of 'Safety Manager' when talking about drug safety specialist since this specific vacancy was the most narrowly defined in terms of chosen categories. Further in the text we will provide more specific elaboration on similarity of the other two mentioned vacancies with the occupation of drug safety specialist.

Sample job advertisement	
Job description (responsibilities and tasks of the job)	- Complex responsibility for managing safety-related activities based on the legislative requirements within the local affiliate - Representing the local safety function on behalf of the country in interactions with regulatory agencies and senior management - Ensuring local compliance with pharmacovigilance requirements in accordance with local regulations and procedures - Active monitoring local/regional operating performance and adverse events reporting - Maintain up-to-date knowledge and compliance with local safety regulations for country - Ensuring the training of local staff regarding the adverse reporting obligations - Ensuring that local processes, strategies and initiatives are aligned with safety defined by the company - Intensive contact with International Safety group - Acting as a contact person for regional safety inspections and audits - Reporting to Regional Safety Lead
Job profile (education, skills and other requirements for the job)	- At least a bachelor's degree in pharmacology or life science - Fluent English - Minimum five years of previous related experience with safety and pharmacovigilance processes - Deep understanding of local pharmacovigilance requirements and practices - Ability to work with significant autonomy - Ability to understand and communicate scientific information - Ability to build strong business relationships - Demonstrated problem-solving abilities - Excellent organisational and communication skills
Job portal tags (tags attached to the vacancy on the job board)	- Safety Manager tags: Drug Safety Specialist - Quality Manager tags: Drug Safety Specialist, Pharmacist, Regulatory Affairs Manager, Regulatory Affairs Specialist - Pharmacist: Drug Safety Specialist, Clinical Data Manager, Pharmacist, Pharmaceutical Laboratorian, Medical Advisor

B. Definition, responsibilities and tasks

Definition

What is 'Drug Safety Specialist'?
Drug Safety Specialist is mainly concerned with pharmacovigilance. According to the World Health Organisation, pharmacovigilance comprises activities related to 'detection, assessment, understanding and prevention of adverse effects or any other drug-related problem'. It is possible to perform this occupation at the clinical level which involves primarily scientific activities in drug research and, secondly, on the administrative level where an individual supervises accordance of processes with internal and external regulations. Needless to say, it is common to find the interconnection of these two aspects, especially abroad. However, in case of Slovakia we have not found the clinical aspects of this occupation in the job vacancies such as scientific involvement in clinical trials. As a result, the majority of the workload of the drug safety specialist in Slovakia consists of communicating with and reporting to state regulatory agencies. Moreover, the drug safety specialist might also operate as an *auditor* for supervising internal regulations on behalf of company management or an international institution.

Examples of job titles:
- *abroad*: Drug Safety Specialist, Clinical Drug Safety Specialist, Product Safety Specialist;
- *in Slovakia*: Safety Manager, Quality Manager/Responsible Pharma.

More information about the specifics of drug safety specialist occupation, i.e. pharmacovigilance may be found on:
- *Wikipedia*: https://en.wikipedia.org/wiki/Pharmacovigilance
- *World Health Organisation*:
  www.who.int/medicines/areas/quality_safety/safety_efficacy/pharmvigi/en/

Is this position related to any existing occupations?
Drug safety specialist combines responsibilities of other similar occupations. It is especially related to *regulatory affairs occupations* and *compliance occupations*, such as regulatory affairs manager, regulatory affairs specialist, corporate regulatory affairs specialist, regulatory affairs officer, compliance officer, compliance specialist, etc. The duties of the regulatory affairs and compliance occupations are specified as analysing local regulations, supervising and ensuring that company's processes are in compliance with local and international law. However, drug safety specialist is closely concerned with the pharmaceutical sector in comparison with other compliance and regulatory affairs occupations which do not have to be necessarily concerned solely with pharmaceuticals. Furthermore, the clear distinction between regulatory affairs/ compliance specialist and drug safety specialist in the pharmaceutical industry seems to be the drug safety specialist's specifically defined interest with processes concerned with pharmacovigilance regulations only.

How prevalent is the occupation of a Drug Safety Specialist in Slovakia?
We looked for similar occupations on several job portals and did a Google search. Results of this exercise:

Job portals
- profesia.sk: three vacancies for the entry 'Drug safety specialist'.
- inzerciapraca.sk: zero vacancies for the entry 'Drug safety specialist'.
- kariera.zoznam.sk: zero vacancies for the entry 'Drug safety specialist'.
- inzeraty.sme.sk: zero vacancies for the entry 'Drug safety specialist'.
- praca.bazos.sk: zero vacancies for the entry 'Drug safety specialist'.
- ponuky.sk: zero vacancies for the entry 'Drug safety specialist'.

Google Search (limited to .sk websites)
- drug safety specialist: about 4,700 results.
- 'drug safety specialist': about 2,600 results.
- compliance specialist: about 3,800 results.
- pharmaceutical compliance specialist: about 4,600 results.
- regulatory affairs: about 10,000 results.
- regulatory affairs specialist: about 4,500 results.
- pharmaceutical regulatory affairs: about 12,000 results.

What are the responsibilities and tasks of a drug safety specialist?
This information is obtained from a sample of job vacancies, extracted from job portals (for Slovakia).

As was mentioned before, the search mechanism on Slovak job portal profesia.sk is based on tags - categories which we also used. Using the tag 'drug safety specialist', we found three vacancies. Only one of these vacancies, 'safety manager', was solely concerned with pharmacovigilance and consisted of only one category, which was searched. The other two vacancies consisted of more categories and were minimally concerned with pharmacovigilance.

- First, the job advertisement for 'pharmacist' was not concerned with pharmacovigilance at all; moreover, this job could be identified as a standard drug dispenser job in public pharmacy. It seems that the advertiser inserted the tag 'drug safety specialist' mistakenly into the advertisement.
- Second, the job advertisement for 'Quality manager/Responsible pharma' included 'drug safety specialist', too; however, we found no pharmacovigilance aspect in the tasks and responsibilities. The only part of the advertisement explicitly mentioning pharmacovigilance was the requirements section, where the applicants were required to have regulatory/drug safety experience. Other than that, this job vacancy can be identified as a vacancy for a head drug dispenser with management responsibilities.

As a consequence, in the following sections we will be working with the advertisement for 'safety manager', since this ad was almost exclusively concerned with pharmacovigilance, regulatory and compliance tasks.

- In general, tasks and responsibilities are closely related to those of *regulatory affairs* and *compliance occupations*. They include maintaining compliance with local drug safety regulations and regular filing of reports to local regulators.
- Ensuring that processes are aligned with internal regulations. At the same time serving as a contact person for inspections and audits. Consequently, we can see aspects of the *auditor's occupation*.
- The tasks also include intensive cooperation with international safe regulation bodies, such as International Safety Group.
- We also notice the requirement of *training/coaching* skills, which are required to provide trainings for local staff with regard to the adverse reporting obligations.

C. Education, skills and other requirements

This information is obtained from a sample of vacancies, extracted from job portals (for Slovakia).

Formal education required	
Is formal education required?	Yes
Level of education	Tertiary education: bachelor's degree
Field of education	Pharmaceutical education

Skills required	
Communication skills	Excellent communication skills, fluent English in written and spoken form
Computer skills	Not required/not specified (in Slovakia)
Non-cognitive skills	Ability to work with significant autonomy, ability to understand and communicate scientific information, ability to build strong business relationships, demonstrated problem-solving abilities, excellent organisational skills
Occupation-specific skills	Deep understanding of local pharmacovigilance requirements and practice

Experience required	
Is experience required?	Minimum two to five years of previous related experience with safety and pharmacovigilance processes
Is job-related experience required?	Yes, previous experience in the sector, experience in communication with local regulators

D. Geographical prevalence

A European perspective

Results from job portals and Google search for countries in different parts of Europe:

In case job descriptions (tasks, requirements) differ significantly in the predefined clusters of countries, we will present them separately.

Similar vacancies in Western Europe	
France	*Pharmacien(ne) assurance qualité, Responsable assurance qualité, Pharmacien responsable assurance qualité, Responsable de l'assurance qualité*
Germany	*Apotheker als stellv. Leiter Qualitätskontrolle, Global Quality Auditor, Manager Drug Safety - Pharmacovigilance, Medical Manager Drug Safety, Drug Safety Manager*
The Netherlands	*Drug Safety Manager, Regulatory affairs officer, Drug Safety and Quality Officer, Pharmacovigilance Liaison Manager*
UK	*Drug Safety Associate, Drug Safety Manager, Drug Safety Officer, Drug Safety Specialist, Drug Safety Physician*
Belgium	*Regulatory Affairs Officer/Regulatory Affairs Specialist (with explicit aim at pharmacovigilance and safety, pharmaceutical development and quality, and other regulatory affairs and operations)*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Slovakia? YES	Tasks/Responsibilities: ensuring that products and processes comply with national and international regulations, preparing documentation for regulatory bodies, managing and participating in the implementation of the quality system, conducting quality audits, managing quality trainings and staff qualifications Requirements: - scientific or medical university degree - in most of the cases experience in the related field is required (could be substituted by a PhD degree in one case) - knowledge of national and international regulations

Similar vacancies in Southern Europe	
Italy	*Medico Farmacovigilanza, Drug safety officer, Addetto alla farmacovigilanza, Drug Safety Specialist, Drug Safety Physician*
Spain	*Responsable de Calidad Sector Químico, Especialista en Farmacovigilancia*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Slovakia? YES	Tasks/Responsibilities: identification of adverse effects, following national and international regulations, communication and collaboration with regulators, providing pharmacovigilance reports resulting from clinical trials, providing pharmacovigilance trainings for the staff, ensuring the maintenance of product quality and quality system Requirements: - degree in medicine, biology, pharmacy, biotechnology or other life science - experience in pharmacovigilance (some jobs had this requirement preferred but not required) - knowledge of current legislation

Similar vacancies in Northern Europe	
Denmark	*Pharmacovigilance Policy Expert*
Sweden	*Regulatory Affairs Konsulter*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Slovakia? PARTLY	Tasks/Responsibilities: DK: reviewing new global pharmacovigilance regulatory guidelines, performing the impact assessment on global safety procedures, writing reports for external regulators and relevant internal departments SWE: to serve as a contact person for regulation affairs with authorities Requirements: - master's degree in pharmacy or other relevant life science - previous experience in the pharmaceutical sector

Similar vacancies in Central and Eastern Europe	
Czech Republic	*Drug Safety Associate*
Hungary	*Gyógyszerbiztonsági munkatárs - Adatmenedzsment területre (Drug Safety Associate - Data Management area, MinŐségbiztosítási auditor -Gyógyszeripar (Quality Assurance Auditor - Pharmaceuticals), Gyógyszerbiztonsági Koordinátor (Pharmaceutical Product Safety Coordinator)*
Poland	*None found*
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Slovakia? PARTLY	<u>Tasks/Responsibilities</u>: CZ: development project specific reporting procedures, workflows and templates; support project specific safety database set-up, development of data entry guidelines, and user acceptance testing; electronic documentation and quality control of drug safety information; coding of data in the safety database and writing case narratives HU: drug safety data processing, keep track of current regulatory and corporate standards in pharmacovigilance, participation in drug safety audits and inspections, IT support for drug safety database; determination of the completeness of single case reports, confirmation of the accuracy of medical coding <u>Requirements</u>: - degree in pharmacy, nursing, life science or other health-related field - appropriate previous experience - ability to interpret and apply global safety regulations - IT skills - database management, MS Office (partly in Hungary)

A global perspective

Results from <u>job portals</u> and <u>Google search</u> for countries in different parts of the world: we focus mainly on the United States, for which we find vacancies for *Drug Safety Specialist, Clinical Drug Safety Specialist, Safety and Pharmacovigilance Specialist, Drug Safety Associate* and *Senior Drug Safety Specialist.*

Do these vacancies involve **<u>similar tasks</u>** and have *<u>similar requirements</u>* as the vacancies for Slovakia? *PARTLY*

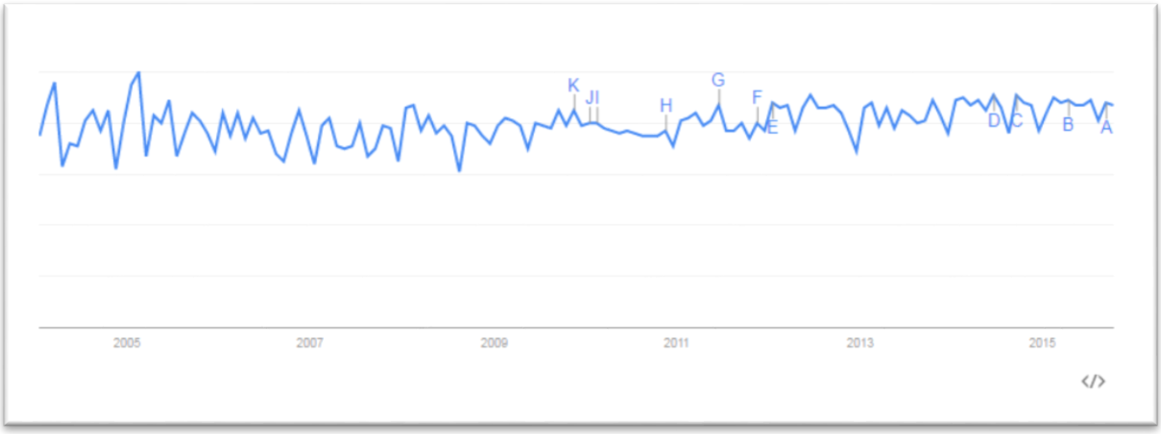
- <u>Tasks/Responsibilities</u> are relatively similar to those for Slovakia when it comes to interaction with regulators. Processes related to drug safety not only have to be in compliance with national and international regulation standards but also with internal standards. Duties and responsibilities also include training of staff, reviewing and filing drug safety reports. These tasks are congruent with the tasks described in Slovakian ads. On the other side, Slovakian ads do not explicitly mention clinical trial involvement. Especially in the US ads, clinical drug safety specialists are required to provide clinical trial support and actively cooperate on the methodology, coding and inspection of the products even in the clinical trial testing. The main difference between clinical drug safety specialist and drug safety specialist is that the drug safety specialist's work is mainly based on reports and data provided by clinical trials team while the clinical drug safety specialist is actively involved in the development of the drug during the clinical trials.
- <u>Requirements</u> are rather similar to Slovakian advertisements. Pharmaceutical, medical or other life science education is required. Almost all vacancies require experience in a similar role and sector. The usual length of required experience in the related field is two to five years. Furthermore, excellent knowledge of local, national and international regulations is necessary. Non-cognitive skills required around the world are often: analytical thinking, organisational skills, ability to work both independently and in a team, and strong ability to work with scientific information. Moreover, excellent communication skills are required, as well as fluent English with understanding of medical/pharmaceutical/scientific terminology.

A Google Trends Analysis

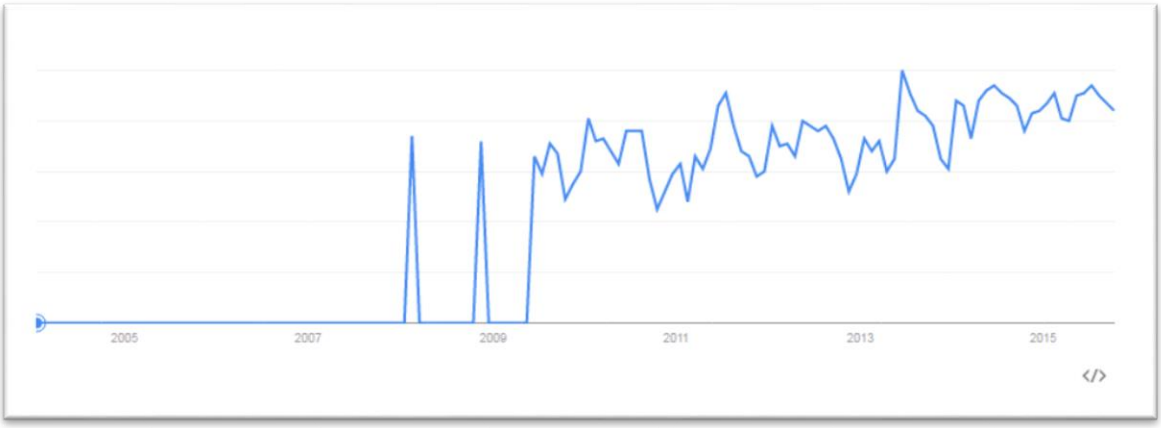
An analysis on the basis of Google Trends reveals the following patterns (see graphs, global):

we can notice that pharmacovigilance, i.e. drug safety, fluctuates around the stable values. Even though a sudden rise in pharmacovigilance in recent years is not apparent, it can be deduced from the graph Google Trends 2 that the term 'pharmacovigilance jobs' has been constantly on the rise since 2009. Before this year, there was almost no interest in pharmacovigilance jobs in via Internet browsing. Furthermore, when looking at the graph Google Trends 3, we can see brief, sharp rises in 2014 and 2015 in the worldwide Internet search for the job 'Drug Safety Specialist'. As a result, we can assume that this occupation has recently emerged as part of the recent, gradual rise of the pharmacovigilance sector.

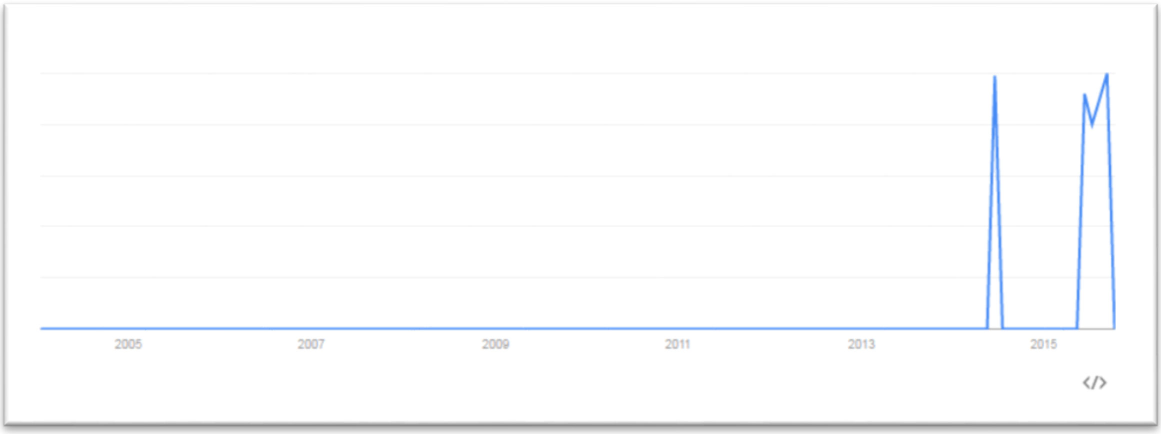
Google Trends 1: 'Pharmacovigilance' worldwide (30/10/2015)



Google Trends 2: 'Pharmacovigilance jobs' worldwide (30/10/2015)



Google Trends 3: 'Drug Safety Specialist' worldwide (30/10/2015)



E. Occupational classification

International classifications

ISCO-08: as was mentioned in the Google Trends Analysis above, pharmacovigilance jobs started emerging in 2009; furthermore, specifically 'drug safety specialist' started to show up only in 2014. As a result, there is not any separate category for these occupations created in the ISCO classification from 2008. Consequently, we determined which categories at least partly cover the aspects of the drug safety specialist occupation.

Where could this occupation fit in the ISCO08 classification?
- 3141 'Life Science Technicians (excluding Medical)' - this category is especially suitable for more clinically oriented pharmacovigilance jobs, as Life Science Technicians are primarily concerned with aspects of research.
- 2262 'Pharmacists' - this category only partially covers pharmacovigilance occupations since pharmacovigilance jobs are not involved in drug dispensing. On the other side, pharmacists are in this category's definition also concerned drug safety and drug standards.

ESCO: it does not appear to exist separately in the ESCO classification.

Where could this occupation fit in the ESCO classification?
- 'Drug Inspector' - according to ESCO, this classification also has the 2262 ISCO code, which is 'pharmacist'. Additionally, skills and competences described in ESCO are related to a drug safety specialist's tasks and responsibilities. For instance, supervision of medical products, clinical testing and, partly, laboratory analysis.

National classifications

Slovakia: the national classification in Slovakia is based on ISCO08 and is fully compatible with it.

<u>In Europe</u>:
- *France*: PCS and PCS-ESE, however, occupation is not included there (the last update of this national occupational classification was in 2003);
- *Germany*: Klassifikation der Berufe (KB) (most recent version is 2010), occupation is not included;
- *Belgium*: based on ISCO (from 2011 onwards);
- *The Netherlands*: based on ISCO (Central Bureau for Statistics, from 2013 onwards);

- *UK*: SOC (most recent version is 2010), drug safety specialist could be included in the category 2642 Quality assurance and Regulatory professionals where these occupations are listed: Compliance manager, Quality assurance manager, Quality manager;
- *Italy*: has the Classificazione delle professioni (CP, most recent version 2011, an update of CP2001 and adapted to ISCO-08), however, there is no relevant category for drug safety specialist;
- *Spain*: has the Clasificación Nacional de Ocupaciones 2011 (CNO-11). The closest classification that suits drug safety specialist is category 3204 Chemical and Pharmaceutical Supervisors. However, this category is sorted under 320 Mining, manufacturing and construction supervisors and since the categories in Spanish occupational classification are not defined more specifically we cannot certainly determine whether the mentioned category is suitable for drug safety specialist;
- *Denmark*: DISCO, Danish national classification based on ISCO, most recent version is DISCO 2008. We have not found any appropriate category for drug safety specialist;
- *Sweden*: has the Standard för svensk yrkesklassificering (SSYK) (most recent version is SSYK2012), based on ISCO08. It does not seem to include the drug safety specialist occupation or similar category;
- *Czech Republic:* Klasifikace zaměstnání (CZ-ISCO), based on ISCO08. No relevant category for drug safety specialist was found;
- *Hungary:* has HCSO/FEOR (edition 2008). The specific occupations are not closely described, but judging from the occupation names, 3135 Quality assurance technician could include some of the working aspects of drug safety specialist;
- *Poland:* has the Klasyfikacja zawodów i specjalności (KZiS 2014), based on ISCO-08 (but it was updated more recently, 2014). In an alphabetical list, a similar occupation was found: *242208 Inspektor farmaceutyczny* (Pharmaceutical Inspector). This occupation most likely involves some aspects of the drug safety specialist occupation such as supervising drug safety standards.

<u>In the rest of the world (US)</u>:
- *US* has SOC (last version is 2010), however, drug safety is not specifically defined in this classification. Other similar occupation in the US SOC is *13-1040/1 Compliance officer*;
- *US* also has the *O*NET* classification where the specifically named occupation 'drug safety specialist/manager/etc' cannot be found; however, the agenda of this occupation can be found in the category *13-1041.07 Regulatory Affairs Specialists* which includes occupations such as *Drug Regulatory Affairs Specialist, Quality Assurance/Regulatory Affairs Specialist.* These occupations fulfil the definition of drug safety specialist to a great extent. Moreover, this occupation is also labelled a '*Bright Outlook*' occupation (in the category 'new and emerging'), i.e. occupations expected to grow rapidly in the next several years, will have large numbers of job openings, or are new and emerging occupations; O*NET summary of regulatory affairs specialists: Coordinate and document internal regulatory processes, such as internal audits, inspections, license renewals, or registrations. May compile and prepare materials for submission to regulatory agencies.

