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'How to prevent unemployment in a changing world of work?'

Workshop 4 "Future of skills"

Discussion paper

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[1] DECISION No 573/2014/EU

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1. Introduction

Many are those who have confidently predicted the future only for subsequent events to leave them with egg on their faces. This should be enough to ward off all but the most battle-hardened pundits from speculating about what the future holds in store. But those involved in public policy and providing guidance to people do not have the luxury of being able to ignore the future and to bury their heads in the sand. They require an informed view of the future, based on the various methodologies concerned with anticipating emerging skill demands, to ensure that any future change does not impose itself as some kind of exogenous shock, the calamitous consequences of which are difficult to unwind. And there's the rub. The more uncertain the outlook – thereby making prediction more difficult – the more public policy requires some form of guide to what the future holds in store. Nowhere is this more evident, perhaps, than in the case of the Fourth Industrial Revolution and its potential impact upon on employment, jobs, and skills.

Notwithstanding the risks attached to predicting the future, there has been no shortage of forecasts about the impact of the Fourth Industrial Revolution on employment. Horror stories abound about the capacity of robots, artificial intelligence, and the like to destroy a substantial tranche of the jobs many people carry out today[2]. The sub-text, often left unsaid, is that if technological change is unable to bring about the creation of new types of jobs – the content of which as yet may well be unknown – then the consequences for employment are ominous. Less apocalyptic views of the future of work, it will be revealed, arguably provide a more nuanced and plausible view of the future. Skills obsolescence and the implied risk to employment are shown to be less pronounced in these studies, especially so when attention is focused on the need to replace those who will retire from their existing jobs over the short- to medium-term[3]. This is not to say that the fourth industrial revolution, however defined, does not pose major challenges to policy makers concerned with employment, skills, and jobs. It clearly does so.

So how can a nuanced and realistic view of the future be obtained? Admittedly it is not easy. It is worth stating at the outset that no single method has a monopoly on realistically assessing what the future holds in store for skills demand. In fact, the plurality of approaches now available – forecasting, foresight, big data analysis, and so on – improves the forecaster's methodological armoury. If the past is no longer as good a guide to the future as it once was, then there is a need to complement what might be regarded as traditional approaches to forecasting – which extrapolate past trends into the future – with something else. Econometric forecasts, for example, are dependent upon sophisticated analyses of historical time series. This is not to decry the value of econometric forecasting – far from it in fact – rather the point is that it needs to be seen as one component amongst others in gauging the future. Should demand for new types of skills result from emerging, nascent forms of technological change, the analysis of the past is unlikely to reveal much about the nature of those skills. Methodologies are required which recognise this potential state of affairs. At the same time, the future will not wholly comprise new jobs requiring new skills. Old jobs and old skills will survive too, though they may need to adapt in some way.

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[2] A now famous study, for example, suggested that up to 47 per cent of jobs in the USA were potentially at risk from being replaced by automation – see Frey, C. and Osborne, M. (2013) *The Future of Employment: How Susceptible are Jobs to Computerization?,* Oxford: Oxford Martin Programme on Technology and Employment, University of Oxford.

[3] For example, see Pouliakas, K. (2018) 'The risk of automation in EU labour markets: A skills-requirements approach' in Hogarth, T. (ed.) *Economy, Employment and Skills: European Regional and Global Perspectives in an Age of Uncertainty*. Rome: FGB Quaderni.

2. Approaches to identifying current and future skill needs

Predicting skill needs typically falls under the rubric of skills anticipation, i.e. the process of being able to identify those skills and jobs which are likely to be in demand over the short- to medium-term, and those which are likely to become obsolescent, potentially leading to job loss unless at-risk job incumbents receive re-training. Much of the focus on skills anticipation has stemmed from the skills matching problem which has affected most European countries in the recent past[4]. There is evidence of vertical skill mismatches, where the level of skill held by individuals is not commensurate with that required in their jobs, and horizontal mismatches, where the qualifications or skills held by individuals are not appropriate to the job. The skills mismatch problem is one which affects the global economy, not just Europe[5].