F. Conclusions

Is Drug Safety Specialist a new or emerging occupation?	
In Slovakia?	We assess that the occupation drug safety specialist is relatively new and emerging in Slovakia. Even though similar occupations have existed since a long time in Slovakia, new pharmacovigilance jobs like drug safety specialist merged tasks and responsibilities from them and narrowed them to a specific objective, which is its dedication to drug safety legislation. Similar occupations are regulatory affairs and compliance jobs aimed at the pharmaceutical sector. Nevertheless, as has been mentioned, the added value of drug safety specialist for the job market in Slovakia is its very narrow specialisation in pharmacovigilance. Moreover, it can be assumed that this sector has extensive growth potential. More specifically, we found only one current advertisement which was exclusively dedicated to drug safety; however, it lacked a clinical aspect, i.e. active involvement in research - clinical trials. As will be described below, in comparison with Slovakia, drug safety occupations abroad are also focused on the active role of the individual and his supervision of the pharmaceutical research and development, whilst in Slovakia the current advertisement is almost solely focused on communication with regulators, maintaining compliance with drug safety regulations and staff training. As a consequence, it can be expected that more pharmacovigilance will start emerging in Slovakia with active involvement in clinical trials because the current requirements for pharmacovigilance jobs in Slovakia demand only understanding scientific information from clinical trials and further working with it. What is the impact on training? What are the skills implications? First of all, promising candidates for pharmacovigilance jobs have to have excellent English language skills, especially regarding pharmaceutical terminology, since all the major employers are supranational pharmaceutical corporations. Additionally, while knowledge of national regulations is required, flawless knowledge of international regulations is requested. Secondly, cross-sectional skills from pharmaceutics, law, computer, database, and statistics are starting to be demanded abroad; as a result, we can anticipate the same trend in Slovakia. As for now, pharmaceutical or other life sciences education is required with quite extensive previous field experience which we assume ensures knowledge of relevant regulatory legislation. Statistical and database skills should also be developed, as we can notice from the abroad experience that one of the tasks of pharmacovigilance occupations might be data processing. One of the solutions for this growing job market seems to be introduction of new study programmes aimed directly and solely at pharmacovigilance, which we already noticed in other countries. For instance: www.postgraduatesearch.com/university-of-hertfordshire/52981048/postgraduate-course.htm.
In Europe?	Similar conclusions can be drawn in Southern, Central, Northern, Eastern, and, in part, Western Europe as those in Slovakia. However, we found no separate occupational classification in national classifications for pharmacovigilance jobs across the studied European countries. On the other side, we can still consider drug safety occupations as new and emerging and see them showing up in a lot of variations in terms of specialisation, e.g. data management, regulatory affairs, research and development involvement, or a combination thereof. In terms of Europe, most job advertisements for drug safety occupations were in Western Europe. For instance, we found no job offer for drug safety/pharmacovigilance specialists in Poland. Requirements and tasks are similar to those in the Slovakian ad, though we notice explicit mentions of clinical trial involvement and clinical data-processing and management (Hungary and, in part, Czech Republic). On the other hand, the overwhelming majority of tasks and responsibilities across Europe was still dedicated to regulatory affairs and compliance maintenance with external regulations.
Worldwide?	In comparison with all the other studied countries, pharmacovigilance jobs seem to be most on the rise in the US. We found a large number of US advertisements for various forms of pharmacovigilance jobs. We could clearly distinguish orientation, whether toward regulatory affairs or research and development, e.g. clinical trials. Either variations, or a combination thereof require pharmaceutical education, but in the case of regulatory affairs the stress is placed on pharmaceutical regulation knowledge while clinical drug safety specialists require a more extensive scientific background. Moreover, the US is the only studied country that included in its national occupational classification, O*NET, *Regulatory affairs specialist,* which includes *Drug Regulatory Affairs Specialist, Quality Assurance/Regulatory Affairs Specialist.*

4.5.4 Summary

- With this pilot, our aim was to test whether it is feasible to identify potentially new or emerging occupations on the basis of the *occupational structure or the metadata available on online job portals*.
- The pilot confirms that this methodology is effective and easy to carry out. The output of the exercise is presented in a series of occupation cards. Each card provides detailed information on the potentially new occupation, in terms of their responsibilities and tasks, requirements, prevalence etc.
- When the benchmark was first established, we noted substantial heterogeneity in terms of the number of tags it contained for each country. Similarly, when the number of new tags is compared, there are many cross-country differences. Yet, these numbers are not easy to compare and may reflect differences in how the portals operate. We detected 57 potentially new occupations over a six-month period, for 6 countries.
- To the best of our knowledge, we are not aware of other research that uses a similar approach to identify new and emerging occupations. Traditionally, the identification is based on trade publications, employer surveys, job postings, interviews, surveys and existing occupational classifications.
- Further improvements of the methodology could involve extracting the list of tags on a quarterly rather than a monthly basis, which seems to be too frequent. Other possibilities are to carry out the work for a longer period, as we only ran the pilot for about six months, use more diverse data sources, automate some of the steps of the process and link the card to existing tools to identify new and emerging skills. This can be achieved by applying machine learning and text mining techniques (Grus, 2015).

4.6 Case Study 5: 'The importance of foreign language skills in the labour markets of Central and Eastern Europe: an assessment based on data from online job portals'

(Beblavý et al., 2016b)

The fifth case study that we carried out in light of the InGRID project was also based on metadata extracted from online job portals. In contrast to the other case study in which we use such data, we do not combine them with vacancies in this case. Instead, our aim was to rely on the occupational classification and the 'tag' system that job boards use to organise their vacancies.[19] We do, however, consider the number of vacancies associated with these tags in our analysis. The reason why we experiment with this system is that using tags and vacancy counts is much easier and faster than extracting a sample of job postings and doing a semantic analysis. At the same time, it brings less information. The aim of this case study was, therefore, to assess whether a simpler methodology could give interesting results.

In order to put this alternative methodology to the test, we investigate the demand for foreign language skills in the Visegrad region (which is composed of the Czech Republic, Hungary, Poland and Slovakia). The Visegrad region (or V4) is a particularly interesting case, as it is well connected to the global economy and has strong historical, cultural and economic times with its German speaking neighbours. Yet the region's population only has a limited knowledge of foreign languages (according to the 2012 Eurobarometer).

4.6.1 Demand for foreign language skills for all occupations

We started our case study by *extracting the total number of vacancies* from each job portal (15,269 vacancies were available on the Czech job board, 11,231 on the Hungarian job board, 36,079 on the Polish job board and 11,344 on the Slovak job board, i.e. about 74,000 advertisements in total across the countries and considering all occupations). Then, we considered *how many of these carried tags refer to foreign language skills*.[20]

19 One also has to keep in mind that the tags are not disjunctive groups: a single vacancy may carry multiple tags.

20 In practice, job seekers can indicate on the website that they are looking for a position where 'English' is a requirement, filtering out jobs for which this is not needed.

Many of the vacancies published on the job portals do not require any foreign language skills, i.e. they carry the ‘no foreign languages needed’ tag. More specifically, 38% of the vacancies of the Czech job board do not call for foreign language skills. This percentage is equal to 25% for Hungary and 43% for Slovakia. As no such tag is available on the Polish job board, we have no information on the share of vacancies that do not require any foreign language skills in this case (and we cannot calculate this number, as a single job advertisement may have multiple tags). In addition, we can only use advertisements that are explicitly tagged. Nevertheless, from these first results we can already conclude that there is substantial heterogeneity across the four countries when it comes to foreign language skills demand. In addition, the demand for such skills can be quite substantial.

We then focus on the occupations that do carry foreign language tags. In Table 4.17, we report the share of vacancies that refer to foreign languages, including English, German, French, Spanish, Italian and Russian. When all vacancies are considered simultaneously, we find that 52% of them is tagged ‘English’, 12% is tagged ‘German’, 2% is tagged ‘French’, and less than 2% is tagged ‘Italian’, ‘Spanish’ or ‘Russian’. English clearly is the most requested foreign language while German comes in the second place. This pattern re-emerges if we focus on each of the countries separately. In all countries, English is the most-frequently-requested foreign language but there is considerable variation: whereas 28% of the Czech vacancies are tagged ‘English’, this number reaches 64% in Poland (for Hungary it is 39%, for Slovakia 49%). German is the second-most-demanded language in each of the countries, though the percentage of vacancies that carries this tag is much smaller than for English. Across the V4, the share ranges from 10% in the Czech Republic to 15% in Slovakia. Even though French, Italian and Spanish are used extensively in the EU, these three languages are hardly demanded in the Visegrad labour markets.

Table 4.17 Share of vacancies for each country and in total that list foreign language skills

	Czech Republic	Hungary	Poland	Slovakia	Total
English	28.19	38.92	63.99	49.26	51.89
German	10.15	10.86	12.45	14.59	12.36
French	0.65	1.25	3.56	1.50	2.33
Italian	0.19	0.67	1.65	0.55	1.05
Spanish	0.15	0.52	2.13	0.48	1.23
Russian	0.54	0.21	1.60	0.48	0.96
None	37.62	23.66	N/A	42.67	N/A

These percentages should be interpreted with some caution, as they might reflect seasonal dynamics (our data were collected in the month of July). To rule out seasonal dynamics, we contacted each of the job boards to inquire about the statistics for the entire year 2015. The Slovak job board informed us that 46% of the vacancies required English, while 14% required German. In the Czech Republic, the 10% share of advertisements for German was confirmed, but the share for English was reported to vary between 28% and 59% depending on whether the vacancies were supplied by public employment agencies or employers. The Hungarian portal reported that 55% the vacancies demanded English or German, 10% specifically requests English and 2% specifically call for German. We did not receive any further information from the Polish job board, unfortunately.

4.6.2 Demand for foreign language skills for a subset of occupations which could be identified in all four countries

As a next step, we reduce our sample and focus only on those occupations for which we can find at least 30 vacancies in each of the V4 countries. To this end, we had to map occupations from the different countries (i.e. to check which occupations match). This mapping resulted in a subsample of 59 occupations which could be identified in all four countries. For these occupations, we again derived the total number of available job advertisements and the share of these advertisements that refer to foreign language skills from the job boards.

The 59 occupations are listed in Table 4.18, which also presents the share of vacancies in each of the countries that require English language skills. Especially occupations with ISCO codes 2 and 4, the professional and administrative occupations, frequently demand English language skills. For occupations involving manual work, such skills seem to be less important. Another interesting result is that particularly in Poland, some of the ISCO 7 occupations (craftsmen), show a relatively high demand for English language skills. This may indicate that these workers are employed by foreign employers or that they work abroad. Figure 4.7 summarises these results, by subdividing the occupations into three groups depending on whether the share of vacancies that call for English language skills is high or low.

Table 4.18 Share of vacancies that require English language skills across the Visegrad region*

ISCO	Occupation	Czech Republic	Hungary	Poland	Slovakia
1135	HR Manager	87	42	67	67
1211	Financial Manager	63	54	62	50
1213	Operations Manager	53	48	65	59
1221	Marketing Manager	71	95	79	86
1221	Sales Director	53	45	49	51
1321	Production Director	69	50	55	74
2139	Consultant	44	64	49	66
2141	Industrial Engineer	86	81	85	83
2142	Civil Engineer	23	24	22	34
2149	Tester	88	87	76	89
2164	Architect	66	50	64	79
2211	Doctor	31	56	44	26
2221	Nurse	27	30	64	21
2330	Teacher	51	15	55	27
2411	Financial Controller	83	78	72	93
2411	Tax Advisor	81	50	86	98
2412	Financial Analyst	81	78	72	88
2431	Business Analyst	74	97	81	70
2431	Key Account Manager	63	90	45	71
2431	Marketing Professional	68	85	55	71
2433	Product Manager	83	94	74	74
2511	IT Analyst	81	87	74	88
2512	Programmer	82	84	77	85
2519	Computer Specialist	82	83	74	80
2519	Project Manager	81	68	75	84
2611	Lawyer	72	42	72	90
3112	Technician	56	35	34	46
3119	Quality Control	72	61	57	50
3122	Foreman	33	15	34	54
3323	Buyer	84	86	68	81
3341	Office Manager	76	91	58	78
3341	Team Leader	73	83	42	76
3511	IT Administrator	81	67	72	87

Table 4.18 Share of vacancies that require English language skills across the Visegrad region* (continued)

ISCO	Occupation	Czech Republic	Hungary	Poland	Slovakia
3512	Customer Support Worker	67	66	58	69
3538	Account Manager	53	93	48	67
4226	Receptionist	87	86	67	87
4232	Transport Clerk	70	69	57	65
4311	Accountant	74	51	73	79
4419	Assistant	73	70	71	68
4419	Office Worker	61	52	61	70
5120	Cook	26	10	27	12
5222	Sales Team Leader	37	36	28	46
5223	Retail assistant	25	15	29	15
5230	Cashier	36	11	10	15
5242	Financial advisor	10	59	18	10
5242	Merchandiser	39	33	15	13
5242	Regional Sales Representative	48	27	35	68
5242	Sales Representative	41	36	29	38
5244	Telesales/Call Centre	29	16	23	50
7212	Welder	3	6	39	10
7231	Mechanic	20	10	32	16
7233	Locksmith	4	7	44	8
7411	Electrical Mechanic	44	3	26	32
7411	Electrician	23	6	42	16
8121	Labourer	5	8	12	5
8322	Driver	21	3	19	18
8344	Forklift Operator	9	5	7	4
9321	Packer/Auxiliary Labourer	4	14	11	11
9333	Warehouse Worker	11	7	10	13

* The occupations with the highest share are indicated in blue, the occupations with the lowest share in red.

Figure 4.7 **Classification of occupations into three classes depending on the demand for English language skills across the Visegrad region**

When repeating this analysis for German, it becomes clear that the results are noisier as there is much less variation across the occupations. For only 14 of the 236 country-occupation combinations, more vacancies were tagged ‘German’ than ‘English’. These are all artisan occupations, particularly welders and locksmiths, as well as nurses in the case of Slovakia. The latter result reflects the high level of circular migration of Slovak nurses to the German-speaking countries, in particular Austria (Bahna, 2014). In general, the demand for German does not seem so dependent on occupation complexity, as it is in the case of demand for English. We find several ‘manual’ occupations in the group with the highest demand for language skills (Figure 4.8).

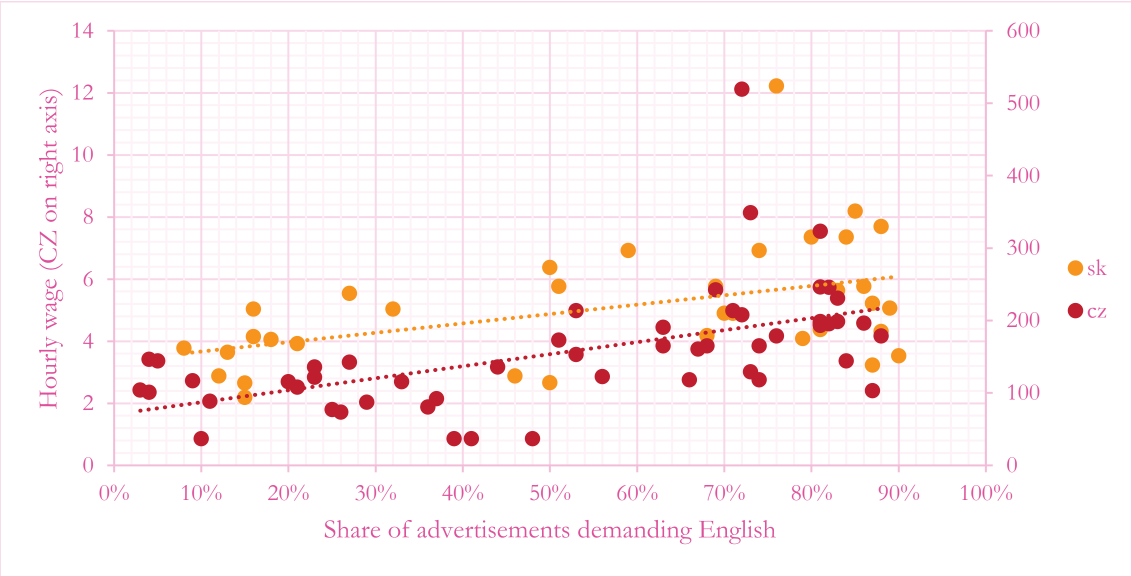
Figure 4.8 **Classification of occupations into three classes depending on the demand for German language skills across the Visegrad region**

highest	intermediate	lowest
Quality Control	Receptionist	Account Manager
Industrial Engineer	Electrical Mechanic	Business Analyst
Office Manager	HR Manager	Doctor
Transport Clerk	Mechanic	Financial Analyst
Buyer	Teacher	Retail assistant
Welder	Project Manager	Financial Controller
Customer Support Worker	Telesales/Call Centre	Consultant
Production Director	Programmer	Financial Manager
Computer Specialist	Tester	Marketing Professional
Office Worker	Locksmith	Civil Engineer
Architect	Operations Manager	Packer/Auxiliary Labourer
Accountant	Sales Director	Warehouse Worker
Assistant	Tax Advisor	IT Analyst
Nurse	Key Account Manager	Cook
Foreman	IT Administrator	Financial advisor
Technician	Product Manager	Forklift Operator
Electrician	Sales Representative	Labourer
Lawyer	Team Leader	Marketing Manager
Regional Sales Representative	Sales Team Leader	Merchandiser
Driver		Cashier

4.6.3 A wage premium for foreign language skills?

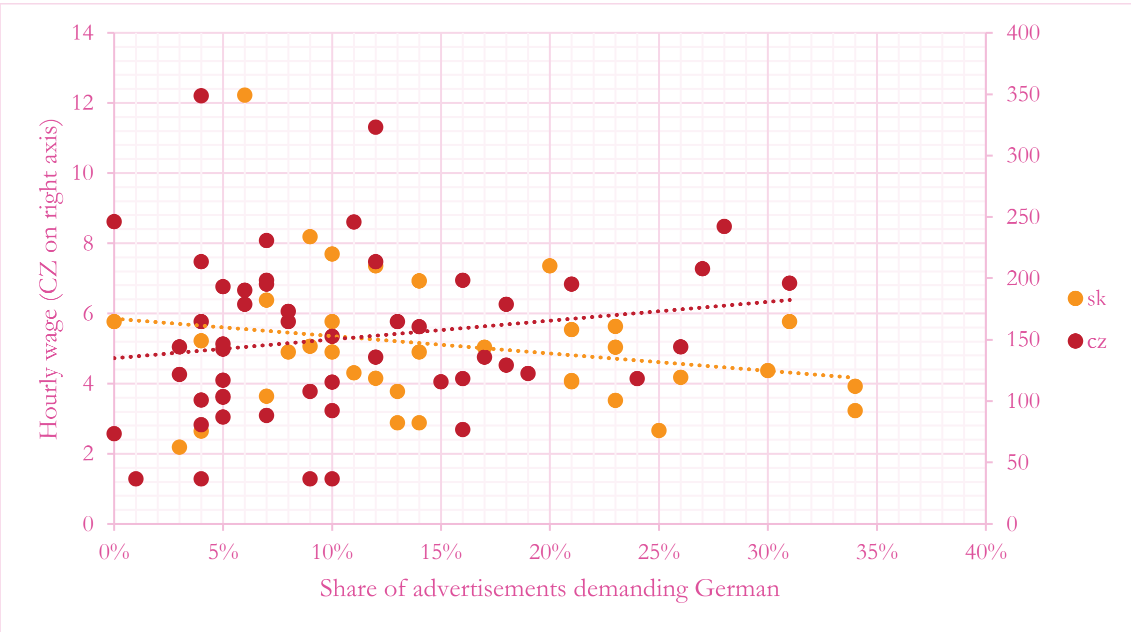
For two of the Visegrad countries, the Czech Republic and Slovakia, we were able to find data on the hourly wages (expressed in the national currency) for some occupations. The data are based on the median hourly gross wages, obtained from the WageIndicator web surveys collected from 2013 to Q1 2016. Our data cover 53 occupations for the Czech Republic and 49 occupations for Slovakia. While there is a clear positive correlation between the shares of vacancies that require English and wages in both (see Figure 4.9), the correlation between the German language demand and wages is much weaker and even negative for Slovakia (Figure 4.10). Following up on our previous line of thought that much of the demand for German speakers might be for jobs located in German-speaking countries, the lack of monetary premium associated with speaking German might be unobservable on the Slovak labour market simply because German speakers are collecting it abroad.

Figure 4.9 **Correlation between the share of job advertisements that require English and the hourly wages in the Czech Republic and Slovakia**



Source WageIndicator data for the Czech Republic and Slovakia

Figure 4.10 **Correlation between the share of job advertisements that require German and the hourly wages in the Czech Republic and Slovakia**



Source WageIndicator data for the Czech Republic and Slovakia

As a question about English proficiency was recently added to the WageIndicator survey, we can test its effect on the individual level as well. Table 4.19 shows by and large results we would intuitively expect: Experience and education increase earnings, along with living in the capital cities of Prague and Bratislava, holding a supervisory position and working in a high-skilled occupation and a partly of fully foreign-owned company. Experience squared, meanwhile, has a negative effect on earnings, along with female gender and being located in Slovakia as opposed to the Czech Republic. Effects of firm size and private sector employment are insignificant. We find that English proficiency matters. Workers skilled in English earn more than those with no or only limited skills. Yet, basic proficiency in English does not seem to make a difference for wages, only workers who reach at least the 'rather skilled' level enjoy the earnings premium.

Table 4.19 OLS analysis of the impact of English proficiency on wages in the Czech Republic and Slovakia

		Coefficient	**Standard error**
Individual characteristics	Years of Experience	0.024***	0.006
	Years of Experience Squared	-0.000***	0.000
	Years of Education	0.023***	0.008
	Female	-0.229***	0.039
	Living in the capital city (Prague or Bratislava)	0.238***	0.048
	Living in Slovakia (compared to living in Czechia)	-0.097**	0.040
	English skill level (reference category: no English)		
	- Basic	0.048	0.055
	- Rather skilled	0.186***	0.063
	- Skilled	0.193***	0.069
Employer Characteristics	Private Company	-0.012	0.040
	Firm ownership (reference category: domestic owned company)		
	- Partly foreign owned company	0.297***	0.090
	- Fully foreign owned Company	0.137***	0.043
	Firm size (reference category: less than 20 workers)		
	- 20 to 50 workers	0.105	0.069
	- 50+ workers	0.092	0.059
Occupation characteristics	ISCO 1-4 job	0.196***	0.039
	Supervisory Position	0.113**	0.048
	Constant	0.811***	0.143
	Number of observations	437	
	R-squared	0.370	

* p<0.1; ** p<0.05; *** p<0.01

4.6.4 Summary

- One-third to three-fourths of the vacancies published on the four job boards demands foreign language skills (i.e. they carry a foreign language tag).
- English is the most-frequently-requested foreign language in the Visegrad group. 52% of the job advertisements calls for English language skills, yet less than one-third of the population is able to have a conversation in the language (according to the 2012 Eurobarometer). The demand for English is higher for occupations that are more complex than for those that are less complex. English thus is a language of professional and white collar workers. Moreover, English language skill comes with a wage premium.
- German, which is found in 12% of the job advertisements, is the second-most-in-demand foreign language in the Visegrad region. Interestingly, the 2012 Eurobarometer results reveal that 15% to 22% of the Visegrad population has sufficient German language skills to hold a conversation in the language. For German, there is no link between the demand for language skills and the complexity of an occupation.
- Other languages, such as French, Italian, Spanish and Russian, are only requested in a small minority of the vacancies. Only very few advertisements carry these tags.

4.7 Case Study 6: 'Cross-cutting work on non-cognitive skills'

Throughout the case studies that are presented so far in this report, we looked into different types of skills, including cognitive skills. The last case study focuses on the *non-cognitive skills* (or 'soft' skills). As already stated earlier in this report, non-cognitive skills can be regarded as personality traits that, alongside cognitive skills, also impact social and economic outcomes such as educational attainment or earnings. Examples of non-cognitive skills are reliability, team-working skills and resistance to stress.

This final case study aims at providing an overview of what can be learnt from online vacancy data about the labour demand, i.e. employers' requirements, in terms of non-cognitive skills. Unlike the other case studies in this report, which are all based on only one research paper, this case study is cross-cutting: it combines results on non-cognitive skills from three research works. Based on the ILO's ISCO classification, the first two research works we present in this case study focus on low-skilled and medium-skilled occupations.[21] The first paper analyses job advertisements posted on EURES, a public EU job portal, in Denmark, the Czech Republic and Ireland (Kureková *et al.*, 2015), whereas the second one explores vacancy data from Profesia.sk, the largest online job portal in Slovakia (Beblavý, *et al.*, 2016e). Finally, the last research work used in this case study is the work using vacancy data obtained from Burning Glass Technologies (Beblavý *et al.*, 2016c). This work was already presented in the second case study of this report, but here, we focus on the results on non-cognitive skills.

In the three works that we present in this case study, our approach uses very similar non-cognitive skills categorisations. They are based on our analysis of advertisements from EURES and Profesia.sk to identify skills that appear most frequently (these papers are not part of the InGRID project, but we discuss them here due to their high relevance). These categorisations divide non-cognitive skills into two different groups, *personal characteristics* and *social skills* (in Table 4.20). The former captures personal traits that determine how one approaches a task, including reliability, timeliness, independence, creativity, flexibility, manners and stress-resistance. The latter captures personal traits that determine how one interacts and communicates with others. This set of skills comprises communication, team-working and service skills.

In the remainder of this section, we first present the main results regarding non-cognitive skills of the three above-mentioned research works. Then we highlight the main differences and similarities across the five countries that are analysed (Denmark, Ireland, the Czech Republic, the United States and Slovakia).

21 Based on the ISCO classification, we consider occupations in category 9 (1st ISCO skill level) as low-skilled, and occupations in categories 4 to 8 (2nd skill level) as medium-skilled.

Table 4.20 Categorisation of non-cognitive skills

Social skills	Personal skills
Communication skills	Timeliness, punctuality
Service skills, customer approach	Independence
Team-working skills	Reliability
	Creativity
	Flexibility
	Resistance to stress
	Responsibility
	Pleasant demeanour and manners

Note: responsibility and pleasant demeanour and manners are not mentioned in Kureková *et al.* (2015); timeliness/punctuality, creativity and resistance to stress are not mentioned in Beblavý, *et al.* (2016e); responsibility is not mentioned in Beblavý *et al.* (2016c).
Source Authors' own compilation

4.7.1 'Employers' skill preferences across Europe: between cognitive and non-cognitive skills'

(Kureková et al., 2015)

In this work, we seek to study the content of job advertisements for low- and medium-skilled occupations published on the public EU job portal EURES - the European Job Mobility Portal -, between March and July 2012. EURES, which was founded in 1993, is a platform that aims at providing information, advice and recruitment/placement services for workers and employers, as well as for any citizen wanting to take advantage of the free movement of persons. It is run by the European Commission (DG EMPL) and is free of charge for job seekers and employers. National public employment services (PES) link their own vacancy databases to the portal, where the openings are collected and posted in a semi-structured way and in pre-designed categories, creating a large 'standardised' collection of job openings across the participant countries. The portal is estimated to cover 30-40% of the overall European market for vacancies (Ackers, 2012). In 2012, on average 750,000 CVs were live in the system at any time in a given month, and about 26,000 employers had accounts.

We focus on three countries that are small open European economies: the Czech Republic, Denmark and Ireland. These countries are comparable in labour market size but differ in a number of aspects, e.g. economic structure, the design of education and skill formation systems, and the degree to which they have been affected by the recent economic crisis.

From the list of predefined occupational groups on the EURES website, we selected a range of medium- and low-skilled occupational groups from the service sector and industry. Medium-skilled occupations in the service sector include hotel, catering and sales staff (ISCO 5) and office staff (ISCO 4). Medium-skilled occupations in industry include metal and machinery workers (ISCO 7) and machine operators and assemblers (ISCO 8). Low-skilled service occupations include elementary occupations in sales, services, cleaning and various types of labourers in industry, all of which belong to ISCO 9. We downloaded the data by using self-developed custom-made software, which we dubbed 'grabber'. The grabber was programmed to download selected and identified fields from vacancies posted in a particular occupational group. A binary code for the job description field was then created to mark those advertisements where a particular skill or capability (from the list of skills in Table 4.20) was mentioned. We then proceeded with the analysis of data to calculate frequencies and simple statistics across occupations and across countries.

Table 4.21 shows how many job advertisements within a particular occupational group requested at least one skill or competence within one of the two groups of non-cognitive skills as defined earlier.[22] The results reveal interesting variations among occupational groups within countries and also point to differences across the three countries analysed. In the Czech Republic, while non-cognitive skills, in particular social skills, are less sought in ‘industrial occupations’ (ISCO 7 and 8), they are also infrequently sought for the hotel and catering group, which is perhaps surprising. In Ireland, differences among occupational groups are less significant than in other countries. In the Danish labour market, employers seek non-cognitive personal characteristics (52.2% of vacancies request at least one particular skill in the non-cognitive personal skills group) more than experience (33.1% of job advertisements request experience), which is not the case in the Czech Republic and Ireland. Even for the non-cognitive social skills group, the share of job advertisements is relatively high in Denmark (31.5%), almost at the same level as experience (33.1%) and at a much higher level than formal degrees (13.5%). Conversely, in Ireland and the Czech Republic, the shares of vacancies referring to non-cognitive social skills and personal skills are lower than the shares of vacancies requesting experience (93.9% in Ireland, 60.7% in the Czech Republic) and formal degrees (22.0% in Ireland, 28.7% in the Czech Republic).

Table 4.21 Share of job advertisements requesting at least one particular non-cognitive skill, depending on the occupational groups (%)

		Hotel, catering and personal services staff	Sales staff and fashion work	Office staff	Metal, machinery and electronic equipment workers	Machine operators and assemblers	Sales, services and cleaning elementary occupations	Labourers in mining, construction manufacturing and transport	Total
Non-cognitive social	Czech Republic	5.2	23.6	27	2.4	3.1	7.2	3	9.2
	Ireland	10.8	-	15.0	6.3	-	10.6	3.5	10.7
	Denmark	22	48.2	52.7	26.1	25	25.5	13	31.5
Non-cognitive personal	Czech Republic	22.3	29.1	40.5	22	23.7	21.4	19.8	24.7
	Ireland	19.2	-	15.2	8.5	-	11.5	11.4	15.2
	Denmark	55.7	48.6	67.2	57.7	0	47.7	54.2	52.2

Source Kureková *et al.* (2015), based on EURES data

The results for each skill, competence or capability are presented separately in Table 4.22. In addition to skill frequencies (the share of job advertisements where a specific skill was explicitly demanded), we provide the sum of skills shares for each skill subcategory.

In the Czech labour market, non-cognitive social skills and personal characteristics are relatively more important for sales and fashion staff, and office staff. Communication skills, independence and reliability dominate. Non-cognitive skills are requested in addition to formal qualifications rather than instead of them, as in the Czech labour market formal qualifications remain important. In Ireland, some non-cognitive skills like communication and flexibility are more demanded than others on average. However, unlike in the Czech Republic, the variability among occupational groups is quite small. In particular, there is no clear-cut difference between service and industry sector occupations with respect to non-cognitive skills. Regarding the Danish labour market, non-cognitive skills are

22 In the Irish data, two occupational categories are missing, because we did not manage to obtain the target number of about 500 vacancies in each given cell.

highly requested, more than in the other two countries. Being service-oriented, having team skills, being independent and especially flexible are widely sought attributes. Among occupations, non-cognitive skills are more widely requested in service-related occupations.

Table 4.22 Share of job advertisements for which a particular skill was demanded (%)

			Hotel, catering and personal services staff	**Sales staff and fashion work**	**Office staff**	**Metal, machinery and electronic equipment workers**	**Machine operators and assemblers**	**Sales, services and cleaning elementary occupations**	**Labourers in mining, construction manufacturing and transport**	**Total**
Czech Republic	Non-cognitive social	Communication	4.8	23.3	25.5	1.9	1.8	6.6	2.2	8.5
		Service-oriented	0.2	1.3	0.3	0.0	0.0	0.6	0.0	0.3
		Team skills	0.3	0.5	2.8	0.9	1.8	1.3	0.9	1.0
		Total	**5.3**	**25.0**	**28.6**	**2.8**	**3.5**	**8.5**	**3.0**	**9.8**
	Non-cognitive personal	Timeliness	0.3	0.0	0.0	0.0	0.0	0.2	0.2	0.1
		Independence	10.1	11.4	21.1	13.7	10.1	6.3	5.2	11.6
		Reliability	9.5	13.0	17.1	9.5	12.7	12.1	12.4	11.4
		Creativity	1.6	1.3	1.0	0.2	0.4	0.2	0.9	0.9
		Flexibility	9.4	13.1	20.6	7.0	11.4	8.9	6.5	10.2
		Stress-resistant	1.0	0.7	4.7	0.4	0.9	1.3	0.2	1.1
		Total	**31.9**	**39.5**	**64.5**	**30.8**	**35.5**	**28.8**	**25.4**	**35.2**
Ireland	Non-cognitive social	Communication	4.8	-	13.0	4.5	-	8.1	0.0	6.8
		Service-oriented	1.2	-	0.7	0.0	-	0.4	0.9	0.8
		Team skills	5.3	-	2.9	2.2	-	2.9	2.6	3.8
		Total	**11.3**	**-**	**16.7**	**6.7**	**-**	**11.5**	**3.5**	**11.5**
	Non-cognitive personal	Timeliness	0.9	-	4.8	0.9	-	1.0	3.5	1.8
		Independence	0.1	-	0.0	0.4	-	0.2	0.0	0.1
		Reliability	5.7	-	1.4	3.1	-	1.9	5.3	3.7
		Creativity	1.9	-	0.5	0.0	-	0.0	0.0	0.9
		Flexibility	13.2	-	8.7	4.9	-	8.5	7.0	10.1
		Stress-resistant	1.4	-	1.2	0.9	-	0.6	0.0	1.1
		Total	**23.2**	**-**	**16.7**	**10.3**	**-**	**12.3**	**15.8**	**17.7**
Denmark	Non-cognitive social	Communication	1.7	1.6	9.9	1.8	0.0	2.2	0.5	2.9
		Service-oriented	9.4	42.1	36.0	11.6	0.0	19.4	1.6	22.0
		Team skills	13.1	21.3	27.4	14.4	25.0	5.6	11.5	15.1
		Total	**24.2**	**65.0**	**73.4**	**27.8**	**25.0**	**27.2**	**13.5**	**40.0**
	Non-cognitive personal	Timeliness	0.5	0.2	2.7	1.1	0.0	4.5	0.0	1.7
		Independence	20.0	19.3	36.0	34.2	0.0	22.1	27.1	24.5
		Reliability	7.4	8.2	3.0	12.0	0.0	6.6	27.1	8.6
		Creativity	12.1	10.9	2.7	1.8	0.0	1.3	0.5	5.9
		Flexibility	37.4	32.0	43.5	31.0	0.0	24.3	20.8	31.9
		Stress-resistant	4.5	6.3	16.4	3.5	0.0	2.2	1.0	5.6
		Total	**81.9**	**76.8**	**104.3**	**83.5**	**0.0**	**60.9**	**76.6**	**78.2**

Source Kureková *et al.* (2015), based on EURES data

4.7.2 'The surprisingly exclusive nature of medium- and low-skilled jobs - evidence from a Slovak job portal'

(Beblavý, et al., 2016e)

This work analyses the characteristics of labour demand by studying the content of job advertisements in Slovakia in selected low- and medium-skilled occupations. The data analysed in this work come from the largest online job portal in Slovakia (Profesia.sk). The company running the portal was established in 1997. The portal became a market leader in the early-to-mid 2000s and currently enjoys a market share of approximately 80% (Štefánik, 2012). It collects both vacancies and CVs.

We selected occupations with the aim of covering a wide range of low- and medium-skilled occupations from industry and services. Raw data were received from the portal database for the selected occupations for all advertisements posted between 2007 and 2011. After cleaning the data, we were left with over 50,000 distinct job advertisements to analyse. This selection of occupations covers 7.4% of all vacancies posted between 2007 and 2011. We used multiple techniques to process and code the data. In particular, the job description field in the advertisement was recoded to mark those vacancies in which a particular skill or capability from the categorisation of skills was mentioned, using a binary code.

Table 4.23 presents the shares of job advertisements requesting each skill, focusing on non-cognitive skills. Among the main results on non-cognitive skills of this work, we found that employers' skills demand for low- and medium-skilled jobs focuses on non-cognitive skills (and also specific cognitive skills) rather than on general cognitive skills. In the analysed vacancies, the most-requested requirement was previous experience (52%), followed by knowledge of languages (38%), responsibility (29%), communication skills (28%) and flexibility (24%). There seems to be a 'basic package' of non-cognitive skills (communication skills, flexibility and responsibility) that is required nearly across the board in Slovakia, together with specific cognitive skills like knowledge of foreign languages.

Another interesting finding is that skill intensity varies for occupations with the same level of education and is driven by demand for non-cognitive skills. For example, the education level required for engine driver and salesperson is similar, though these occupations differ markedly in their overall skill intensity. A much higher share of job advertisements for salesmen than for engine drivers requires non-cognitive skills. Non-cognitive skills are in particular related to interactive service occupations.

Table 4.23 Share of job advertisements requesting skills, depending on the occupation (%)

	Non-cognitive social				Non-cognitive personal					
	Communic	Team work	Pro-client	Average	Responsible	Reliable	Independent	Flexible	Demeanor	Average
Salesperson	59.0	9.3	9.8	**26.0**	31.5	16.9	25.6	32.7	32.3	**27.8**
Bartender	29.3	6.9	5.7	**14.0**	25.0	9.1	14.1	28.3	31.3	**21.6**
Waiter	28.2	7.3	5.1	**13.5**	27.1	9.4	14.4	26.2	29.9	**21.4**
Electrician	14.7	8.6	3.1	**8.8**	35.6	20.2	33.1	26.4	1.2	**23.3**
Courier	38.2	1.7	2.8	**14.2**	18.6	13.3	8.8	15.9	29.6	**17.2**
Au-pair	14.9	0.0	0.0	**5.0**	35.8	20.2	10.6	23.4	12.1	**20.4**
Romm staff	9.1	3.9	5.3	**6.1**	18.0	7.5	7.6	26.1	13.7	**14.6**
Cook	15.2	7.3	3.9	**8.8**	29.5	10.6	19.2	23.5	9.6	**18.5**
Driver	14.5	2.5	0.5	**5.8**	35.6	22.5	14.7	24.6	10.6	**21.6**
Forklift driver	3.9	8.9	0.3	**4.4**	40.1	21.5	19.8	24.1	0.3	**21.2**
Maintenance	10.6	7.1	0.1	**5.9**	27.6	9.2	27.3	18.8	1.3	**16.8**
Porter	22.5	1.3	0.7	**8.2**	27.2	21.2	6.0	19.2	21.2	**18.9**
Plumber	16.7	3.3	0.3	**6.8**	28.3	8.2	19.8	19.8	4.9	**16.2**
Bus driver	12.8	2.3	0.8	**5.3**	19.5	11.3	15.8	26.3	15.0	**17.6**
Cleaner	8.3	2.1	3.3	**4.6**	34.2	21.5	12.0	17.4	11.5	**19.3**
Truck driver	5.8	0.9	0.6	**2.4**	24.9	17.5	16.8	19.4	5.9	**16.9**
Caretaker	7.2	0.9	0.0	**2.7**	14.3	3.7	6.0	12.5	4.1	**8.1**
Assembly worker	8.4	9.0	1.4	**6.3**	25.7	13.1	19.3	15.1	2.4	**15.1**
Security guard	18.9	1.0	0.3	**6.7**	24.9	14.4	3.6	5.7	17.6	**13.3**
Tailor	12.9	14.6	1.0	**9.5**	30.9	6.1	20.9	5.6	3.5	**13.4**
Labourer	2.8	4.5	0.0	**2.4**	23.7	12.4	8.8	11.6	0.4	**11.4**
Engine driver	13.0	1.1	0.0	**4.7**	13.0	2.2	21.7	19.6	0.0	**11.3**
Postman	12.3	1.1	0.0	**4.5**	5.4	5.0	4.6	11.1	8.4	**6.9**
Total	**28.4**	**6.7**	**4.6**	**13.2**	**28.8**	**14.3**	**18.3**	**23.9**	**17.9**	**20.6**

Source Beblavý, *et al.* (2016e), based on profesia.sk data

4.7.3 'Skills Requirements for the 30 most-frequently advertised occupations in the United States'

(Beblavý et al., 2016c)

This work is based on vacancy data obtained from Burning Glass Technologies for the United States (Beblavý *et al.*, 2016c). It is already presented in the second case study of this report (in Section 3.1.2); so we only present results for non-cognitive skills here.

With regards to the non-cognitive skills, we examined three sets of *social skills*, i.e. the service skills, communication skills and team-working skills, and 7 sets of *personal skills*, i.e. timeliness, independence, reliability, pleasant demeanour/manners, creativity, flexibility, and stress-resistant. Neither social nor personal skills appear to dominate one another. Both types of non-cognitive skills are frequently requested in vacancies. However, there are substantial differences between the subcategories within the groups of social and personal skills and across occupations. The range of values (i.e. the percentages of advertisements that contain the skills) is extensive.

Among the social skills, service skills are requested more than team-working and communication skills. Service skills (which also captures applicants' customer approach, client-orientation) appear in about 49% of the advertisements (and 45% if the average is calculated). This number varies between 7% and 91%. Variation across occupations is thus rather large. For 12 occupations, over half of the vacancies refer to service skills. For five occupations, no less than two-thirds of the vacancies mention service skills. These occupations are customer service representatives (66%), tellers (74%), retail salesperson (80%), sales agents, financial services (82%) and meeting, convention, event planners (91%). Given the nature of these occupations, which are all in the sales, services and support domains, it does not come as a surprise that they are at the top of the list in terms of percentages.

Communication skills are found in 23% of the vacancies. Across the 30 occupations, it is present in 3% to 63% of the vacancies. For four occupations, communication skills are listed in at least 30% of the vacancies: installation, maintenance, repair workers (31%), first-line office supervisors (32%), merchandise displayers (38%) and security guards (63%). Besides communication and service skills, team-working skills are also frequently mentioned in job advertisements: 31% of the vacancies refer to team work. For most of the 30 occupations, team work skills could be valuable. Of course, the role of the worker within the company and the firm's internal organisation can also have an impact on whether or not team work is needed. The percentage of vacancies that refers to team work ranges from 5% to 49%. 12 occupations show higher percentages than the average. The occupations with the highest percentages are supervisors of food preparation, serving workers (49%), general and operations managers (48%), combined food preparation workers (46%), retail salesperson (41%) and tellers (39%). For each of these occupations, one can imagine that team working skills are an important part of the position.

Table 4.24 **Share of job advertisements across occupations with communication skills, service skills and team-working skills requirements**

ISCO	Occupation	Share with communication skills (%)	Share with service skills (%)	Share with team-working skills (%)
1	General and Operations Managers	27	48	48
2	Computer Support Specialists	23	54	28
2	HR Specialists	24	34	30
3	Bookkeeping, Accounting, Auditing Clerks	21	34	25
3	First-Line Office Supervisors	32	57	34
3	Medical Assistants	19	27	26
3	Meeting, Convention, Event Planners	3	91	5
3	Nursing Assistant	18	12	25
4	Cashiers	27	58	23
4	CS Representatives	20	66	38
4	Medical Secretaries	22	29	21
4	Office Clerks	18	33	21
4	Secretaries	23	30	24
4	Tellers	30	74	39
5	Combined Food Preparation Workers	17	44	46
5	Cooks, Restaurant	19	21	29
5	Merchandise Displayers	38	46	31
5	Personal Care Aides	14	7	21
5	Retail Salesperson	22	80	41
5	Sale Worker Supervisors	28	61	37
5	Sales Agents, Financial Services	8	82	24
5	Sales Representative Wholesale	21	62	33
5	Security Guards	63	51	27
5	Supervisors Of Food Preparation, Serving Workers	22	43	49
7	Installation, Maintenance, Repair Workers	31	56	24
7	Maintenance Worker	18	19	22
8	Heavy Truck And Tractor Drivers	13	35	16
8	Light Truck, Delivery Service Drivers	20	43	19
9	Janitors and Cleaners	16	16	17
9	Labourers	12	26	23
	Across occupations	**23**	**49**	**31**

Source Beblavý *et al.* (2016c), based on Burning Glass data

We then zoom in on the personal non-cognitive skills. At first sight, the personal skills appear to be somewhat less related to specific jobs or occupations than the social skills. The percentages indeed vary from 3 to 33% across the 7 sets of skills (the averages range from 3 to 32%). More specifically, when considering all occupations, the percentage of job advertisements that lists timeliness and punctuality is 27% (ranging from 6 - 55%), independence 18% (2 - 44%), reliability 3% (0 - 13%), pleasant demeanour, manners 15% (5-47%), creativity 24% (3-44%), flexibility 33% (15-60%) and stress-resistant 5% (0-35%). The highest correlations between the percentage of vacancies and the ISCO classification are found for timeliness (-0.45) and creativity (-0.48). As occupations become more complex, punctuality and creativity are required more often.

Table 4.25 below presents the five occupations with the highest share of vacancies that require a specific personal non-cognitive skill. When the share was the same for multiple occupations, all these occupations are reported. Interestingly, there are a number of occupations that are in the top 5 for several of the skills: security guards, general and operations managers, meeting, convention, event planners, first-line office supervisors and tellers are present for at least three of the skills.

Table 4.25 **The five occupations with the highest share of vacancies that require each of the 7 skills listed (when more than five occupations are listed - there were multiple occupations with the same percentages, 1 = highest percentage, 5 = lowest)**

	Timeliness	**Independence**	**Reliability**	**Demeanour**	**Creativity**	**Flexibility**	**Stress-resistant**
1	Meeting, Convention, Event Planners	Security Guards	Tellers	Security Guards	Sale Worker Supervisors	Merchandise Displayers	Security Guards
2	Security Guards	Merchandise Displayers	Personal Care Aides	Cashiers	Tellers	Sales Agents, Financial Services	Medical Secretaries
3	General and Operations Managers	HR Specialists, Secretaries	Bookkeeping, Accounting, Auditing Clerks	Meeting, Convention, Event Planners	Computer Support Specialists	Meeting, Convention, Event Planners	First-Line Office Supervisors
4	First-Line Office Supervisors		First-Line Office Supervisors, CS Representatives, Office Clerks, Secretaries	Merchandise Displayers	CS Representatives, General and Operations Managers	Sale Worker Supervisors	Personal Care Aides, Medical Assistants
5	Sales Representatives Wholesale	General and Operations Managers		Medical Secretaries		Tellers	

Source Beblavý *et al.* (2016c), based on Burning Glass data

4.7.4 What are the main similarities and the main differences among the five countries analysed in this case study?

Regarding low-skilled and medium-skilled occupations, the first important difference among the five countries analysed in this case study is the separation between a group of 'more formalised' labour markets (Czech Republic, Ireland and US) and a group of 'less formalised labour market' (Denmark and Slovakia). In this study, we use this term to indicate that cognitive skills are more demanded than non-cognitive skills. In other words, the former group comprises countries where cognitive skills are more demanded than non-cognitive ones, whereas the latter comprises countries where non-cognitive skills are more demanded.