To some extent, the matching debate has largely fallen within the ambit of education policy insofar as it has been concerned with making the supply side (i.e. education and training institutions) more responsive to signals from the demand side (i.e. the skills the labour market indicates that it requires). For example, there is an interest in skill shortages, i.e. those vacancies which employers struggle to fill because applicants do not have the required skills, education or experience. This is, manifestly, useful information for those engaged in guiding people towards acquiring certain skills. The importance of this should not be underplayed given the scope for skill shortages to stymie adaptation to technological change and consequently constrain economic growth. It is also apparent that the emphasis skills anticipation places on being able to identify those workers at risk of losing their jobs stresses its relevance to public employment services (PES) and employment policy more generally.

From a European perspective, skills anticipation can be regarded as a process. The Skills Panorama hosted by the EU Agency Cedefop provides detailed descriptions of each EU member state's skills anticipation system[6]. Figure 1 outlines the main methodological components in place in skills anticipation systems across the EU. As will be explained, across the EU as a whole there is a large body of evidence on:

- the current demand for skills;
- the specific skills which comprise occupations or jobs; and
- the degree of skills mismatch in the economy.

Historically, skills have been measured using occupation and qualification. Across Europe, information on the occupation in which people work, the qualifications they possess, and how this has changed over time are readily available via the European Labour Force Survey (EU-LFS). Whilst this proves to be useful, policy makers have increasingly sought additional information on the specific skills which comprise a job (or in aggregate an occupation). Classifying skills proves to be less than straightforward compared with classifying occupations, such that various classifications of skills have been developed in reference to, amongst other things, cognitive versus non-cognitive, job-specific versus general, and so on.

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[4] Cedefop (2010) The Skill Matching Challenge: Analysing skill mismatch and policy implications. Luxembourg: Publications Office of the European Union.

[5] World Economic Forum (2014) *Matching Skills and Labour Market Needs: Partnerships for Better Skills and Jobs*. Online: http://www3.weforum.org/docs/GAC/2014/WEF_GAC_Employment_MatchingSkillsLabourMarket_Report_2014.pdf

[6] Further information on skill anticipation systems in each of the member states can be found on the Skills Panorama website - https://skillspanorama.cedefop.europa.eu/en.

Figure 1: Constituent parts of skills anticipation systems

Time horizon	Methodological approach	Activities undertaken
Current perspectives	Stock taking	Estimates of overall demand and supply of skills
	Employer Skill Surveys	Assessments of both the demand for, and supply of, skills, usually with an assessment of the extent to which demand and supply are in balance
	Surveys of economically active individuals	Assessments of the skills individuals use at work, whether skills match job, experience of training, etc.
	Tracer studies	Tracking of students – often higher education ones – through their initial years in the labour market after graduation. Increasingly, use of administrative datasets can undertake the tracking function
	Rates of return analyses	Measuring occupational wage dispersion and wage growth to identify skill surpluses and shortages (assuming wages move in relation to the supply/demand for skills)
	Sectoral/occupational studies	Detailed assessment using various data sources to identify skill demand at the sectoral or occupational level
Future perspectives	Quantitative forecasting	Forecasting or projecting the future demand for skills typically using econometric modelling / CGE modelling
	Foresight	Critical thinking about the future of skills supply/demand using a range of methodologies.
	Big data analysis	Use of text mining approaches to collect data about skills, vacancies, technologies, etc. to provide information on emerging demand
	Expert panels	Use of experts from various domains to gauge how occupational/sectoral skill demands are likely to pan out in the future, using a range of methodologies to understand future demand

Source: FGB

Whilst surveys such as the EU-LFS provide detailed information on occupation and qualifications, they are not able to provide data on the skills which may be associated with a given occupation or the skills which a qualification confers on an individual. This has tended to be addressed through other types of survey, most notably by the OECD's PIAAC survey[7] and the European Skills and Jobs Survey (ESJS)[8], which provide information on, amongst other things, the transferable skills typically required in most jobs such as literacy, numeracy, and computer literacy. In these types of survey, information is typically collected on the level at which a particular skill is held (e.g. high, medium, or low), and

7 https://www.oecd.org/skills/piaac/

8 Cedefop (2018). Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey. Luxembourg: Publications Office See also https://www.cedefop.europa.eu/en/events-and-projects/projects/european-skills-and-jobs-esj-survey

the importance of particular skills to the job/occupation, as reported by workers in those jobs.