In the group of 'more formalised' labour market, the Czech Republic is the first example. In the Czech Republic, formal education is requested widely with the exception of selected service occupations. More than non-cognitive skills, cognitive abilities prevail and this is the case also in the service-related occupations. In the least skilled segment, reliability and flexibility are sought. Regarding the dominance of cognitive skills, there are similarities between the Czech Republic and Ireland, where experience and a range of cognitive skills (including knowledge of English) prevail over non-cognitive skills and characteristics. The US can also be included in this group of 'more formalised' labour markets, as the role of non-cognitive social skills and personal traits seem to be relatively small in the skills required for low- and mid-skilled occupations.

Conversely, employers in the Danish labour market demand much less formal education and cognitive abilities, and from this perspective labour demand is less formalised. In Denmark, it is strongly focused on non-cognitive skills and abilities across occupational types, with flexibility, good customer skills and team skills considered as asset. Similarly, in Slovakia, low- and medium-skilled jobs advertisements focuses on non-cognitive skills and specific cognitive skills rather than on general cognitive skills (e.g. the ability to learn).

Another important finding, when we compare the results for the five countries, is the confirmation of the hypothesis that the specific skill set demanded in service occupations differs from other, mainly industrial-sector (manual) jobs: there is greater focus on non-cognitive social skills and personal characteristics. At the same time, there is great variation in the content of skill demand across the labour markets analysed, and while on average non-cognitive skills might be more desired in interactive service jobs, these requirements might appear in addition to formal education, not instead of it.

Finally, we also find interesting differences among countries when it comes to the specific non-cognitive skills that are required. One example is the hierarchy among the three specific social skills (communication, service skills, and team-working skills). In the US and Denmark, service skills are requested more than team-work and communication skills. Conversely, in Slovakia, Ireland and the Czech Republic, communication seems to be the most important of the three specific social skills.

4.7.5 Summary

- Non-cognitive skills have received much attention in recent years, as there is a growing number of academic and policy contributions that highlights their importance in the labour market.
- Our work focuses on the prevalence of non-cognitive skills in vacancies and is comparative in nature. More specifically, we examined the Czech Republic, Denmark, Ireland, Slovakia and the United States.
- In four of the countries studied, cognitive skills are more often requested than non-cognitive skills. In the other two countries, the opposite holds.
- Demand for non-cognitive skills is widespread, even for low- and medium-skilled occupations. Moreover, non-cognitive skills are particularly important in the service sector (and the emphasis there seems to be on social skills rather than personal non-cognitive skills).

4.8 Conclusions

This paper presented the findings of six case studies, each based on web data, to assess the potential of using vacancies and metadata extracted from online job boards to study occupations and skills. We show how such data can be used to analyse different types of *occupations*, of all skill levels, and *skills*, such as education, experience, cognitive and non-cognitive skills. Our case studies covered several different countries and topics, e.g. mismatches in the educational requirements listed in job vacancies and the educational attainments of jobholders in the Czech Republic, requirements of US employers for the 30 most-frequently-advertised occupations, foreign languages skills in the Visegrad region and a new way to identify new and emerging occupations in Europe. Our study is a successful proof-of-concept and contributes to a rapidly expanding research field.

5. Do educational requirements in vacancies match with educational attainments of jobholders? An analysis of web-based data for 279 occupations in the Czech Republic

Prepared by Kea Tijdens, Miroslav Beblavý and Anna Thum-Thysen

European labour market policies aim to develop an early-warning tool for mismatches by monitoring job vacancies. Few studies have been able to measure these mismatches, among others because systematic information on educational requirements in vacancies is lacking. Our study explores mismatch for occupations by investigating the relationship between demand & supply ratios and the vacancies' educational requirements and jobholders' attainments. It compares the distributional characteristics of requirements and attainments using data of 14,092 vacancies of the web-database of the Czech Public Employment Service with data of 10,364 jobholders from the WageIndicator web-survey, merged into a database aggregated by 4-digit level occupations (totalling to 279 occupations). The demand & supply ratio is unbalanced with one fourth of the 279 occupations in excessive demand and one third in excessive supply. A high demand correlates with lower educational requirements. At lower skill levels, requirements are more condensed, but attainments less so. At higher skill levels, requirements are less condensed, but attainments more so. For most occupations the lowest attainment is at least one level above the required level, pointing to an overeducated workforce. For all skill levels the mean educational requirements are lower when occupations are in high demand, though not all results are statistically significant.

5.1 Introduction

As part of the Europe 2020 initiative 'An Agenda for New Skills and Jobs', the Commission launched the project 'Monitoring labour market developments in Europe' (European Commission, 2014). This project aims to gather up-to-date information on job vacancies, serving as an early-warning tool for bottlenecks and mismatches on the labour market. This approach firstly refers to the mismatch of the number of vacancies vis-à-vis the number of job seekers, as is regularly updated in the Commission's Vacancy Monitor (http://ec.europa.eu/social/main.jsp?catId=955). This is by far the most studied approach and the body of knowledge is known as the Help-Wanted Advertising, Job Vacancies, and Unemployment relationship (Cardullo & Guerrazzi, 2013). Secondly, the approach refers to skills mismatch: to what extent do the job seekers and the vacancies match in terms of the attained vis-à-vis required skills? Our study aims to contribute to this latter approach.

Analyses of skills mismatch need data about the attained skills of job seekers in relation to the required skills in vacancies but few studies have been able to measure this mismatch, among others because information on the latter is lacking (e.g. Pellizzari & Fichen, 2013). Information about vacancies stem from three sources. Job Vacancy Surveys, held in quite a number of industrialised countries, ask employers about their most recent vacancies but neither about the required skills nor the skills of the hired workers. Job ads are a rich source of information concerning required skills, but ads need coding of unstructured text. Therefore skill requirement data from ads is not widely available. Proxies for the required skills of new hires can be taken from Labour Force Surveys, because individuals - with known educational attainments - are asked whether they have been hired for a new job in the period under study. Yet, these surveys do not ask whether the individuals have been hired because the employer had a vacancy. To phrase it differently, 'some data is available on the supply side, but there exists no comparable measure on the demand side, in which the level of the skill required for the job is measured on an equivalent or comparable metric. As a result, we find ourselves in a situation in which literal skill mismatches cannot be directly measured.' (Allen *et al.*, 2013, p. 2).

Our study addresses this gap in the body of knowledge regarding labour supply and demand skill characteristics by comparing the educational requirements in vacancies and the educational attainments of jobholders at the aggregate level of 4-digit occupational units. For this purpose we used Czech data of a large scale web survey of jobholders and data of the large scale EURES vacancy database of the European Employment Service. Regarding the latter, we followed Kureková *et al.* (2013), who used the data of the EURES vacancies portal for such purpose, which at that time also was a novelty. This paper first explores how demand and supply ratios for 4-digit occupations relate to educational requirements and attainments. Second, it investigates the skills mismatch in 4-digit occupations by comparing the skills sets required in vacancies and attained by jobholders. Third, it studies whether educational requirements are downward or upward adjusted when occupations are in short or abundant supply? The outline of our paper is as follows. Section 5.2 discusses the main theoretical models. Section 5.3 details the research objectives and the data. Section 5.4 presents the empirical results, whereas Section 5.5 provides the main conclusions of the study and discusses the results.

5.2 Challenges in comparing vacancy and jobholder data

5.2.1 Skill mismatch and the concepts of jobs and occupations

For an exploration of skills mismatches the skills required for the jobs as reported by employers need to be compared to the skills in the labour pool as reported by jobholders and job seekers. In both employer and jobholder surveys it is possible to measure generic skills, but extremely difficult to measure job-specific skills and therefore educational levels are typically used as a proxy for skills (Tijdens *et al.*, 2012). Even when applying a proxy measure, very few studies have been able to measure skill mismatch based on a comparison between jobholders' educational attainment and the specific skill requirements of their occupations, because in many studies information on the latter is lacking (Leuven & Oosterbeek, 2011). This problem could - partly - be solved by aggregating jobs or vacancies and jobholders or job seekers into occupations, as we will do in this paper by comparing the required skills in vacancies and the attained skills of jobholders at a detailed level of occupations.

An occupation-level comparison of the required skills in vacancies and the attained skills of jobholders should preferably be investigated at the lowest level of occupational aggregation which is the 4-digit level when using the International Standard Classification of Occupations (ISCO), maintained by the International Labour Organisation (ILO). ISCO has become the global standard. In 1998 the third version of the classification was released (ISCO-88), followed by the fourth version in 2008. This ISCO-08 is a hierarchical system ranging from 433 occupational units at 4-digit level to 9 major occupational groups at 1-digit level (Hunter, 2009). On the basis of similarities in the tasks and duties performed, the 4-digit units are grouped into 3- and 2-digit groups, which on the basis of their skill level are regrouped on 1-digit level, which in turn are clustered into four skill levels, ranging from 1 = Unskilled (ISCO group 9), to 2 = Semi-skilled (ISCO group 4-8), 3 = Skilled (ISCO group 1 and 3), and 4 = Highly skilled (ISCO group 2). These levels are related to the International Standard Classification of Education ISCED-1997 (UNESCO, 2006). Given the 433 occupational units at 4-digits and the labour forces' skewed occupational distribution however, a comparison of a substantial number of occupational units poses high demands to the sample sizes at scrutiny. For this reason the European Centre for the Development of Vocational Training uses the 3-digit aggregation for its European survey about employers' skills needs (Cedefop, 2013). To the best of our knowledge, this is currently the most disaggregated mismatch analysis. In this paper, we use the ISCO 4-digit occupations as the unit of analysis.

5.2.2 Supply and demand rates

In a macroeconomic approach the unemployment-vacancy (UV) space or Beveridge Curve relates unemployment to vacancy data. The UV curve determines how efficiently workers will find new jobs. For insight into the job-vacancy matching processes beyond the macroeconomic approach the job allocation processes need to be disaggregated, either by industry, region or occupation. In his study of the labour market in the United States, Hobijn (2012) uses data about vacancies and about hires to construct an annual time series of job openings and hires by occupation, industry and state. He finds that job openings vary largely across occupations. Davis *et al.* (2010) argue that even at more aggregated levels, our knowledge of vacancy behaviour is very thin compared to our knowledge of unemployment. Based on the US Job Openings and Labor Turnover Survey (JOLTS) survey, these authors show that job-filling rates rise steeply with the gross hires rate across industries, employer size classes, worker turnover groups, and employer growth rates. Following these authors, we find also that little is known about the demand & supply ratios for occupations.

Our first research objective is to cumulate know ledge by exploring the occupational distribution of vacancies and jobholders, resulting in supply and demand ratios for the 4-digit occupations. In Hypothesis $H1_0$ we assume that the labour supply and demand ratio is equal across the 4-digit occupations. If rejected, in Hypothesis H1a we assume that the higher the demand in an occupation the lower its skill level. In H1b we assume that labour demand is relative more frequent for occupations where vacancies have lower educational requirements. In H1c we assume that labour demand is relative more frequent for occupations where jobholders have lower educational attainments.

5.2.3 Skill mismatches

The political discussion about skill mismatch mostly relates to the skills of job seekers and the skill requirements of vacancies. Yet, according to Allen *et al.* (2013), measuring the demand side job requirements is still far from perfect and the mismatch research has been hindered by a relative lack of data on heterogeneity at the demand side. Demand side job requirements relate to multiple skill dimensions, covering concepts such as generic skills, soft skills, occupation-specific skills, educational attainments, and alike. Job requirements can be measured by means of systematic vacancy monitoring or by employer surveys, which both focus on the requirements for job entrants. Job requirements can - for a restricted set of occupations - be measured using licensing registers or expert surveys, indicating job requirements for job entrants and jobholders alike. Job requirements can be measured by asking jobholders about the requirements for their current jobs. However, the response might be biased towards their current attainments and mostly educational attainments of jobholders are used as a proxy for job requirements. A focus on jobholders implies that the measure is not able to grasp changes in job requirements due to new technologies or organisational changes, whereas a focus on vacancies might stress the new requirements too much.

Before the Internet era researchers typically collected and counted the job requirements from newspaper ads, such as the Help-Wanted series in the United States. This millennium has opened up new possibilities by crawling job ads posted on the Internet (Kureková *et al.*, 2012; 2013). Increasingly, the public employment services in European countries manage to collect and harmonise these data, as the European Union's Vacancy Monitors shows (Van der Ende *et al.*, 2012).[23] Measuring job requirements in vacancies assumes that employers formulate educational requirements for their vacancies, but according to Jackson (2001), who analysed 322 job ads chosen from national, regional and local newspapers, only 40% contained a requirement for qualifications of any kind. From these, educational qualifications were very important for the managerial and professional class, while vocational qualifications were more important for the remaining classes (Kureková *et al.*, 2013).

Our second research objective is to explore the skills mismatch in occupations by comparing the educational requirements in vacancies with the educational attainments of jobholders. Due to data limitations the concept of skills had to be restricted to educational levels. In Hypothesis $H2_0$ we assume that across occupations the mean educational requirements of vacancies and the mean educational attainments are equal. If rejected, we explore whether the range of educational requirements in vacancies is more condensed for occupations at higher skill levels (H2a), whether the range of educational attainments of jobholders is so for occupations at higher skill levels (H2b) and whether the differences between the two ranges are more condensed at higher skill levels (H2c).

5.2.4 Employers' adjustment strategies

Do employers adjust the educational requirements in vacancies for occupations in short or abundant supply? Studies about adjustment strategies in response to labour and skill shortages reveal strategies such as adoption of flexible working hours and increases in overtime hours, greater reliance on flexible job design and part-time workers, and implementation of self-directed work groups and problem-solving teams (Fang, 2009). Adjustment of job requirements is not often studied. One study indicates that firms vary their skills requirements over the business cycle: our empirical analysis shows that, for a given wage offer, requirements are stricter in recessions and downturns (Chen & Eriksson, 2009). Our third research objective is to explore adjustment strategies in vacancies. In Hypothesis H3 we assume that at comparable skill levels occupations in relative high demand have lower mean educational requirements compared to occupations in relative low demand.

5.3 Methodology

5.3.1 The data sources

For a comparison of the characteristics of vacancies and jobholders by 4-digit occupational units, the data sources need to be large enough to have sufficient observations for a sufficient number of occupations. Given this requirement, we choose to use data from the EURES vacancy database and from the WageIndicator jobholder web survey. Both sources are explained hereafter. We had to limit our analysis to one country, the Czech Republic, because this country provides a large number of their vacancies to EURES, these vacancies are coded at 4-digits in the occupational classification ISCO-88 and the skill requirements are coded in ISCED-1997. The Czech Republic also provides large numbers of observations in the WageIndicator jobholder database, and the respondent's occupation and education are coded ISCO-08 respectively ISCED-1997. Other EU countries lack at least one of these conditions.

The jobholder data used in this study stem from the self-administered, volunteer, multi-country web survey, which is posted continuously at the 80 national WageIndicator websites, all providing job related content. In 2013 the websites received 23 million visitors. In return for the free information provided, web visitors are invited to voluntarily complete a continuous web survey with a

23 See Eurostat Metadata Job vacancy statistics (jvs), last update 16/04/2013, (http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/EN/jvs_esms.htm#unit_measure1392278550953 accessed 2014-MAR-31).

lottery prize incentive. Given the need for a large dataset, we merged the annual data of the Czech WageIndicator web survey data from 2010/01 to 2013/12, thereby increasing the number of observations substantially (2010 n=2,519; 2011 n=1,326; 2012 n=2,924; 2013 n=3,751; total n=10,520). We trust pooling the annual data, because the means and standard deviations of the educational attainments of the jobholders within occupations hardly vary across the years. Moreover, the number of vacancies is much more likely to vary with the business cycle than the labour force (Hobijn, 2012).

Being an online non-probability sample, we investigated the self-selection bias by comparing our sample to Eurostat's Czech labour force data for the years 2010-2012 (2013 data was incomparable because education was coded according to ISCED-2011). The comparison shows that in all years the high educated are overrepresented in the web sample for both genders, whereas the low and middle educated are underrepresented (see Appendix 4). On average over the three years, the low educated comprise 6% of the Labour Force and 4% of the web sample for women, and respectively 3% and 2% for men. The middle educated comprises respectively 74% and 60% for women and 78% and 56% for men. The high educated comprise 20% and 37% for women respectively 19% and 42% for men. Eurostat does not provide a cross table for education by occupation. Therefore, we preferred not to apply proportional weights and decided to use the unweighted data and consider the results as exploratory rather than representative. Other studies into the sample bias of the WageIndicator survey also indicate that higher educated people are overrepresented in European countries (de Pedraza *et al.*, 2010). This is partly also an effect of the fact that illiterate workers, who most likely are unskilled, by definition will not complete the web survey.

In December 2013 the job vacancy data was collected from the EURES website, which constitutes a European network and platform with harmonized job vacancy data with the aim to improve labour mobility in Europe.[24] EURES was set up 1993 by the European Union's DG Employment, operating on a partnership principle with national Public Employment Services (PES). The PES's provide a total or partial selection of job vacancies to the EURES platform. Kureková *et al.* (2012) summarised key features of the dataset: the portal holds around 1.5 million job vacancy advertisements in 31 EU and associated countries. The average number of monthly visits amounted to 3.6 million and it is further increasing (Ackers, 2012). Despite the selective nature of the job vacancy posting, Ackers (2012) estimates that the portal covers on average around 30-40% of overall job vacancies in the concerned countries. The Czech Republic requires all vacancies to be notified to the national PES, and therefore coverage is much higher. A comparison between the number of vacancies posted on the Czech PES website and the EURES website shows that the ratio of vacancies not uploaded on the EURES database is negligible. On December 9th 2013 the Czech PES registered 15,140 vacancies and the EURES database shows 15,198. The small difference is mainly due to the uploading delay as the EURES database is only uploaded once a day.

5.3.2 Coding occupations and educations

Two variables are critical for our study: occupation and education. For the latter we restrict the concept of skill requirements to educational requirements. The Czech PES has coded the required educational levels of the vacancies, but we are unable to trace how they exactly did so. Although they applied their own educational classification, this was rather comparable to ISCED-1997. In the jobholders survey, the respondents are asked to tick their highest educational category from a list of national educational categories, which are mapped to ISCED-1997. The vacancy database has a category 0 'None specified' and the jobholder database has 0 'No education', but in both databases these categories have very few observations (vacancies 0.5%, jobholders 0.2%). Therefore, we merged category 0 with category 1. See Table 5.1 for the comparability of the educational categories. In sum, educations range from 1 = primary education, to 5 = higher education.

24 https://ec.europa.eu/eures/home.jsp?lang=en

Table 5.1 Educational categories in the vacancy and jobholder databases

Code	Vacancy database EURES	Code	Jobholder database WageIndicator
1	Compulsory Education/Professional Initiation, incl. none specified	1	Primary education, incl. no education
2	Vocational Training/ Apprenticeships	2	Lower secondary education
3	Higher Technical Training	3	Upper secondary education
4	Advanced Technical Training	4	Post-secondary non-tertiary education
5	Higher Training, Incl. academic	5	First and second stage of tertiary education

Regarding occupations, the Czech PES has coded the vacancies' job titles according to ISCO-88, mostly with a 4-digit code but few with only 1-, 2-, or 3-digit codes. For the purpose of comparison with the jobholder data, our analysis is restricted to the vacancies with a 4-digit code, thereby excluding the higher-level coded vacancies. In the jobholders survey, the respondents are asked to self-identify their occupation using text search with a look-up database of approximately 1,700 occupational titles, all coded according to ISCO-08. The ISCO-88 classification includes 388 occupational units at 4-digit level, whereas ISCO-08 counts 433 units. ILO's correspondence tables ISCO-88 to ISCO-08 and vice versa are of the multi-parent-multi-children nature. Hence, our study faces the problem of mapping the two versions. We recoded the ISCO-88 occupational units into ISCO-08, because the 88-08 correspondence table has approximately a quarter less partial mappings than the 08-88 one, making the former more reliable. We assigned only one ISCO-08 code to the ISCO-88 occupational units with multiple ISCO-08 correspondence codes. For example, the Production and operations department managers in construction (ISCO-88 code 1223) falls apart into two ISCO-08 codes, 1323 and 3123, of which we chose code 3123 Construction supervisors. Accordingly, in the jobholder database the not-assigned ISCO-08 codes are recoded into the chosen ISCO-08 code, thus all cases with code 1323 are recoded into 3123. The three occupational units 10for the armed forces are excluded from the analysis and so are all ISCO-08 occupational units without an equivalent in the ISCO-88 classification, for example the Web and multimedia developers (code 2513), which did not exist in 1988. Appendix 5 shows the details of our mapping exercise. Our final ISCO-08 list counts 309 occupational units (see Table 5.2).

5.3.3 The aggregated database

The initial EURES dataset holds data about 14,092 vacancies and the initial WageIndicator dataset does so for 10,364 jobholders. Both data sources have been aggregated and then merged into one database of occupational units. After recoding ISCO-88 into ISCO-08, the vacancies database holds data for 244 occupational units and the jobholders' database holds data for 238 units, with 203 units from both sources (Table 5.2). The merged database has data for 279 units from either source.

For the 279 occupations we computed a variable indicating the demand & supply ratio, based on its proportion in the entire database, thereby clustering the ratio into thirteen groups, ranging from 1 'Supply, no demand', 2 'Supply > 5 * demand', 3 'Supply is 4-5 * demand', etcetera to 12 'Demand >5*supply' and 13 'Demand, no supply' (see Figure 5.1). For the second research objective we have restricted the aggregated database to those occupations for which both sources deliver at least 5 observations per 4-digit ISCO-08 unit, resulting in 133 units with observations ranging from 5 to 925 vacancies and from 5 to 902 jobholders per unit.

For each occupational unit, we have extracted the lowest and highest educational requirements and attainments from the vacancy database respectively the jobholder's database. In the merged database we computed the mean and standard deviation of the educational requirements respectively attainments. From now on, to serve readability, we prefer the word occupation instead of occupational unit.