In combination, surveys such as the EU-LFS, PIAAC, and the ESJS have been able to provide a detailed picture of occupational change over time (i.e. the changing nature of skill demand) and to gain an insight into the specific types of skill which are important within jobs. But as noted above, policy makers and guidance professionals also have an interest in gauging the extent to which skills supply is matched to demand. It is all well and good to provide detailed information on skill demand, but there is a need to ensure that this is used to inform the provision of education and training. It is here that surveys – of employers and tracer studies of individuals who have recently graduated – and the use of administrative data have been particularly adept at identifying the extent of skills mismatch.

With regard to skill mismatches, measures have been developed which indicate the occupations/jobs in which employers experience difficulty recruiting people (skill shortages), the extent to which the existing workforce is proficient at their current job (skill gaps), and analysis of the relative employment and wage returns attached to possessing various qualifications. While surveys and analysis of administrative data have been able to provide estimates of the aforementioned measures, they have also been able to demonstrate where supply is matched to demand. It is not always a bad news story. It is notable in this regard that the evidence from a study of higher education graduates – now a little dated – showed that five years after graduation most were employed in jobs which fitted well with their qualifications[9]. The pilot EUROGRADUATE Survey potentially provides scope to update this type of information[10]. It is also apparent that surveys of emerging skill needs have been able to provide a sense of realism where there are sometimes scare stories about the impending impact of the 4th Industrial Revolution on employment. For example, econometric modelling of ESJS data revealed that 8 per cent of employment was estimated to be at risk of being substituted by machines in the EU – typically employment at the lower end of the occupational hierarchy (i.e. those working as plant and machine operatives or in elementary occupations)[11]. This is substantially lower than some of the more sensationalist estimates which are bandied around from time to time.

As well as looking to the recent past, there is also an interest in identifying future trends. One of the principal means of identifying future skill demand is skills forecasting. Skills forecasting tends to use occupation and qualification as measures of skill. Macroeconomic models are used to determine the scale of employment by industrial sector ten or so years ahead. Then, from time-series analysis, one derives the share of employment within each sector accounted for by each occupation. Cedefop's skills forecasts use this type of approach to provide an indication of future employment demand by occupation and qualification. Importantly, the projections of future skill demand make a distinction between demand which arises from an overall projected growth or decline in an occupation (new/lost jobs) and the number of people who will need to enter an occupation to replace those who have left it for whatever reason (mainly retirement). Figure 2, from Cedefop's skills forecast, provides an indication of the extent of the projected level of skill demand