Table 5.2 Number of occupational units in the aggregated vacancy and jobholder dataset

Occupational units	Number	%
Maximum set of ISCO-08 occupational units	309	100
Occupational units in EURES vacancy database	244	79
Occupational units in WageIndicator jobholder database	238	77
Occupational units in either database	279	90
Occupational units in both databases	203	66
Occupational units in both databases, excl. occupations with equal demand/supply ratio	192	62
Occupational units in both databases with 5 or more lower level observations (vacancies and job-holders)	133	43

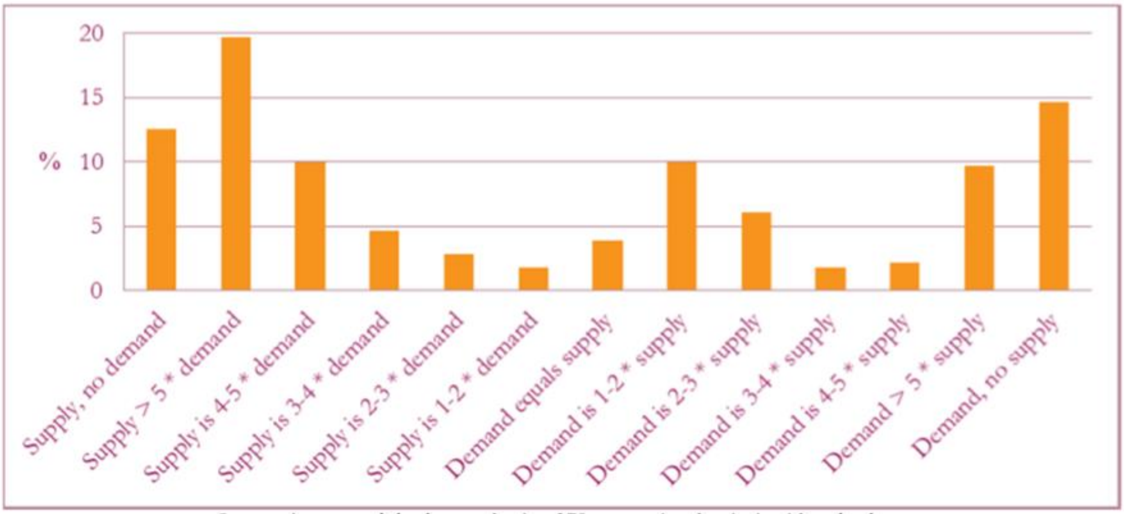
Source Aggregated database

5.4 Results

5.4.1 Supply and demand ratios by occupation

We assume that the labour supply and demand ratios are equal across the 4-digit occupations ($H1_0$). Using the aggregated database with 279 occupations for which either supply or demand data are available, Figure 5.1 depicts a very unequal distribution in the thirteen demand & supply ratio groups. In 144 of the 279 occupations, the relative supply is higher than the relative demand, including no demand, whereas in 124 occupation the opposite holds. When defined as at least five times the supply, for one in three occupations the demand is excessive (32%). At the other end of the spectrum, for one in four the supply is excessive (25%). For less than one in five occupations the demand & supply ratios are balanced with less than twice vacancies to jobholders (2%), equal shares of vacancies to jobholders (4%) or at most twice jobholders to vacancies (10%). Hence, supply and demand are largely mismatched across occupations and H1 0 is therefore rejected. This is in line with findings for the United States that job openings vary largely across occupations (Hobijn, 2012).

Figure 5.1 Distribution of 279 occupations over demand & supply ratio groups



Source Aggregated database, selection 279 occupational units in either database

Having rejected the equal distribution assumption, we aim to explore the relationship between the demand & supply ratios and the occupations' skill levels, the vacancies' educational requirements and the jobholders' educational attainments (H1a, H1b, H1c). As explained in Section 5.3, for each occupation the lowest, mean and highest educational levels of both vacancies and jobholders are known. Limiting the analysis to the 203 occupations with both vacancy and jobholder data, we show that the mean skill level of occupations in relative large supply are slightly higher than when in large demand, though bivariate analyses for the 203 occupations reveal no significant relationship between the skill levels and the demand & supply ratio, only when correlating to demand & supply ratio groups ($r=-0.09$, ns, respectively $r=-0.21$, $p<0.001$). Hence, we find only partial support for assumption H1a that the higher the demand in an occupation the lower its skill level.

When turning to the educational requirements in vacancies, Table 5.3 shows that the demand & supply ratios and the ratio groups are negatively correlated to the means of the mean educational requirements of occupations, as hypothesized ($r=-0.13$, $p<0.1$ for ratios; $r=-0.30$, $p<0.01$ for ratio groups). The relationship to the means of the lowest educational requirements is even stronger ($r=-0.17$, $p<0.05$ for ratios; $r=-0.39$, $p<0.01$ for ratio groups). The relationship to the means of the highest educational requirements is weaker with no significance for the demand & supply ratios, only for the ratio groups ($r=-0.02$, ns; respectively $r=-0.16$, $p<0.05$). Hence, in large demand occupations we find that the distribution of educational requirements within these occupations becomes more skewed to the left. We conclude that our assumption H1b is supported. The higher the demand in occupations, the lower the educational requirements of the vacancies in these occupations.

When turning to the educational attainments in the occupations, the third panel in Table 5.3 shows that the means of the mean educational attainments in occupations are not significantly correlated to the demand & supply ratios, but they are to the ratio groups ($r=-0.07$, ns; respectively $r=-0.22$, $p<0.01$). A similar though stronger relationship can be noticed for the means of the highest educational attainments ($r=-0.17$, $p<0.01$; respectively $r=-0.29$, $p<0.01$). However, when focussing on the lowest educational attainments a reverse mechanism can be noticed. The higher the demand in occupations, the higher the means of the lowest attainments ($r=0.17$, $p<0.05$ for ratios; $r=0.22$, $p<0.01$ for ratio groups). This may indicate that the jobholders with low educations are squeezed out of the occupations in large demand, but we are not able to explore this empirically. We conclude that our assumption H1c is in part supported. The higher the demand in occupations, the lower the educational attainments of the jobholders in these occupations, though not for the lowest educational attainment.

Table 5.3 **Descriptive statistics of occupational skill levels (1 = unskilled, ..., 4 = highly skilled) and required and attained educational levels (1 = primary, ..., 5 = tertiary) by demand & supply ratio groups**

	Occupations: mean skill levels	Occupations: mean educational requirements in vacancies			Occupations: mean educational attainments in jobholders			N
		Lowest	Mean	Highest	Lowest	Mean	Highest	
Supply > 5 * demand	2.85	2.56	3.20	3.87	2.24	3.88	4.89	55
Supply is 3-5 * demand	2.59	1.85	2.74	3.93	2.41	3.60	4.66	41
Supply is 1-3 * demand	2.38	1.31	2.57	3.69	2.38	3.49	4.69	13
Demand equals supply	2.45	1.55	2.38	3.09	2.36	3.11	3.64	11
Demand is 1-3 * supply	2.60	1.56	2.60	3.60	2.84	3.67	4.60	45
Demand is 3-5 * supply	2.00	1.27	1.98	3.27	2.27	3.08	4.18	11
Demand > 5 * supply	2.33	1.33	2.34	3.41	2.81	3.46	4.19	27
Total	2.58	1.83	2.71	3.67	2.50	3.61	4.57	203
Correlations to d/s ratio	-0.09	-0.17**	-0.13*	-0.02	0.17**	-0.07	-0.17**	
Corr. to d/s ratio group	-0.21***	-0.39***	-0.30***	-0.16**	0.22***	-0.22***	-0.29***	

*significant at 10%; **significant at 5%; ***significant at 1%.
Source Aggregated database, selection 203 occupational units in both databases

5.4.2 Educational requirements and educational attainments by occupation.

The second research objective aims to explore occupational skills mismatch by comparing the educational requirements of the vacancies and the educational attainments of the jobholders for the 4-digit occupations. In Hypothesis $H2_0$ we assume that across occupations the mean educational requirements of vacancies and the mean educational attainments are equal. We restrict the aggregated database to the 133 occupations with at least five jobholder and five vacancy observations to achieve sufficient variation of educational levels of vacancies and jobholders within each occupation. For these 133 occupations $H2_0$ is not supported (mean educational requirements = 2.72, sd=0.96; mean educational attainments = 3.64, sd=0.61). The assumption is also not supported when focusing on the lowest educations in occupations (mean lowest educational requirements = 1.62, sd=0.93; mean lowest educational attainments = 2.35, sd=0.90). It is also not supported when focussing on the highest educations in occupations (mean highest educational requirements = 3.93, sd=1.15; mean highest educational attainments = 4.77, sd=0.58).

To shed further light on the differences between vacancies and jobholders, Table 5.4 reveals the distributional characteristics. For only one in three occupations the lowest educational levels of vacancies and jobholders are equal (33% of the 133 occupations, Table 5.4). For the majority of occupations the lowest education of the jobholders is at least one level above that of the vacancies (57%). In two occupations the lowest attained educational level is even three levels above the lowest required education, notably the Chemical engineers and the Medical imaging and therapeutic equipment technicians. In only twelve occupations the lowest education of the jobholders is one or two levels lower than that of the vacancies (9%). Hence, educational levels of vacancies and jobholders are not equal when comparing the lowest levels across occupations.

The second panel of Table 5.4 compares the mean attained and required educational levels of the 133 occupations. For almost half of the occupations the mean attained and required educations are equal (47%), whereas for a fourth the attained education is one level above the required education (24%) and for another fourth the attained education is even two levels above the required education (25%). Only in three occupations the attained level is below the required level (2%).

The third panel of Table 5.4 compares the highest attained and required educations. Here $H2_0$ is also not supported, though not as strong as in the previous panels. In more than half of the occupations the highest attained and required education levels are equal (55%). In more than a third the attained education is one or two levels above the required level (37%), and in a minority this is three levels (7%). Only in one occupation the highest attained education is one level below the highest required education, notably the home-based personal care workers.

In conclusion, we confirm again that $H2_0$ is not supported. In the 133 occupations the required educational levels in vacancies are largely below the attained levels of the jobholders. This analysis emerges a picture of an overeducated workforce compared to the skills needs of the employers.

Table 5.4 Distribution of occupations across six categories of educational differences for the lowest, mean and highest educations of vacancies and jobholders (1 = primary, ..., 5 = tertiary education)

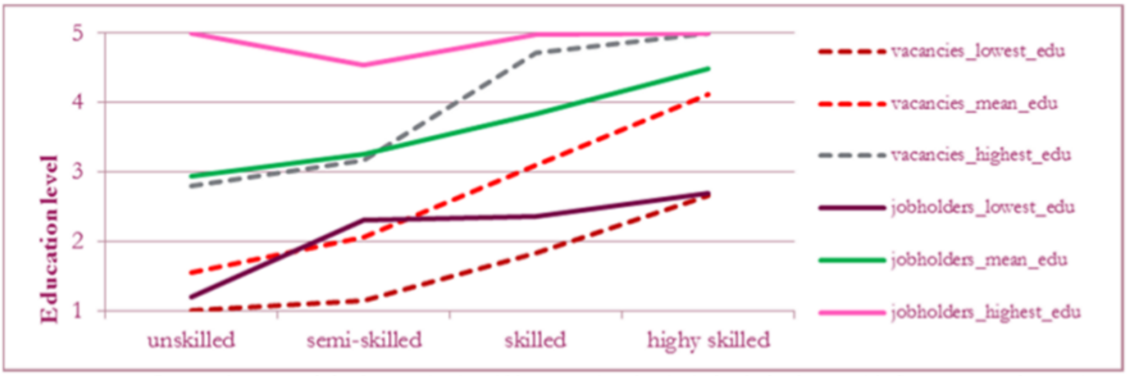
	Lowest educations		Mean educations		Highest educations	
	%	N	%	N	%	N
Vacancies 2 edulvls higher than jobholders	3.00	4	0.00	0	0.00	0
Vacancies 1 edulvls higher than jobholders	6.00	8	2.30	3	0.80	1
Vacancies edulvls equals jobholders	33.10	44	46.60	62	54.90	73
Vacancies 1 edulvls lower than jobholders	32.30	43	24.10	32	11.30	15
Vacancies 2 edulvls lower than jobholders	24.10	32	24.80	33	26.30	35
Vacancies 3 edulvls lower than jobholders	1.50	2	2.30	3	6.80	9
Total (n=133)	**100.00**	**133**	**100.00**	**133**	**100.00**	**133**
Mean (range -2 to +3)	0.73		0.78		0.83	
Std Dev	1.07		0.92		1.05	

Source Aggregated database, selection 133 occupational units in both databases with five or more observations per occupational unit

Rejecting the assumption about the equal educational requirements and attainments in occupations, we explore whether the range of educational requirements in vacancies is more condensed for occupations at higher skill levels compared to lower skill levels (H2a) and whether the range of educational attainments of jobholders is more condensed for higher skilled occupations (H2b) and whether the differences between the two ranges are more condensed at higher skill levels (H2c).

Figure 5.2 provides descriptive information about the means of the occupations' lowest, mean and highest educational requirements and attainments by skill level. It shows clearly that for higher occupations' skill levels the educational requirements and attainments increase both. The exception concerns the unskilled occupations where the highest educational attainment of the jobholders is at level 5, the highest education level.

Figure 5.2 **Educational requirements (dotted) and educational attainments (lines) in occupations, by skill group**



Source Aggregated database, selection 133 occupational units in both databases with five or more observations per occupational unit

Table 5.5reveals the mean ranges and standard deviations for the three hypotheses. H2a is not supported, on the contrary. The range of educational requirements in vacancies is wide instead of condensed in skilled and highly skilled occupations, whereas it is most condensed for the unskilled occupations ($r=0.22$, $p<0.05$). H2b is also not supported, though here the correlation between range and skill level is insignificant ($r=-0.04$, ns). However, H2c is supported, showing that in the unskilled occupations the range is widest. The correlation coefficient has the expected sign and is significant ($r=-0.22$, $p<0.05$).

Table 5.5 **Means ranges between the lowest and highest educational levels (range varies between 0 and 4) for vacancies and jobholders and for range differences, by four skill levels**

	Vacancies		Jobholders		Range difference		N
	Mean range	**SD**	**Mean range**	**SD**	**Mean range**	**SD**	
Unskilled occupations	1.80	0.45	3.80	0.45	2.00	0.71	5
Semi-skilled occupations	2.02	0.92	2.24	1.11	0.23	1.26	66
Skilled occupations	2.89	1.04	2.61	0.84	-0.28	1.00	36
High-skilled occupations	2.35	1.20	2.31	1.19	-0.04	1.31	26
Total	**2.31**	**1.06**	**2.41**	**1.08**	**0.111**	**1.26**	**133**
Pearson correlation	0.22**		-0.04		-0.22**		

** significant at 5%

Source Aggregated database, selection 133 occupational units in both databases with five or more observations per occupational unit

5.4.3 Adjustment strategies of educational requirements in vacancies by occupation

Do employers adjust the educational requirements downwards in vacancies in case of large demand for occupations in similar skill levels? As shown in Section 4.1, in case of large demand the educational requirements in vacancies are lower. To explore this, we hypothesize that at comparable skill levels occupations in relative high demand have lower mean educational requirements compared to occupations in relative low demand (H3). We restrict the aggregated database of 203 occupations to 192 occupations, thereby excluding occupations in the group with equal supply and demand. For each skill level we applied a t-test of the mean educational requirements of occupations in high and in low demand. As Table 5.6 shows, for all skill levels the mean educational requirements are lower when occupations are in high demand, but this is only significant for the skill levels with large numbers of observations.

Table 5.6 **Means, standard deviations and significance levels of the t-test of the mean educational requirements in vacancy's occupations, by skill level and by demand & supply divide**

		Mean	SD	Sign. T-test	N
Unskilled occupations	Low demand: supply > demand	1.49	0.35	ns	4
	High demand: demand > supply	1.45	0.16		4
Semi-skilled occupations	Low demand: supply > demand	2.26	0.63	***	52
	High demand: demand > supply	1.92	0.24		50
Skilled occupations	Low demand: supply > demand	3.19	0.71	ns	26
	High demand: demand > supply	3.10	0.26		18
High-skilled occupations	Low demand: supply > demand	4.26	0.65	ns	27
	High demand: demand > supply	4.04	0.79		11
All occupations	Low demand: supply > demand	2.95	1.08	***	109
	High demand: demand > supply	2.43	0.88		83

Source Aggregated database, selection 192 occupational units in both databases, excluding units with equal supply & demand

5.5 Conclusions and discussions

5.5.1 Conclusion

Mismatches on the labour market are a main worry for policy makers, referring to both the numerical mismatch of job seekers vis-a-vis vacancies and the mismatch of the attained skills of job seekers and the required skills of vacancies. Beyond national-level data on employed and unemployed for the numerical mismatch, data sources to investigate the skills mismatch are little and a comparison between jobholders' attainment and the required skills in vacancies is difficult, because information on the latter is lacking when aiming to cover an entire national labour market. Aggregating data seems a viable way to solve this problem of unmatched micro-data, for example by aggregating into occupations. However, analyses for detailed occupations require huge datasets when aiming for sufficient observations in each unit, because the distribution over occupations of both vacancies and jobholders is very skewed.

This paper provides a first attempt to explore mismatch at such a detailed level. It investigates the relationship between demand and supply ratios and the educational requirements in vacancies and attainments of jobholders for ISCO 4-digit occupations. It then compares the distributional characteristics of the educational requirements in vacancies and the educational attainments of jobholders for these occupations. Finally, it explores the educational requirements adjustment strategies when labour is in large supply or large demand. Using the educational characteristics of 15,140 vacancies from the Public Employment Service and 10,520 jobholders from a web survey on work and wages, a database was merged, aggregated by ISCO 4-digit occupations. The Czech Republic is the only European country for which such data is available. For these occupations and for vacancies and for jobholders the lowest, mean, and highest educational requirements respectively attainment were analysed. The merged database resulted in data for 279 occupations.

Our analyses of the mismatch show that supply and demand are largely mismatched across occupations, as was also found for the US. More specifically, the higher the demand in an occupation - when measured in demand & supply ratio groups - the lower the occupation's skill level, the lower the educational requirements of vacancies, and the lower the educational attainments of the jobholders in these occupations, though the latter does not hold for the lowest educational attainment. The range of educational attainments is wide for the unskilled occupations, and more condensed in skilled and highly skilled occupations. In contrast, the range of educational requirements in vacancies is most condensed for the unskilled occupations, whereas it is wide in the skilled and highly skilled occupations. This indicates that whereas the ISCO skill levels are assumed to reflect the required educational levels, this does not turn out to be the case in our study.

When comparing the distributional characteristics of the educational requirements in vacancies and the educational attainments of jobholders for the same occupations a picture arises of an overeducated workforce. When comparing the lowest educational levels of vacancies and jobholders, it turns out that in one in three occupations the required and attained levels are equal, but that for the majority of occupations the lowest education of jobholders is at least one level above that of the vacancies. When comparing the mean educational levels, in almost half of the occupations these are equal, for a fourth the attained education is one level above the required education and for another fourth this is even two levels above the required education. When comparing the highest educational levels, in more than half of the occupations these are equal, in one in ten this is one level above and in a quarter this is two levels above the required level.

Finally, we analysed whether employers adjust the educational requirements downwards when occupations when occupations are in large demand. Indeed, for all skill levels the mean educational requirements are lower when occupations are in high demand, though not all results are statistically significant.

5.5.2 Discussion

Being one of the first comparisons of vacancy data and jobholder data by occupation, further discussions are definitely needed about the underlying concepts. The first consideration concerns the concept of registered vacancies, as the demand for labour will be broader. A second consideration is that educational levels may be a poor proxy of the skills mismatch in the labour market, requiring greater detail with respect to attained and required skills. A legitimate question addresses the issue to what extent the educational requirements in vacancies reflect the true requirements for the job at scrutiny. This worry is also expressed by Allen *et al.* (2013). Additionally the validity of the educational coding of vacancies may need further investigation. A third consideration relates to the concept of skills mismatch, mostly referred to as the relationship between the skills requirements in jobs and the skills and competencies of jobholders. However, skills mismatch sometimes refers to the skills and competencies of job seekers and not jobholders or, as in this paper, it refers to the skills requirements in vacancies, which of course also is different from all jobs. Findings for selected groups cannot be generalised to the entire population.

Finally, limitations of the data must be mentioned. Online data may entail some concerns about selection of the data. The first one relates to the finding of the overeducated workforce. This may in part be attributed to the bias in the WageIndicator jobholders web survey, but this finding is fully in line with general findings indicating that one quarter to one third of the labour force in industrialised countries is overeducated (Leuven & Oosterbeek, 2012). The EURES vacancy database might underestimate the educational requirements of the stock of vacancies, because vacancies for jobs with high educational requirements may selectively be posted at the Public Employment Agencies. Yet, given that it is obligatory to post all vacancies at the national PES, this most likely hardly will be the case in the Czech Republic. Despite these limitations, this explorative study contributes to the understanding of supply and demand mismatch.

6. Conclusions

This report has brought together four chapters that CEPS prepared in light of WP21 of the InGRID research infrastructure project. Each of these chapters aspired to shed light on the identification of new occupations and skills, from different angles. The first three chapters are closely linked, as they present the academic and policy literature, existing and new methodologies sources and data, and findings on new occupations and skills. The final chapter zooms in on one particular application and presents an analysis of skill mismatch on the basis of WageIndicator data and data extracted from online vacancies.

The first chapter of the report reveals that while there is an extensive literature on new jobs and skills, which extends beyond academic research, many issues remain obscure. The conceptualisation of new occupations and new skills often is unclear, imprecise or narrow in scope (yet, concepts like occupation, job, skill and task are clearly defined, but are not always easy to disentangle in practice). Only a handful of contributions explicitly study these concepts, their meaning and ways to identify them. The first chapter further reveals that generally new jobs (and skills) are identified through surveys, interviews, classifications, forecasts, trade literature or other data sources.

The second chapter of the report builds on the findings of the first chapter. It evaluates the data sources and methodologies that are commonly used to capture new occupations and skills. It starts with a thorough discussion of the strengths and limitations of these methods and data sources, pointing to issues related to timing, precision and scope. The report then explores what alternative methodologies and data sources could be used to overcome these limitations. More specifically, we turn to web data and carefully explain how these sources could be used and what advantages they could bring. Web data are a very promising source but their use is still limited. In addition, a lot of methodological research is needed to further support the development of this research field.

The third chapter presents the results of the pilots we carried out for InGRID. It shows what information can be derived from online job boards and their vacancies with regards to language skills, IT skills and other education, skills or related requirements in labour markets in Europe and the US. The chapter also presents the findings obtained from our occupations observatory prototype, which builds on metadata extracted from online job boards, and their occupational classification in particular. One of the pilots is highlighted in the fourth chapter of the report, linking educational requirements in vacancies to the educational attainment of jobholders to assess skill mismatches in the Czech Republic.

Even though we did not pilot any methods based on data from social media, Google Trends or online surveys, these web-based data sources carry high potential for future research. An extensive discussion on these sources is provided in the first chapter of the report, and surveys in particular are widely used by other partners in InGRID.

New jobs and skills have been high on the agenda of policymakers for several years now, as evidenced by the Europe 2020 strategy, the 'New Skills for New Jobs Agenda' and other policy documents. At the same time, current approaches used to capture and understand these dynamics may not fully meet their goal. It is, therefore, worthwhile to explore alternative methods and data sources, with web data as a promising candidate.

appendix 1 Overview of new occupation tags identified

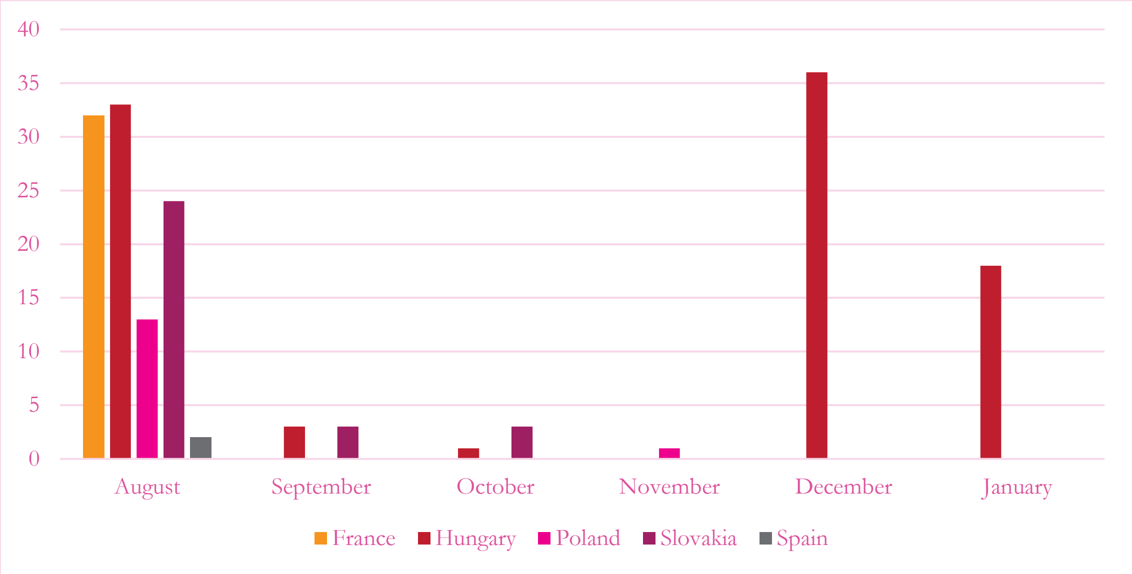
Table a1.1 List of potentially new occupations: 57 occupations were identified

Country	Occupation	Translated
France	Agent de sécurité incendie	Fire safety officer
France	Formateur logiciel	Software trainer
France	Ingénieur commercial aéronautique	Aviation sales engineer
France	Ingénieur traitement image	Image processing engineer
France	Technico commercial informatique	IT technical sales
France	Agent technico commercial	Technical sales agent
France	Technicien acoustique	Sound technician
France	Technicien support système	System support technician
France	Ingénieur commercial assurance	Insurance sales engineer
France	Agent de sûreté	Security officer
France	Ingénieur acoustique	Sound engineer
Belgium	Software ontwikkelaar	Software developer
Belgium	Commercieel technisch adviseur (b3182)	Commercial technical advisor (b3182)
Belgium	Product manager	Product manager
Belgium	Storingstechnieker (m/v)	Failure technician (m/f)
Belgium	Technicus beveiliging regio antwerpen	Security technician region Antwerp
Belgium	Business development manager (m/v)	Business development manager (m/f)
Belgium	Customer technical support & quality specialist	Customer technical support & quality specialist
Belgium	Chemical sales	Chemical sales
Belgium	Technical designer	Technical designer
Belgium	Ultrasound	Ultrasound
Belgium	Automation engineer - vaste job	Automation engineer - fixed position
Belgium	Embedded	Embedded
Belgium	Software engineer	Software engineer
Slovakia	Choreograaf	Choreographer
Slovakia	Ortopedický technik	Orthopedic technician
Slovakia	Zvukár	Sound engineer
Slovakia	Drug Safety Specialist	Drug safety specialist
Slovakia	Špecialista optimalizácie rádiovej siete	Specialist radio network optimisation
Slovakia	Špecialista vývoja programov zdravia	Development specialist health programmes
Slovakia	Špecialista plánovania rádiovej siete	Radio network planning specialist
Slovakia	Špecialista rozvoja spojovacej siete	Development specialist switching network
Slovakia	Klinický psychológ	Clinical psychology
Slovakia	Spa terapista	Spa therapist

Country	Occupation	Translated
Slovakia	Lesný inžinier	Forest engineer
Slovakia	Geológ	Geologist
Slovakia	Revízny farmaceut	Revision pharmacist
Slovakia	Špecialista OSS/BSS	Specialist OSS/BSS
Slovakia	Lesný technik	Forest technician
Spain	Refractory engineer	Refractory engineer
Poland	Animator Kultury	Cultural animator
Poland	Kierownik ds. Operacji Dokumentowych	Manager. Documentary operations
Poland	Inżynier ds. Testów	Engineer. Testing
Poland	Inżynier Biomedyczny	Biomedical engineer
Poland	Inżynier ds. Ciągłego Doskonalenia	Engineer. Continuous improvement
Poland	Inżynier Procesu	Process engineer
Poland	Opiekunka Środowiskowa	Environmental supervisor
Poland	Inżynier Biomedyczny	Biomedical engineer
Hungary	Nyomdász	Typographer
Hungary	Terméktervező	Product designer
Hungary	Gyógypedagógus	Special education teacher
Hungary	Telemarketinges	Telemarketing
Hungary	Gyártómérnök	Manufacturing engineer
Hungary	Dekoratőr	Decorator
Hungary	Telekommunikációs szakértő	Telecommunications expert
Hungary	Webdesigner	Web designer
Hungary	Szoftver tesztmérnök	Software test engineer
Hungary	Data analyst	Data analyst
Hungary	Kertészmérnök	Horticulturist

Figure a1.1displays the number of tags detected over time in all countries, where new occupation tags were detected except for Belgium, which was left out due to a huge number of occupation tags detected every month. Most vacancies were detected in the first month. The reason is that the lists of tags often contain only those tags, which are currently used for at least one vacancy.

Figure a1.1 Number of new occupation tags detected across time (all countries except Belgium)



appendix 2 Template of an occupation card

a2.1 New occupation title

Date: when picked up by the algorithm

a2.1.1 Identification

In the beginning of *Month X Year X*, a new tag was added to the online job board of *Country X*. This tag was picked up (either via the API or using a web crawling technique that extracts the list of tags) and stored in a database. As a next step, we search for a vacancy for *new occupation X* on the job portal - to discover what triggered the new tag. More details on this tag and vacancy can be found below; these details cover (i) the portal to which the tag was added and where the vacancy was found, and (ii) the content of the sample vacancy that we study in more depth (to identify tasks and responsibilities - skills and other requirements).

Details on the tag and the job advertisement	
When did the tag/vacancy appear online? On which online job board was the tag/vacancy published? Which country is covered by this job portal? In which industry is the employer active? What type of employer has posted the vacancy?	

Sample job advertisement	
Job description (responsibilities and tasks of the job) Job profile (education, skills and other requirements for the job) Job portal tags (tags attached to the vacancy on the job board)	

a2.1.2 Definition, responsibilities and tasks

a2.1.2.1 Definition

What is 'new occupation X'?
Is this position related to any existing occupations?
How prevalent is new occupation X in Country X?

a2.1.2.2 What are the responsibilities and tasks of new occupation X?

This information is obtained from a sample of job vacancies, extracted from job portals (for Country X)

a2.1.3 Education, skills and other requirements

This information is obtained from a sample of job vacancies, extracted from job portals (for Country X)

Formal education required	
Is formal education required? Level of education Field of education	

Skills required	
Communication skills Computer skills Non-cognitive skills Occupation-specific skills	

Experience required	
Is experience required? Is job-related experience required?	

a2.1.4 Geographical prevalence

a2.1.4.1 A European perspective

Results from job portals and Google search for countries in different parts of Europe:
Some of the job portals consulted: Indeed, Monster, Stepstone…

Similar vacancies in Western Europe	
Western Europe Country 1 Western Europe Country 2 Etc.	
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Country X?	Tasks/Responsibilities: Requirements:

Similar vacancies in Southern Europe	
Southern Europe Country 1 Southern Europe Country 2 Etc.	
Do these vacancies involve similar tasks and have similar requirements as the vacancies for Country X?	Tasks/Responsibilities: Requirements:

Similar vacancies in Northern Europe	
Northern Europe Country 1 Northern Europe Country 2 Do these vacancies involve similar tasks and have similar requirements as the vacancies for Country X?	Tasks/Responsibilities: Requirements:

Similar vacancies in Central and Eastern Europe	
Central and Eastern Europe Country 1 Central and Eastern Europe Country 1 Etc. **Do these vacancies involve similar tasks and have similar requirements as the vacancies for Country X?**	**Tasks/Responsibilities**: **Requirements**:

a2.1.4.2 A global perspective

Results from *job portals* and *Google search* for countries in different parts of the world
Some of the job portals consulted: Indeed, Monster, Stepstone…

Do these vacancies involve *similar tasks* and have *similar requirements* as vacancies for Country X?
- Tasks/Responsibilities:

- Requirements:

a2.1.4.3 A Google Trends Analysis

a2.1.5 Occupational classification

a2.1.5.1 International classifications

ISCO 08: New occupation X found or not?
Where could this occupation fit in the ISCO08 classification?

ESCO: New occupation X found or not?
Where could this occupation fit in the ESCO classification?

a2.1.5.2 National classifications

Country X:
In Europe:
In the rest of the world:

a2.1.6 Conclusions

Is New occupation X a new or emerging occupation?	
In Country X? In Europe? Worldwide?	

appendix 3 List of the 30 most-frequently advertised occupations in the US

Table a1.2 below presents the 30 most-frequently-advertised occupations in the United States (as obtained from Burning Glass Technologies). For each occupation, it shows the ISCO code and the number of job advertisements available in the dataset. On average, there are 66,292 vacancies for each occupation. There are no occupations for which fewer than 30,000 job advertisements are available. For five occupations, there are over 100,000 vacancies in the database. These occupations are: retail salesperson (233,851 vacancies), CS (i.e. customer service) representative (197,232 vacancies), sale worker supervisor (164,298 vacancies), secretary (114,918 vacancies) and sales representative wholesale (111,177 vacancies).

The ISCO code of each occupation is reported in the first column of Table a1.2 (the ISCO-08 code). The *ISCO-08 classification* is the most recent version of the International Labour Organisation's (ILO) '*International Standard Classification of Occupations*', which was first launched in the 1980s. In ISCO-08, occupations are categorised into 9 classes on the basis of the skill level and the skill specialisation needed to perform the tasks that they involve. Occupations with complexer tasks have a lower ISCO code (e.g. 'managers' are grouped under ISCO code 1), whereas occupations with less complex tasks have a higher ISCO code (e.g. 'elementary occupations' are grouped under ISCO code 9). The nine ISCO-08 groups are: 1 '*Managers*', 2 '*Professionals*', 3 '*Technicians and associate professionals*', 4 '*Clerical support workers*', 5 '*Service and sales workers*', 6 '*Skilled agricultural, forestry and fishery workers*', 7 '*Craft and related trades workers*', 8 '*Plant and machine operators, and assemblers*', and 9 '*Elementary occupations*' (not considering 0 Armed forces occupations).

Table a3.1 Overview of the 30 most-frequently-advertised occupations in the US, their ISCO codes and the number of vacancies collected

ISCO	Occupation	Number of vacancies
1	General and Operations Managers	30,641
2	Computer Support Specialists	37,705
2	HR Specialists	36,243
3	Bookkeeping, Accounting, Auditing Clerks	43,445
3	First-Line Office Supervisors	35,841
3	Medical Assistants	40,127
3	Meeting, Convention, Event Planners	32,204
3	Nursing Assistant	96,937
4	Cashiers	29,722
4	CS Representatives	197,232
4	Medical Secretaries	35,263
4	Office Clerks	42,948
4	Secretaries	114,918
4	Tellers	68,339
5	Combined Food Preparation Workers	46,912
5	Cooks, Restaurant	30,252
5	Merchandise Displayers	60,100
5	Personal Care Aides	38,106
5	Retail Salesperson	233,851
5	Sale Worker Supervisors	164,298
5	Sales Agents, Financial Services	36,172
5	Sales Representative Wholesale	111,177
5	Security Guards	66,122
5	Supervisors of Food Preparation, Serving Workers	45,957
7	Installation, Maintenance, Repair Workers	43,157
7	Maintenance Worker	94,066
8	Heavy Truck and Tractor Drivers	33,180
8	Light Truck, Delivery Service Drivers	38,405
9	Janitors and Cleaners	33,779
9	Labourers	71,669

appendix 4 Distribution over gender and education levels for Eurostat LFS data and WageIndicator web survey data by year

Source	Gender	ISCED	2010_n	2011_n	2012_n	2010_%	2011_%	2012_%
Eurostat	Females	ISCED 0-2	134.30	125.50	115.00	0.07	0.06	0.06
Eurostat	Females	ISCED 3-4	1,539.70	1,521.50	1,502.60	0.75	0.74	0.72
Eurostat	Females	ISCED 5-6	382.60	416.30	460.70	0.19	0.20	0.22
Eurostat	Females Total	ISCED-1997 levels	2,057.10	2,063.50	2,078.60	1.00	1.00	1.00
Eurostat	Males	ISCED 0-2	100.20	90.90	90.30	0.04	0.03	0.03
Eurostat	Males	ISCED 3-4	2,162.70	2,120.80	2,105.70	0.79	0.78	0.77
Eurostat	Males	ISCED 5-6	489.10	520.90	535.50	0.18	0.19	0.20
Eurostat	Males Total	ISCED-1997 levels	2,752.50	2,732.80	2,731.80	1.00	1.00	1.00
WageIndicator	Females	ISCED 0-2	35	26	21	0.03	0.05	0.02
WageIndicator	Females	ISCED 3-4	693	336	455	0.69	0.63	0.48
WageIndicator	Females	ISCED 5-6	279	170	481	0.28	0.32	0.50
WageIndicator	Females Total	ISCED-1997 levels	1007	532	957	1.00	1.00	1.00
WageIndicator	Males	ISCED 0-2	14	19	48	0.02	0.03	0.02
WageIndicator	Males	ISCED 3-4	545	423	853	0.65	0.60	0.43
WageIndicator	Males	ISCED 5-6	275	267	1,066	0.33	0.38	0.54
WageIndicator	Males Total	ISCED-1997 levels	834	709	1,967	1.00	1.00	1.00

appendix 5 Correspondence table ISCO-88 into ISCO-08 according to ILO and according to this study

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Legislators	1110	1111		1111	Legislators
Senior government officials	1120	1112		1112	Senior government officials
Traditional chiefs and heads of villages	1130	1113		1113	Traditional chiefs and heads of villages
Senior officials of political-party organisations	1141	1114	p	1114	Senior officials of special-interest organizations
Senior officials of employers', workers' and other economic-interest organisations	1142	1114	p	1114	Senior officials of special-interest organizations
Senior officials of humanitarian and other special-interest organisations	1143	1114	p	1114	Senior officials of special-interest organizations
Directors and chief executives	1210	1120		1120	Managing directors and chief executives
Production and operations department managers in agriculture, hunting, forestry and fishing	1221	1311		1311	Agricultural and forestry production managers
Production and operations department managers in agriculture, hunting, forestry and fishing	1221	1312		1311	Aquaculture and fisheries production managers
Production and operations department managers in manufacturing	1222	1321	p	1321	Manufacturing managers
Production and operations department managers in manufacturing	1222	1322	p	1321	Mining managers
Production and operations department managers in construction	1223	1323	p	3123	Construction managers
Production and operations department managers in construction	1223	3123	p	3123	Construction supervisors
Production and operations department managers in wholesale and retail trade	1224	1420	p	1420	Retail and wholesale trade managers
Production and operations department managers in restaurants and hotels	1225	1411	p	1411	Hotel managers
Production and operations department managers in restaurants and hotels	1225	1412	p	1411	Restaurant managers
Production and operations department managers in transport, storage and communications	1226	1324	p	1324	Supply, distribution and related managers
Production and operations department managers in transport, storage and communications	1226	1330	p	1324	Information and communications technology service managers
Production and operations department managers in business services	1227	1219	p	1219	Business services and administration managers not elsewhere classified
Production and operations department managers in business services	1227	1346		1219	Financial and insurance services branch managers
Production and operations department managers in personal care, cleaning and related services	1228	1219	p	1219	Business services and administration managers not elsewhere classified
Production and operations department managers not elsewhere classified	1229	1213	p	1219	Policy and planning managers
Production and operations department managers not elsewhere classified	1229	1219	p	1219	Business services and administration managers not elsewhere classified
Production and operations department managers not elsewhere classified	1229	1341	p	1219	Child care services managers
Production and operations department managers not elsewhere classified	1229	1342	p	1219	Health services managers
Production and operations department managers not elsewhere classified	1229	1343	p	1219	Aged care services managers

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Production and operations department managers not elsewhere classified	1229	1344	p	1219	Social welfare managers
Production and operations department managers not elsewhere classified	1229	1345	p	1219	Education managers
Production and operations department managers not elsewhere classified	1229	1349	p	1219	Professional services managers not elsewhere classified
Production and operations department managers not elsewhere classified	1229	1439	p	1219	Services managers not elsewhere classified
Production and operations department managers not elsewhere classified	1229	2654	p	1219	Film, stage and related directors and producers
Production and operations department managers not elsewhere classified	1229	3435	p	1219	Other artistic and cultural associate professionals
Finance and administration department managers	1231	1211	p	1219	Finance managers
Finance and administration department managers	1231	1219	p	1219	Business services and administration managers not elsewhere classified
Personnel and industrial relations department managers	1232	1212	p	1212	Human resource managers
Sales and marketing department managers	1233	1221	p	1221	Sales and marketing managers
Advertising and public relations department managers	1234	1222	p	1222	Advertising and public relations managers
Supply and distribution department managers	1235	1324	p	1324	Supply, distribution and related managers
Computing services department managers	1236	1330	p	1330	Information and communications technology service managers
Research and development department managers	1237	1223	p	1223	Research and development managers
Other department managers not elsewhere classified	1239	1213	p	1213	Policy and planning managers
General managers in agriculture, hunting, forestry and fishing	1311	6111	p	6113	Field crop and vegetable growers
General managers in agriculture, hunting, forestry and fishing	1311	6112	p	6113	Tree and shrub crop growers
General managers in agriculture, hunting, forestry and fishing	1311	6113	p	6113	Gardeners, horticultural and nursery growers
General managers in agriculture, hunting, forestry and fishing	1311	6114	p	6113	Mixed crop growers
General managers in agriculture, hunting, forestry and fishing	1311	6121	p	6113	Livestock and dairy producers
General managers in agriculture, hunting, forestry and fishing	1311	6122	p	6113	Poultry producers
General managers in agriculture, hunting, forestry and fishing	1311	6130	p	6113	Mixed crop and animal producers
General managers in agriculture, hunting, forestry and fishing	1311	6210	p	6113	Forestry and related workers
General managers in agriculture, hunting, forestry and fishing	1311	6221	p	6113	Aquaculture workers
General managers in agriculture, hunting, forestry and fishing	1311	6222	p	6113	Inland and coastal waters fishery workers
General managers in agriculture, hunting, forestry and fishing	1311	6223	p	6113	Deep-sea fishery workers
General managers in manufacturing	1312	1321	p	1321	Manufacturing managers
General managers in manufacturing	1312	1322	p	1321	Mining managers
General managers in construction	1313	1323	p	1323	Construction managers
General managers in wholesale and retail trade	1314	1420	p	1420	Retail and wholesale trade managers
General managers in wholesale and retail trade	1314	5221		1420	Shopkeepers
General managers of restaurants and hotels	1315	1411	p	1411	Hotel managers
General managers of restaurants and hotels	1315	1412	p	1411	Restaurant managers
General managers in transport, storage and communications	1316	1324	p	1324	Supply, distribution and related managers
General managers in transport, storage and communications	1316	1330	p	1324	Information and communications technology service managers
General managers of business services	1317	1211	p	1219	Finance managers
General managers of business services	1317	1212	p	1219	Human resource managers
General managers of business services	1317	1219	p	1219	Business services and administration managers not elsewhere classified
General managers of business services	1317	1221	p	1219	Sales and marketing managers
General managers of business services	1317	1222	p	1219	Advertising and public relations managers

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
General managers of business services	1317	1330	p	1219	Information and communications technology service managers
General managers of business services	1317	1346		1219	Financial and insurance services branch managers
General managers in personal care, cleaning and related services	1318	1219	p	1219	Business services and administration managers not elsewhere classified
General managers not elsewhere classified	1319	1223	p	1349	Research and development managers
General managers not elsewhere classified	1319	1341	p	1349	Child care services managers
General managers not elsewhere classified	1319	1342	p	1349	Health services managers
General managers not elsewhere classified	1319	1343	p	1349	Aged care services managers
General managers not elsewhere classified	1319	1344	p	1349	Social welfare managers
General managers not elsewhere classified	1319	1345	p	1349	Education managers
General managers not elsewhere classified	1319	1349	p	1349	Professional services managers not elsewhere classified
General managers not elsewhere classified	1319	1431		1349	Sports, recreation and cultural centre managers
General managers not elsewhere classified	1319	1439	p	1349	Services managers not elsewhere classified
Physicists and astronomers	2111	2111		2111	Physicists and astronomers
Meteorologists	2112	2112		2112	Meteorologists
Chemists	2113	2113		2113	Chemists
Chemists	2113	2262	p	2113	Pharmacists
Geologists and geophysicists	2114	2114		2114	Geologists and geophysicists
Mathematicians and related professionals	2121	2120	p	2120	Mathematicians, actuaries and statisticians
Statisticians	2122	2120	p	2120	Mathematicians, actuaries and statisticians
Computer systems designers and analysts	2131	2511		2519	Systems analysts
Computer systems designers and analysts	2131	2512		2519	Software developers
Computer systems designers and analysts	2131	2513	p	2519	Web and multimedia developers
Computer systems designers and analysts	2131	2519	p	2519	Software and applications developers and analysts not elsewhere classified
Computer systems designers and analysts	2131	2521		2519	Database designers and administrators
Computer systems designers and analysts	2131	2522		2519	Systems administrators
Computer systems designers and analysts	2131	2523		2519	Computer network professionals
Computer programmers	2132	2513	p	2519	Web and multimedia developers
Computer programmers	2132	2514		2519	Applications programmers
Computer programmers	2132	2519	p	2519	Software and applications developers and analysts not elsewhere classified
Computing professionals not elsewhere classified	2139	2513	p	2529	Web and multimedia developers
Computing professionals not elsewhere classified	2139	2519	p	2529	Software and applications developers and analysts not elsewhere classified
Computing professionals not elsewhere classified	2139	2529	p	2529	Database and network professionals not elsewhere classified
Architects, town and traffic planners	2141	2161		2161	Building architects
Architects, town and traffic planners	2141	2162		2161	Landscape architects
Architects, town and traffic planners	2141	2164		2161	Town and traffic planners
Civil engineers	2142	2142		2142	Civil engineers
Electrical engineers	2143	2151		2151	Electrical engineers
Electronics and telecommunications engineers	2144	2152		2153	Electronics engineers

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Electronics and telecommunications engineers	2144	2153		2153	Telecommunications engineers
Mechanical engineers	2145	2144		2144	Mechanical engineers
Chemical engineers	2146	2145		2145	Chemical engineers
Mining engineers, metallurgists and related professionals	2147	2146		2146	Mining engineers, metallurgists and related professionals
Cartographers and surveyors	2148	2165		2165	Cartographers and surveyors
Architects, engineers and related professionals not elsewhere classified	2149	2141		2149	Industrial and production engineers
Architects, engineers and related professionals not elsewhere classified	2149	2143		2149	Environmental engineers
Architects, engineers and related professionals not elsewhere classified	2149	2149		2149	Engineering professionals not elsewhere classified
Biologists, botanists, zoologists and related professionals	2211	2131	p	2131	Biologists, botanists, zoologists and related professionals
Biologists, botanists, zoologists and related professionals	2211	2133		2131	Environmental protection professionals
Pharmacologists, pathologists and related professionals	2212	2131	p	2131	Biologists, botanists, zoologists and related professionals
Pharmacologists, pathologists and related professionals	2212	2212		2212	Specialist medical practitioners
Pharmacologists, pathologists and related professionals	2212	2250	p	2212	Veterinarians
Agronomists and related professionals	2213	2132	p	2132	Farming, forestry and fisheries advisers
Medical doctors	2221	2211		2212	Generalist medical practitioners
Medical doctors	2221	2212		2212	Specialist medical practitioners
Dentists	2222	2261		2261	Dentists
Veterinarians	2223	2250	p	2250	Veterinarians
Pharmacists	2224	2262	p	2262	Pharmacists
Health professionals (except nursing) not elsewhere classified	2229	2263	p	2269	Environmental and occupational health and hygiene professionals
Health professionals (except nursing) not elsewhere classified	2229	2269	p	2269	Health professionals not elsewhere classified
Nursing and midwifery professionals	2230	1342	p	2221	Health services managers
Nursing and midwifery professionals	2230	1343	p	2221	Aged care services managers
Nursing and midwifery professionals	2230	2221	p	2221	Nursing professionals
Nursing and midwifery professionals	2230	2222	p	2221	Midwifery professionals
Nursing and midwifery professionals	2230	3221	p	3221	Nursing associate professionals
Nursing and midwifery professionals	2230	3222	p	2221	Midwifery associate professionals
College, university and higher education teaching professionals	2310	2310		2310	University and higher education teachers
College, university and higher education teaching professionals	2310	2320	p	2310	Vocational education teachers
Secondary education teaching professionals	2320	2320	p	2330	Vocational education teachers
Secondary education teaching professionals	2320	2330		2330	Secondary education teachers
Primary education teaching professionals	2331	2341	p	2341	Primary school teachers
Pre-primary education teaching professionals	2332	2342	p	2342	Early childhood educators
Special education teaching professionals	2340	2352	p	2352	Special needs teachers
Education methods specialists	2351	2351	p	2351	Education methods specialists
School inspectors	2352	2351	p	2351	Education methods specialists
Other teaching professionals not elsewhere classified	2359	2353	p	2359	Other language teachers
Other teaching professionals not elsewhere classified	2359	2354		2359	Other music teachers
Other teaching professionals not elsewhere classified	2359	2355	p	2359	Other arts teachers
Other teaching professionals not elsewhere classified	2359	2356	p	2359	Information technology trainers
Other teaching professionals not elsewhere classified	2359	2359	p	2359	Teaching professionals not elsewhere classified

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Accountants	2411	2411	p	2411	Accountants
Accountants	2411	2412	p	2411	Financial and investment advisers
Personnel and careers professionals	2412	2263	p	2423	Environmental and occupational health and hygiene professionals
Personnel and careers professionals	2412	2423		2423	Personnel and careers professionals
Personnel and careers professionals	2412	2424		2423	Training and staff development professionals
Business professionals not elsewhere classified	2419	2412	p	3339	Financial and investment advisers
Business professionals not elsewhere classified	2419	2413		3339	Financial analysts
Business professionals not elsewhere classified	2419	2421		3339	Management and organization analysts
Business professionals not elsewhere classified	2419	2422		3339	Policy administration professionals
Business professionals not elsewhere classified	2419	2431		3339	Advertising and marketing professionals
Business professionals not elsewhere classified	2419	2432		3339	Public relations professionals
Business professionals not elsewhere classified	2419	3339	p	3339	Business services agents not elsewhere classified
Lawyers	2421	2611		2611	Lawyers
Judges	2422	2612		2612	Judges
Legal professionals not elsewhere classified	2429	2619		2619	Legal professionals not elsewhere classified
Archivists and curators	2431	2621		2621	Archivists and curators
Librarians and related information professionals	2432	2622		2622	Librarians and related information professionals
Economists	2441	2631		2631	Economists
Sociologists, anthropologists and related professionals	2442	2632		2632	Sociologists, anthropologists and related professionals
Philosophers, historians and political scientists	2443	2633		2633	Philosophers, historians and political scientists
Philologists, translators and interpreters	2444	2643		2643	Translators, interpreters and other linguists
Psychologists	2445	2634		2634	Psychologists
Social work professionals	2446	2635		2635	Social work and counselling professionals
Authors, journalists and other writers	2451	2431		2642	Advertising and marketing professionals
Authors, journalists and other writers	2451	2432		2642	Public relations professionals
Authors, journalists and other writers	2451	2641		2642	Authors and related writers
Authors, journalists and other writers	2451	2642	p	2642	Journalists
Sculptors, painters and related artists	2452	2651		2651	Visual artists
Composers, musicians and singers	2453	2652	p	2652	Musicians, singers and composers
Choreographers and dancers	2454	2653	p	2653	Dancers and choreographers
Film, stage and related actors and directors	2455	2654	p	2654	Film, stage and related directors and producers
Film, stage and related actors and directors	2455	2655		2654	Actors
Religious professionals	2460	2636		2636	Religious professionals
Chemical and physical science technicians	3111	3111		3111	Chemical and physical science technicians
Civil engineering technicians	3112	3112	p	3112	Civil engineering technicians
Electrical engineering technicians	3113	3113	p	3113	Electrical engineering technicians
Electronics and telecommunications engineering technicians	3114	3114	p	3522	Electronics engineering technicians
Electronics and telecommunications engineering technicians	3114	3522		3522	Telecommunications engineering technicians
Mechanical engineering technicians	3115	3115	p	3115	Mechanical engineering technicians
Chemical engineering technicians	3116	3116		3116	Chemical engineering technicians
Mining and metallurgical technicians	3117	3117	p	3117	Mining and metallurgical technicians

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Draughtspersons	3118	3118		3118	Draughtspersons
Physical and engineering science technicians not elsewhere classified	3119	3119		3119	Physical and engineering science technicians not elsewhere classified
Computer assistants	3121	3512		3512	Information and communications technology user support technicians
Computer assistants	3121	3513	p	3512	Computer network and systems technicians
Computer assistants	3121	3514	p	3512	Web technicians
Computer equipment operators	3122	3511		3511	Information and communications technology operations technicians
Computer equipment operators	3122	3514	p	3511	Web technicians
Industrial robot controllers	3123	3139	p	3139	Process control technicians not elsewhere classified
Photographers and image and sound recording equipment operators	3131	3431		3521	Photographers
Photographers and image and sound recording equipment operators	3131	3521	p	3521	Broadcasting and audio-visual technicians
Broadcasting and telecommunications equipment operators	3132	3521	p	3522	Broadcasting and audio-visual technicians
Broadcasting and telecommunications equipment operators	3132	3522		3522	Telecommunications engineering technicians
Medical equipment operators	3133	3211		3211	Medical imaging and therapeutic equipment technicians
Ships' engineers	3141	3151		3151	Ships' engineers
Ships' deck officers and pilots	3142	3152		3152	Ships' deck officers and pilots
Aircraft pilots and related associate professionals	3143	3153	p	3153	Aircraft pilots and related associate professionals
Air traffic controllers	3144	3154		3154	Air traffic controllers
Air traffic safety technicians	3145	3155		3155	Air traffic safety electronics technicians
Building and fire inspectors	3151	3112	p	3112	Civil engineering technicians
Building and fire inspectors	3151	3359	p	3112	Regulatory government associate professionals not elsewhere classified
Safety, health and quality inspectors	3152	2263	p	3257	Environmental and occupational health and hygiene professionals
Safety, health and quality inspectors	3152	3113	p	3257	Electrical engineering technicians
Safety, health and quality inspectors	3152	3114	p	3257	Electronics engineering technicians
Safety, health and quality inspectors	3152	3115	p	3257	Mechanical engineering technicians
Safety, health and quality inspectors	3152	3117	p	3257	Mining and metallurgical technicians
Safety, health and quality inspectors	3152	3257	p	3257	Environmental and occupational health inspectors and associates
Safety, health and quality inspectors	3152	7543		3257	Product graders and testers (excluding foods and beverages)
Life science technicians	3211	3141		3141	Life science technicians (excluding medical)
Life science technicians	3211	3212		3141	Medical and pathology laboratory technicians
Agronomy and forestry technicians	3212	3142		3142	Agricultural technicians
Agronomy and forestry technicians	3212	3143		3142	Forestry technicians
Farming and forestry advisers	3213	2132	p	2132	Farming, forestry and fisheries advisers
Medical assistants	3221	2240		3256	Paramedical practitioners
Medical assistants	3221	3253		3256	Community health workers
Medical assistants	3221	3256		3256	Medical assistants
Sanitarians	3222	2263	p	3257	Environmental and occupational health and hygiene professionals

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Sanitarians	3222	3257	p	3257	Environmental and occupational health inspectors and associates
Dieticians and nutritionists	3223	2265		2265	Dieticians and nutritionists
Optometrists and opticians	3224	2267		2267	Optometrists and ophthalmic opticians
Optometrists and opticians	3224	3254		2267	Dispensing opticians
Dental assistants	3225	3251		3251	Dental assistants and therapists
Physiotherapists and related associate professionals	3226	2264		2264	Physiotherapists
Physiotherapists and related associate professionals	3226	2269	p	2264	Health professionals not elsewhere classified
Physiotherapists and related associate professionals	3226	3255		2264	Physiotherapy technicians and assistants
Physiotherapists and related associate professionals	3226	3259	p	2264	Health associate professionals not elsewhere classified
Veterinary assistants	3227	3240		3240	Veterinary technicians and assistants
Pharmaceutical assistants	3228	3213		3213	Pharmaceutical technicians and assistants
Modern health associate professionals (except nursing) not elsewhere classified	3229	2230	p	3259	Traditional and complementary medicine professionals
Modern health associate professionals (except nursing) not elsewhere classified	3229	2266		3259	Audiologists and speech therapists
Modern health associate professionals (except nursing) not elsewhere classified	3229	2267	p	3259	Optometrists and ophthalmic opticians
Modern health associate professionals (except nursing) not elsewhere classified	3229	2269	p	3259	Health professionals not elsewhere classified
Modern health associate professionals (except nursing) not elsewhere classified	3229	3259	p	3259	Health associate professionals not elsewhere classified
Nursing associate professionals	3231	3221	p	3221	Nursing associate professionals
Midwifery associate professionals	3232	3222	p	3222	Midwifery associate professionals
Traditional medicine practitioners	3241	2230	p	3259	Traditional and complementary medicine professionals
Traditional medicine practitioners	3241	3230	p	3259	Traditional and complementary medicine associate professionals
Faith healers	3242	3413	p	3413	Religious associate professionals
Primary education teaching associate professionals	3310	2341	p	2341	Primary school teachers
Pre-primary education teaching associate professionals	3320	2342	p	2342	Early childhood educators
Special education teaching associate professionals	3330	2352	p	2352	Special needs teachers
Other teaching associate professionals	3340	2353	p	2359	Other language teachers
Other teaching associate professionals	3340	2355	p	2359	Other arts teachers
Other teaching associate professionals	3340	2356	p	2359	Information technology trainers
Other teaching associate professionals	3340	2359	p	2359	Teaching professionals not elsewhere classified
Other teaching associate professionals	3340	3153	p	2359	Aircraft pilots and related associate professionals
Other teaching associate professionals	3340	3423	p	2359	Fitness and recreation instructors and program leaders
Other teaching associate professionals	3340	3435	p	2359	Other artistic and cultural associate professionals
Other teaching associate professionals	3340	5165		2359	Driving instructors
Securities and finance dealers and brokers	3411	2412	p	3311	Financial and investment advisers
Securities and finance dealers and brokers	3411	3311		3311	Securities and finance dealers and brokers
Insurance representatives	3412	3321		3321	Insurance representatives
Estate agents	3413	3334		3334	Real estate agents and property managers
Travel consultants and organisers	3414	4221	p	4221	Travel consultants and clerks
Technical and commercial sales representatives	3415	2433		3322	Technical and medical sales professionals (excluding ICT)
Technical and commercial sales representatives	3415	2434		3322	Information and communications technology sales professionals
Technical and commercial sales representatives	3415	3322		3322	Commercial sales representatives
Buyers	3416	3323		3323	Buyers
Appraisers, valuers and auctioneers	3417	3315		3315	Valuers and loss assessors

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Appraisers, valuers and auctioneers	3417	3339	p	3315	Business services agents not elsewhere classified
Finance and sales associate professionals not elsewhere classified	3419	3312		3312	Credit and loans officers
Trade brokers	3421	3324		3324	Trade brokers
Clearing and forwarding agents	3422	3331		3331	Clearing and forwarding agents
Employment agents and labour contractors	3423	3333	p	3333	Employment agents and contractors
Business services agents and trade brokers not elsewhere classified	3429	3339	p	3339	Business services agents not elsewhere classified
Administrative secretaries and related associate professionals	3431	3341	p	3341	Office supervisors
Administrative secretaries and related associate professionals	3431	3342	p	3343	Legal secretaries
Administrative secretaries and related associate professionals	3431	3343	p	3343	Administrative and executive secretaries
Administrative secretaries and related associate professionals	3431	3344	p	3343	Medical secretaries
Legal and related business associate professionals	3432	3411		3411	Legal and related associate professionals
Bookkeepers	3433	3313	p	3313	Accounting associate professionals
Statistical, mathematical and related associate professionals	3434	3313	p	3313	Accounting associate professionals
Statistical, mathematical and related associate professionals	3434	3314		3313	Statistical, mathematical and related associate professionals
Administrative associate professionals not elsewhere classified	3439	3332		3343	Conference and event planners
Administrative associate professionals not elsewhere classified	3439	3343	p	3343	Administrative and executive secretaries
Administrative associate professionals not elsewhere classified	3439	3359	p	3343	Regulatory government associate professionals not elsewhere classified
Administrative associate professionals not elsewhere classified	3439	3433	p	3343	Gallery, museum and library technicians
Customs and border inspectors	3441	3351		3351	Customs and border inspectors
Government tax and excise officials	3442	3352		3352	Government tax and excise officials
Government social benefits officials	3443	3353		3353	Government social benefits officials
Government licensing officials	3444	3354		3354	Government licensing officials
Customs, tax and related government associate professionals not elsewhere classified	3449	3359	p	3359	Regulatory government associate professionals not elsewhere classified
Police inspectors and detectives	3450	3355		3411	Police inspectors and detectives
Police inspectors and detectives	3450	3411		3411	Legal and related associate professionals
Social work associate professionals	3460	3412		3412	Social work associate professionals
Decorators and commercial designers	3471	2163		2166	Product and garment designers
Decorators and commercial designers	3471	2166		2166	Graphic and multimedia designers
Decorators and commercial designers	3471	3432		2166	Interior designers and decorators
Decorators and commercial designers	3471	3433	p	2166	Gallery, museum and library technicians
Decorators and commercial designers	3471	3435	p	2166	Other artistic and cultural associate professionals
Radio, television and other announcers	3472	2642	p	2656	Journalists
Radio, television and other announcers	3472	2656		2656	Announcers on radio, television and other media
Street, night-club and related musicians, singers and dancers	3473	2652	p	2652	Musicians, singers and composers
Street, night-club and related musicians, singers and dancers	3473	2653	p	2652	Dancers and choreographers
Clowns, magicians, acrobats and related associate professionals	3474	2659		2659	Creative and performing artists not elsewhere classified
Athletes, sportspersons and related associate professionals	3475	3421		3421	Athletes and sports players
Athletes, sportspersons and related associate professionals	3475	3422		3421	Sports coaches, instructors and officials
Athletes, sportspersons and related associate professionals	3475	3423	p	3421	Fitness and recreation instructors and program leaders
Religious associate professionals	3480	3413	p	3413	Religious associate professionals

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Stenographers and typists	4111	3341	p	4131	Office supervisors
Stenographers and typists	4111	4131	p	4131	Typists and word processing operators
Word-processor and related operators	4112	3341	p	4131	Office supervisors
Word-processor and related operators	4112	4131	p	4131	Typists and word processing operators
Data entry operators	4113	4132	p	4132	Data entry clerks
Calculating-machine operators	4114	3341	p	4132	Office supervisors
Calculating-machine operators	4114	4132	p	4132	Data entry clerks
Secretaries	4115	3341	p	4120	Office supervisors
Secretaries	4115	3342	p	4120	Legal secretaries
Secretaries	4115	3344	p	4120	Medical secretaries
Secretaries	4115	4120		4120	Secretaries (general)
Accounting and bookkeeping clerks	4121	3341	p	4311	Office supervisors
Accounting and bookkeeping clerks	4121	4311		4311	Accounting and bookkeeping clerks
Accounting and bookkeeping clerks	4121	4313		4311	Payroll clerks
Statistical and finance clerks	4122	3341	p	4312	Office supervisors
Statistical and finance clerks	4122	4312		4312	Statistical, finance and insurance clerks
Stock clerks	4131	3341	p	4321	Office supervisors
Stock clerks	4131	4321		4321	Stock clerks
Production clerks	4132	3341	p	4322	Office supervisors
Production clerks	4132	4322		4322	Production clerks
Transport clerks	4133	3341	p	4323	Office supervisors
Transport clerks	4133	4323		4323	Transport clerks
Library and filing clerks	4141	3341	p	4411	Office supervisors
Library and filing clerks	4141	4411		4411	Library clerks
Library and filing clerks	4141	4415		4411	Filing and copying clerks
Mail carriers and sorting clerks	4142	3341	p	4412	Office supervisors
Mail carriers and sorting clerks	4142	4412		4412	Mail carriers and sorting clerks
Coding, proof-reading and related clerks	4143	3252		4413	Medical records and health information technicians
Coding, proof-reading and related clerks	4143	3341	p	4413	Office supervisors
Coding, proof-reading and related clerks	4143	4413		4413	Coding, proof-reading and related clerks
Scribes and related workers	4144	3341	p	4414	Office supervisors
Scribes and related workers	4144	4414		4414	Scribes and related workers
Other office clerks	4190	3341	p	4110	Office supervisors
Other office clerks	4190	4110		4110	General office clerks
Other office clerks	4190	4227		4110	Survey and market research interviewers
Other office clerks	4190	4416		4110	Personnel clerks
Other office clerks	4190	4419		4110	Clerical support workers not elsewhere classified
Cashiers and ticket clerks	4211	4211	p	5230	Bank tellers and related clerks
Cashiers and ticket clerks	4211	4212	p	5230	Bookmakers, croupiers and related gaming workers
Cashiers and ticket clerks	4211	5230		5230	Cashiers and ticket clerks
Tellers and other counter clerks	4212	4211	p	4211	Bank tellers and related clerks
Bookmakers and croupiers	4213	4212	p	4212	Bookmakers, croupiers and related gaming workers

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Pawnbrokers and money-lenders	4214	4213		4213	Pawnbrokers and money-lenders
Debt-collectors and related workers	4215	4214		4214	Debt-collectors and related workers
Travel agency and related clerks	4221	4221	p	4221	Travel consultants and clerks
Receptionists and information clerks	4222	3341	p	4226	Office supervisors
Receptionists and information clerks	4222	4222		4226	Contact centre information clerks
Receptionists and information clerks	4222	4224		4226	Hotel receptionists
Receptionists and information clerks	4222	4225		4226	Enquiry clerks
Receptionists and information clerks	4222	4226		4226	Receptionists (general)
Receptionists and information clerks	4222	4229		4226	Client information workers not elsewhere classified
Telephone switchboard operators	4223	3341	p	4223	Office supervisors
Telephone switchboard operators	4223	4223		4223	Telephone switchboard operators
Travel attendants and travel stewards	5111	5111		5111	Travel attendants and travel stewards
Transport conductors	5112	5112		5112	Transport conductors
Travel guides	5113	5113		5113	Travel guides
Housekeepers and related workers	5121	5151		5152	Cleaning and housekeeping supervisors in offices, hotels and other establishments
Housekeepers and related workers	5121	5152		5152	Domestic housekeepers
Cooks	5122	3434		5120	Chefs
Cooks	5122	5120		5120	Cooks
Cooks	5122	9411		5120	Fast food preparers
Waiters, waitresses and bartenders	5123	5131		5131	Waiters
Waiters, waitresses and bartenders	5123	5132		5131	Bartenders
Child-care workers	5131	5311		5311	Child care workers
Child-care workers	5131	5312		5311	Teachers' aides
Institution-based personal care workers	5132	3258		5321	Ambulance workers
Institution-based personal care workers	5132	5321		5321	Health care assistants
Institution-based personal care workers	5132	5329		5321	Personal care workers in health services not elsewhere classified
Home-based personal care workers	5133	5322		5322	Home-based personal care workers
Personal care and related workers not elsewhere classified	5139	5164		5329	Pet groomers and animal care workers
Personal care and related workers not elsewhere classified	5139	5329		5329	Personal care workers in health services not elsewhere classified
Hairdressers, barbers, beauticians and related workers	5141	5141		5141	Hairdressers
Hairdressers, barbers, beauticians and related workers	5141	5142		5141	Beauticians and related workers
Companions and valets	5142	5162		5162	Companions and valets
Undertakers and embalmers	5143	5163		5163	Undertakers and embalmers
Other personal services workers not elsewhere classified	5149	5169	p	5169	Personal services workers not elsewhere classified
Astrologers and related workers	5151	5161	p	5161	Astrologers, fortune-tellers and related workers
Fortune-tellers, palmists and related workers	5152	5161	p	5161	Astrologers, fortune-tellers and related workers
Fire-fighters	5161	5411		5411	Fire fighters
Police officers	5162	5412		5412	Police officers
Prison guards	5163	5413		5413	Prison guards
Protective services workers not elsewhere classified	5169	5414	p	5414	Security guards
Protective services workers not elsewhere classified	5169	5419		5414	Protective services workers not elsewhere classified

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Fashion and other models	5210	5241		5241	Fashion and other models
Shop salespersons and demonstrators	5220	5222		5223	Shop supervisors
Shop salespersons and demonstrators	5220	5223		5223	Shop sales assistants
Shop salespersons and demonstrators	5220	5242		5223	Sales demonstrators
Shop salespersons and demonstrators	5220	5245		5223	Service station attendants
Shop salespersons and demonstrators	5220	5246	p	5223	Food service counter attendants
Shop salespersons and demonstrators	5220	5249		5223	Sales workers not elsewhere classified
Stall and market salespersons	5230	5211		5211	Stall and market salespersons
Stall and market salespersons	5230	5246	p	5211	Food service counter attendants
Field crop and vegetable growers	6111	6111	p	6111	Field crop and vegetable growers
Tree and shrub crop growers	6112	6112	p	6112	Tree and shrub crop growers
Gardeners, horticultural and nursery growers	6113	6113	p	6113	Gardeners, horticultural and nursery growers
Gardeners, horticultural and nursery growers	6113	9214		6113	Garden and horticultural labourers
Mixed-crop growers	6114	6114	p	6114	Mixed crop growers
Dairy and livestock producers	6121	6121	p	6121	Livestock and dairy producers
Poultry producers	6122	6122	p	6122	Poultry producers
Apiarists and sericulturists	6123	6123	p	6123	Apiarists and sericulturists
Mixed-animal producers	6124	6121	p	6121	Livestock and dairy producers
Mixed-animal producers	6124	6122	p	6121	Poultry producers
Mixed-animal producers	6124	6123	p	6121	Apiarists and sericulturists
Market-oriented animal producers and related workers not elsewhere classified	6129	5164		6129	Pet groomers and animal care workers
Market-oriented animal producers and related workers not elsewhere classified	6129	6129		6129	Animal producers not elsewhere classified
Market-oriented crop and animal producers	6130	6130	p	6130	Mixed crop and animal producers
Forestry workers and loggers	6141	6210	p	6210	Forestry and related workers
Charcoal burners and related workers	6142	6210	p	6210	Forestry and related workers
Aquatic-life cultivation workers	6151	6221	p	6221	Aquaculture workers
Inland and coastal waters fishery workers	6152	6222	p	6222	Inland and coastal waters fishery workers
Inland and coastal waters fishery workers	6152	7541	p	6222	Underwater divers
Deep-sea fishery workers	6153	6223	p	6223	Deep-sea fishery workers
Hunters and trappers	6154	6224		6224	Hunters and trappers
Subsistence agricultural and fishery workers	6210	6310		6330	Subsistence crop farmers
Subsistence agricultural and fishery workers	6210	6320		6330	Subsistence livestock farmers
Subsistence agricultural and fishery workers	6210	6330		6330	Subsistence mixed crop and livestock farmers
Subsistence agricultural and fishery workers	6210	6340		6330	Subsistence fishers, hunters, trappers and gatherers
Miners and quarry workers	7111	3121		8111	Mining supervisors
Miners and quarry workers	7111	8111	p	8111	Miners and quarriers
Shotfirers and blasters	7112	7542		7542	Shotfirers and blasters
Stone splitters, cutters and carvers	7113	7113	p	7113	Stonemasons, stone cutters, splitters and carvers
Builders, traditional materials	7121	7111	p	7111	House builders
Bricklayers and stonemasons	7122	7112		7112	Bricklayers and related workers
Bricklayers and stonemasons	7122	7113	p	7112	Stonemasons, stone cutters, splitters and carvers
Concrete placers, concrete finishers and related workers	7123	7114		7114	Concrete placers, concrete finishers and related workers

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Carpenters and joiners	7124	7115		7115	Carpenters and joiners
Building frame and related trades workers not elsewhere classified	7129	3123	p	7119	Construction supervisors
Building frame and related trades workers not elsewhere classified	7129	7111	p	7119	House builders
Building frame and related trades workers not elsewhere classified	7129	7119		7119	Building frame and related trades workers not elsewhere classified
Roofers	7131	7121		7121	Roofers
Floor layers and tile setters	7132	7122		7122	Floor layers and tile setters
Plasterers	7133	7123		7123	Plasterers
Insulation workers	7134	7124		7124	Insulation workers
Glaziers	7135	7125		7125	Glaziers
Plumbers and pipe fitters	7136	7126		7126	Plumbers and pipe fitters
Building and related electricians	7137	7411		7411	Building and related electricians
Painters and related workers	7141	7131		7131	Painters and related workers
Varnishers and related painters	7142	7132		7132	Spray painters and varnishers
Building structure cleaners	7143	7133		7133	Building structure cleaners
Building structure cleaners	7143	7544		7133	Fumigators and other pest and weed controllers
Metal moulders and coremakers	7211	7211		7211	Metal moulders and coremakers
Welders and flamecutters	7212	7212		7212	Welders and flamecutters
Sheet-metal workers	7213	7213		7213	Sheet-metal workers
Structural-metal preparers and erectors	7214	7214		7214	Structural-metal preparers and erectors
Riggers and cable splicers	7215	7215		7215	Riggers and cable splicers
Underwater workers	7216	7541	p	7541	Underwater divers
Blacksmiths, hammer-smiths and forging-press workers	7221	7221		7221	Blacksmiths, hammersmiths and forging press workers
Tool-makers and related workers	7222	7222		7222	Toolmakers and related workers
Machine-tool setters and setter-operators	7223	7223	p	7223	Metal working machine tool setters and operators
Metal wheel-grinders, polishers and tool sharpeners	7224	7224		7224	Metal polishers, wheel grinders and tool sharpeners
Motor vehicle mechanics and fitters	7231	7231		7231	Motor vehicle mechanics and repairers
Motor vehicle mechanics and fitters	7231	7234		7231	Bicycle and related repairers
Aircraft engine mechanics and fitters	7232	7232		7232	Aircraft engine mechanics and repairers
Agricultural- or industrial-machinery mechanics and fitters	7233	7127		7233	Air conditioning and refrigeration mechanics
Agricultural- or industrial-machinery mechanics and fitters	7233	7233		7233	Agricultural and industrial machinery mechanics and repairers
Electrical mechanics and fitters	7241	7412		7412	Electrical mechanics and fitters
Electronics fitters	7242	7421	p	7422	Electronics mechanics and servicers
Electronics fitters	7242	7422	p	7422	Information and communications technology installers and servicers
Electronics mechanics and servicers	7243	7421	p	7422	Electronics mechanics and servicers
Electronics mechanics and servicers	7243	7422	p	7422	Information and communications technology installers and servicers
Telegraph and telephone installers and servicers	7244	7422	p	7422	Information and communications technology installers and servicers
Electrical line installers, repairers and cable jointers	7245	7413		7413	Electrical line installers and repairers

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Electrical line installers, repairers and cable jointers	7245	7422	p	7413	Information and communications technology installers and servicers
Precision-instrument makers and repairers	7311	3214		7311	Medical and dental prosthetic technicians
Precision-instrument makers and repairers	7311	7311		7311	Precision-instrument makers and repairers
Musical instrument makers and tuners	7312	7312		7312	Musical instrument makers and tuners
Jewellery and precious-metal workers	7313	7313		7313	Jewellery and precious-metal workers
Abrasive wheel formers, potters and related workers	7321	7314		7314	Potters and related workers
Glass-makers, cutters, grinders and finishers	7322	7315		7315	Glass makers, cutters, grinders and finishers
Glass-makers, cutters, grinders and finishers	7322	7549		7315	Craft and related workers not elsewhere classified
Glass engravers and etchers	7323	7316	p	7316	Sign writers, decorative painters, engravers and etchers
Glass, ceramics and related decorative painters	7324	7316	p	7316	Sign writers, decorative painters, engravers and etchers
Handicraft workers in wood and related materials	7331	7317	p	7319	Handicraft workers in wood, basketry and related materials
Handicraft workers in wood and related materials	7331	7319	p	7319	Handicraft workers not elsewhere classified
Handicraft workers in textile, leather and related materials	7332	7318	p	7318	Handicraft workers in textile, leather and related materials
Compositors, typesetters and related workers	7341	7321	p	7322	Pre-press technicians
Compositors, typesetters and related workers	7341	7322	p	7322	Printers
Stereotypers and electrotypers	7342	7321	p	7321	Pre-press technicians
Printing engravers and etchers	7343	7321	p	7321	Pre-press technicians
Photographic and related workers	7344	8132	p	8132	Photographic products machine operators
Bookbinders and related workers	7345	7323	p	7323	Print finishing and binding workers
Silk-screen, block and textile printers	7346	7322	p	7322	Printers
Butchers, fishmongers and related food preparers	7411	7511		7511	Butchers, fishmongers and related food preparers
Bakers, pastry-cooks and confectionery makers	7412	7512		7512	Bakers, pastry-cooks and confectionery makers
Dairy-products makers	7413	7513		7513	Dairy-products makers
Fruit, vegetable and related preservers	7414	7514		7514	Fruit, vegetable and related preservers
Food and beverage tasters and graders	7415	7515		7515	Food and beverage tasters and graders
Tobacco preparers and tobacco products makers	7416	7516		7516	Tobacco preparers and tobacco products makers
Wood treaters	7421	7521		7521	Wood treaters
Cabinet-makers and related workers	7422	7522		7522	Cabinet-makers and related workers
Woodworking-machine setters and setter-operators	7423	7523	p	7523	Woodworking-machine tool setters and operators
Basketry weavers, brush makers and related workers	7424	7317	p	7317	Handicraft workers in wood, basketry and related materials
Fibre preparers	7431	7318	p	7318	Handicraft workers in textile, leather and related materials
Weavers, knitters and related workers	7432	7318	p	7318	Handicraft workers in textile, leather and related materials
Weavers, knitters and related workers	7432	8152	p	7318	Weaving and knitting machine operators
Tailors, dressmakers and hatters	7433	7531	p	7531	Tailors, dressmakers, furriers and hatters
Furriers and related workers	7434	7531	p	7531	Tailors, dressmakers, furriers and hatters
Textile, leather and related pattern-makers and cutters	7435	7532		7532	Garment and related pattern-makers and cutters
Sewers, embroiderers and related workers	7436	7533		7533	Sewing, embroidery and related workers
Upholsterers and related workers	7437	7534		7534	Upholsterers and related workers
Pelt dressers, tanners and fellmongers	7441	7535		7535	Pelt dressers, tanners and fellmongers
Shoe-makers and related workers	7442	7536		7536	Shoemakers and related workers
Mining-plant operators	8111	3121		8111	Mining supervisors

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Mining-plant operators	8111	8111	p	8111	Miners and quarriers
Mineral-ore- and stone-processing-plant operators	8112	8112		8112	Mineral and stone processing plant operators
Well drillers and borers and related workers	8113	8113		8113	Well drillers and borers and related workers
Ore and metal furnace operators	8121	3135	p	8121	Metal production process controllers
Ore and metal furnace operators	8121	8121	p	8121	Metal processing plant operators
Metal melters, casters and rolling-mill operators	8122	3135	p	8121	Metal production process controllers
Metal melters, casters and rolling-mill operators	8122	8121	p	8121	Metal processing plant operators
Metal-heat-treating-plant operators	8123	3135	p	8121	Metal production process controllers
Metal-heat-treating-plant operators	8123	8121	p	8121	Metal processing plant operators
Metal drawers and extruders	8124	3135	p	8121	Metal production process controllers
Metal drawers and extruders	8124	8121	p	8121	Metal processing plant operators
Glass and ceramics kiln and related machine operators	8131	8181	p	8181	Glass and ceramics plant operators
Glass, ceramics and related plant operators not elsewhere classified	8139	8181	p	8181	Glass and ceramics plant operators
Wood-processing-plant operators	8141	8172		8172	Wood processing plant operators
Paper-pulp plant operators	8142	3139	p	8171	Process control technicians not elsewhere classified
Paper-pulp plant operators	8142	8171	p	8171	Pulp and papermaking plant operators
Papermaking-plant operators	8143	3139	p	8171	Process control technicians not elsewhere classified
Papermaking-plant operators	8143	8171	p	8171	Pulp and papermaking plant operators
Crushing-, grinding- and chemical-mixing machinery operators	8151	8131	p	8131	Chemical products plant and machine operators
Chemical-heat-treating-plant operators	8152	3133	p	8131	Chemical processing plant controllers
Chemical-heat-treating-plant operators	8152	8131	p	8131	Chemical products plant and machine operators
Chemical-filtering- and separating-equipment operators	8153	3133	p	8131	Chemical processing plant controllers
Chemical-filtering- and separating-equipment operators	8153	8131	p	8131	Chemical products plant and machine operators
Chemical-still and reactor operators (except petroleum and natural gas)	8154	3133	p	8131	Chemical processing plant controllers
Chemical-still and reactor operators (except petroleum and natural gas)	8154	8131	p	8131	Chemical products plant and machine operators
Petroleum- and natural-gas-refining-plant operators	8155	3134		8131	Petroleum and natural gas refining plant operators
Petroleum- and natural-gas-refining-plant operators	8155	8131	p	8131	Chemical products plant and machine operators
Chemical-processing-plant operators not elsewhere classified	8159	3133	p	8131	Chemical processing plant controllers
Chemical-processing-plant operators not elsewhere classified	8159	8131	p	8131	Chemical products plant and machine operators
Power-production plant operators	8161	3131		3131	Power production plant operators
Steam-engine and boiler operators	8162	8182		8182	Steam engine and boiler operators
Incinerator, water-treatment and related plant operators	8163	3132		3132	Incinerator and water treatment plant operators
Automated-assembly-line operators	8171	3122	p	3139	Manufacturing supervisors
Automated-assembly-line operators	8171	3139	p	3139	Process control technicians not elsewhere classified
Industrial-robot operators	8172	3122	p	3139	Manufacturing supervisors
Industrial-robot operators	8172	3139	p	3139	Process control technicians not elsewhere classified
Machine-tool operators	8211	3122	p	7223	Manufacturing supervisors
Machine-tool operators	8211	7223	p	7223	Metal working machine tool setters and operators
Cement and other mineral products machine operators	8212	8114		8114	Cement, stone and other mineral products machine operators
Pharmaceutical- and toiletry-products machine operators	8221	3122	p	8131	Manufacturing supervisors
Pharmaceutical- and toiletry-products machine operators	8221	8131	p	8131	Chemical products plant and machine operators
Ammunition- and explosive-products machine operators	8222	3122	p	8131	Manufacturing supervisors

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Ammunition- and explosive-products machine operators	8222	8131	p	8131	Chemical products plant and machine operators
Metal finishing-, plating- and coating-machine operators	8223	3122	p	8122	Manufacturing supervisors
Metal finishing-, plating- and coating-machine operators	8223	8122		8122	Metal finishing, plating and coating machine operators
Photographic-products machine operators	8224	3122	p	8132	Manufacturing supervisors
Photographic-products machine operators	8224	8132	p	8132	Photographic products machine operators
Chemical-products machine operators not elsewhere classified	8229	3122	p	8131	Manufacturing supervisors
Chemical-products machine operators not elsewhere classified	8229	8131	p	8131	Chemical products plant and machine operators
Rubber-products machine operators	8231	3122	p	8141	Manufacturing supervisors
Rubber-products machine operators	8231	8141		8141	Rubber products machine operators
Plastic-products machine operators	8232	3122	p	8142	Manufacturing supervisors
Plastic-products machine operators	8232	8142		8142	Plastic products machine operators
Wood-products machine operators	8240	3122	p	7523	Manufacturing supervisors
Wood-products machine operators	8240	7523	p	7523	Woodworking-machine tool setters and operators
Printing-machine operators	8251	3122	p	7322	Manufacturing supervisors
Printing-machine operators	8251	7322	p	7322	Printers
Bookbinding-machine operators	8252	3122	p	7323	Manufacturing supervisors
Bookbinding-machine operators	8252	7323	p	7323	Print finishing and binding workers
Paper-products machine operators	8253	3122	p	8143	Manufacturing supervisors
Paper-products machine operators	8253	8143		8143	Paper products machine operators
Fibre-preparing-, spinning- and winding-machine operators	8261	3122	p	8151	Manufacturing supervisors
Fibre-preparing-, spinning- and winding-machine operators	8261	8151		8151	Fibre preparing, spinning and winding machine operators
Weaving- and knitting-machine operators	8262	3122	p	8152	Manufacturing supervisors
Weaving- and knitting-machine operators	8262	8152	p	8152	Weaving and knitting machine operators
Sewing-machine operators	8263	3122	p	8153	Manufacturing supervisors
Sewing-machine operators	8263	8153		8153	Sewing machine operators
Bleaching-, dyeing- and cleaning-machine operators	8264	3122	p	8157	Manufacturing supervisors
Bleaching-, dyeing- and cleaning-machine operators	8264	8154		8157	Bleaching, dyeing and fabric cleaning machine operators
Bleaching-, dyeing- and cleaning-machine operators	8264	8157		8157	Laundry machine operators
Fur- and leather-preparing-machine operators	8265	3122	p	8155	Manufacturing supervisors
Fur- and leather-preparing-machine operators	8265	8155		8155	Fur and leather preparing machine operators
Shoemaking- and related machine operators	8266	3122	p	8156	Manufacturing supervisors
Shoemaking- and related machine operators	8266	8156		8156	Shoemaking and related machine operators
Textile-, fur- and leather-products machine operators not elsewhere classified	8269	3122	p	8159	Manufacturing supervisors
Textile-, fur- and leather-products machine operators not elsewhere classified	8269	8159		8159	Textile, fur and leather products machine operators not elsewhere classified
Meat- and fish-processing-machine operators	8271	3122	p	8160	Manufacturing supervisors
Meat- and fish-processing-machine operators	8271	8160	p	8160	Food and related products machine operators
Dairy-products machine operators	8272	3122	p	8160	Manufacturing supervisors
Dairy-products machine operators	8272	8160	p	8160	Food and related products machine operators
Grain- and spice-milling-machine operators	8273	3122	p	8160	Manufacturing supervisors
Grain- and spice-milling-machine operators	8273	8160	p	8160	Food and related products machine operators
Baked-goods, cereal and chocolate-products machine operators	8274	3122	p	8160	Manufacturing supervisors

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Baked-goods, cereal and chocolate-products machine operators	8274	8160	p	8160	Food and related products machine operators
Fruit-, vegetable- and nut-processing-machine operators	8275	3122	p	8160	Manufacturing supervisors
Fruit-, vegetable- and nut-processing-machine operators	8275	8160	p	8160	Food and related products machine operators
Sugar production machine operators	8276	3122	p	8160	Manufacturing supervisors
Sugar production machine operators	8276	8160	p	8160	Food and related products machine operators
Tea-, coffee-, and cocoa-processing-machine operators	8277	3122	p	8160	Manufacturing supervisors
Tea-, coffee-, and cocoa-processing-machine operators	8277	8160	p	8160	Food and related products machine operators
Brewers-, wine and other beverage machine operators	8278	3122	p	8160	Manufacturing supervisors
Brewers-, wine and other beverage machine operators	8278	8160	p	8160	Food and related products machine operators
Tobacco production machine operators	8279	3122	p	8160	Manufacturing supervisors
Tobacco production machine operators	8279	8160	p	8160	Food and related products machine operators
Mechanical-machinery assemblers	8281	3122	p	8211	Manufacturing supervisors
Mechanical-machinery assemblers	8281	8211		8211	Mechanical machinery assemblers
Electrical-equipment assemblers	8282	3122	p	8212	Manufacturing supervisors
Electrical-equipment assemblers	8282	8212	p	8212	Electrical and electronic equipment assemblers
Electronic-equipment assemblers	8283	3122	p	8212	Manufacturing supervisors
Electronic-equipment assemblers	8283	8212	p	8212	Electrical and electronic equipment assemblers
Metal-, rubber- and plastic-products assemblers	8284	3122	p	8219	Manufacturing supervisors
Metal-, rubber- and plastic-products assemblers	8284	8219	p	8219	Assemblers not elsewhere classified
Wood and related products assemblers	8285	3122	p	8219	Manufacturing supervisors
Wood and related products assemblers	8285	8219	p	8219	Assemblers not elsewhere classified
Paperboard, textile and related products assemblers	8286	3122	p	8219	Manufacturing supervisors
Paperboard, textile and related products assemblers	8286	8219	p	8219	Assemblers not elsewhere classified
Other machine operators and assemblers	8290	3122	p	8183	Manufacturing supervisors
Other machine operators and assemblers	8290	8183		8183	Packing, bottling and labelling machine operators
Other machine operators and assemblers	8290	8189		8219	Stationary plant and machine operators not elsewhere classified
Other machine operators and assemblers	8290	8219	p	8219	Assemblers not elsewhere classified
Locomotive-engine drivers	8311	8311		8311	Locomotive engine drivers
Railway brakers, signallers and shunters	8312	8312		8312	Railway brake, signal and switch operators
Motor-cycle drivers	8321	8321		8321	Motorcycle drivers
Car, taxi and van drivers	8322	8322		8322	Car, taxi and van drivers
Bus and tram drivers	8323	8331		8331	Bus and tram drivers
Heavy truck and lorry drivers	8324	8332		8332	Heavy truck and lorry drivers
Motorised farm and forestry plant operators	8331	8341		8341	Mobile farm and forestry plant operators
Earth-moving- and related plant operators	8332	8342		8342	Earthmoving and related plant operators
Crane, hoist and related plant operators	8333	8343		8343	Crane, hoist and related plant operators
Lifting-truck operators	8334	8344		8344	Lifting truck operators
Ships' deck crews and related workers	8340	8350		8350	Ships' deck crews and related workers
Street food vendors	9111	5212		5212	Street food salespersons
Street vendors, non-food products	9112	9520		9520	Street vendors (excluding food)
Door-to-door and telephone salespersons	9113	5243		5244	Door to door salespersons
Door-to-door and telephone salespersons	9113	5244		5244	Contact centre salespersons

ISCO-88 Title EN	ISCO88 code	ISCO 08 code	ISCO 08 partial	ISCO 08 study	ISCO 08 Title EN
Shoe cleaning and other street services elementary occupations	9120	9510		9510	Street and related service workers
Domestic helpers and cleaners	9131	9111		9111	Domestic cleaners and helpers
Helpers and cleaners in offices, hotels and other establishments	9132	9112		9112	Cleaners and helpers in offices, hotels and other establishments
Helpers and cleaners in offices, hotels and other establishments	9132	9412		9112	Kitchen helpers
Hand-launderers and pressers	9133	9121		9121	Hand launderers and pressers
Building caretakers	9141	5153		5153	Building caretakers
Vehicle, window and related cleaners	9142	9122		9129	Vehicle cleaners
Vehicle, window and related cleaners	9142	9123		9129	Window cleaners
Vehicle, window and related cleaners	9142	9129		9129	Other cleaning workers
Messengers, package and luggage porters and deliverers	9151	9621	p	9621	Messengers, package deliverers and luggage porters
Doorkeepers, watchpersons and related workers	9152	5414	p	5414	Security guards
Doorkeepers, watchpersons and related workers	9152	9621	p	5414	Messengers, package deliverers and luggage porters
Doorkeepers, watchpersons and related workers	9152	9629		5414	Elementary workers not elsewhere classified
Vending-machine money collectors, meter readers and related workers	9153	9623		9623	Meter readers and vending-machine collectors
Garbage collectors	9161	9611		9611	Garbage and recycling collectors
Garbage collectors	9161	9612	p	9611	Refuse sorters
Sweepers and related labourers	9162	9613		9622	Sweepers and related labourers
Sweepers and related labourers	9162	9622		9622	Odd job persons
Sweepers and related labourers	9162	9624		9622	Water and firewood collectors
Farm-hands and labourers	9211	9211		9214	Crop farm labourers
Farm-hands and labourers	9211	9212		9214	Livestock farm labourers
Farm-hands and labourers	9211	9213		9214	Mixed crop and livestock farm labourers
Farm-hands and labourers	9211	9214		9214	Garden and horticultural labourers
Forestry labourers	9212	9215		9215	Forestry labourers
Fishery, hunting and trapping labourers	9213	9216		9216	Fishery and aquaculture labourers
Mining and quarrying labourers	9311	9311		9311	Mining and quarrying labourers
Construction and maintenance labourers: roads, dams and similar constructions	9312	9312		9312	Civil engineering labourers
Building construction labourers	9313	9313		9313	Building construction labourers
Assembling labourers	9321	9329	p	9329	Manufacturing labourers not elsewhere classified
Assembling labourers	9321	9612	p	9329	Refuse sorters
Hand packers and other manufacturing labourers	9322	9321		9329	Hand packers
Hand packers and other manufacturing labourers	9322	9329	p	9329	Manufacturing labourers not elsewhere classified
Hand or pedal vehicle drivers	9331	9331		9331	Hand and pedal vehicle drivers
Drivers of animal-drawn vehicles and machinery	9332	9332		9332	Drivers of animal-drawn vehicles and machinery
Freight handlers	9333	9333		9333	Freight handlers
Freight handlers	9333	9334		9333	Shelf fillers

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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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