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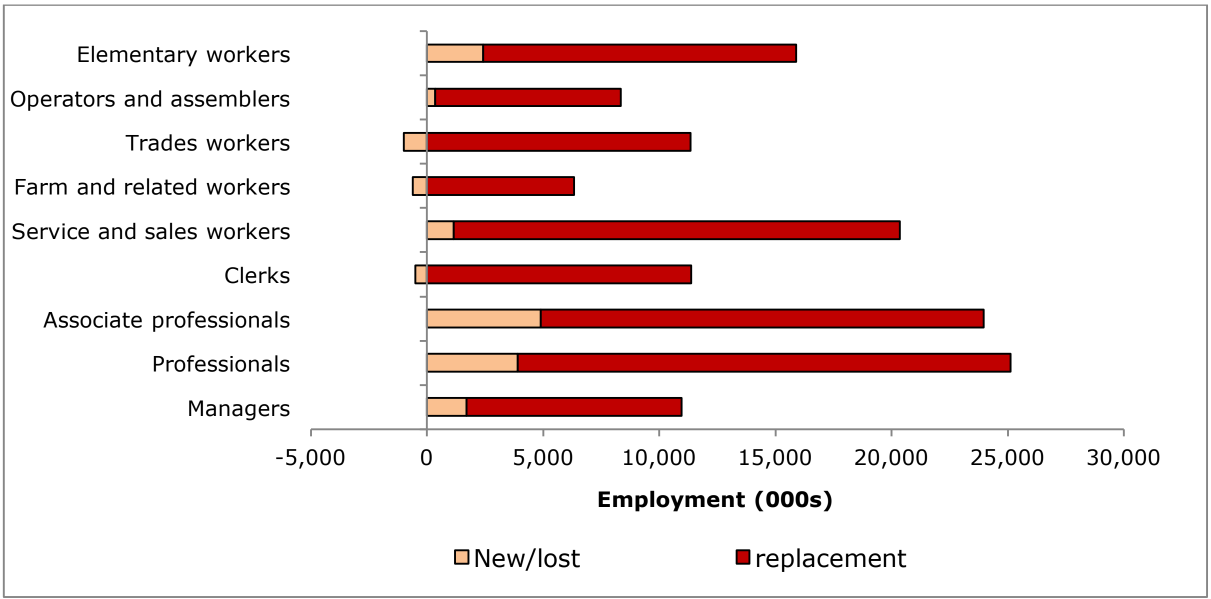
[9] HEGESCO (2009) Findings from the European Project "Higher Education as a Generator of Strategic Competences" (HEGESCO). Online: http://www.decowe.org/static/uploaded/htmlarea/finalreportshegesco/HEGESCO_Summary.pdf

[10] See: https://www.eurograduate.eu/index_html.

[11] Pouliakas, K. (2018) 'The risk of automation in EU labour markets: A skills-requirements approach' in Hogarth, T. (ed.) *Economy, Employment and Skills: European Regional and Global Perspectives in an Age of Uncertainty*. Rome: FGB Quaderni.

across the EU to 2030, factoring in replacement demand. As can be seen, replacement demand tends to dominate the picture.

Figure 2: Total future job openings in EU in 2018-2030 by type of demand



Source: Cedefop Skills Forecast (data from the EU Skills Panorama).

All of the above provides a detailed picture of skill demand, but it is based on information gathered in the past, using classifications of occupations and industries developed five or ten years ago. Depending upon one's view of how fast technological change can transform the demand for skills and the content of jobs, this may not be a problem. If one may be allowed to take a single lesson from the past, it is that the take-up of new technologies by business often takes places at a slower rate than initially suggested, such that the demand for skills over the short to medium term at least tends not to look too different from that in the past[12]. But what if the demand for skills in the future is different from that in the past? What if the Industry 4.0 proves to be truly disruptive with respect to skills and jobs? This is where other techniques can be used to complement the relatively robust measures of future skill demand provided by skills forecasting.

Big data analysis using text mining algorithms has been used to collect data on vacancies from online recruitment websites. Data can be captured about specific job titles, and from the information provided in the job descriptions accompanying the vacancy, information can be collated on the skills required in the vacant job. This potentially provides a rich source of data which can be used to detect, over time, emerging skill needs within jobs. There are various applications which use this approach to identify emerging skill needs, including OVATE, developed by Cedefop[13]. In OVATE, job vacancies have been coded to the International Standard Classification of Occupations (ISCO), and the detailed skills contained within each occupation have been documented and classified (e.g. by using the European Classification of Skills/Competences, Qualifications and Occupations, ESCO). Over time, this provides an invaluable means of identifying how the skill content of jobs is changing at a detailed level. Strictly speaking, big data analysis of vacancy data is not forward-looking, rather it provides a much more rapid (real-time) analysis of changes in

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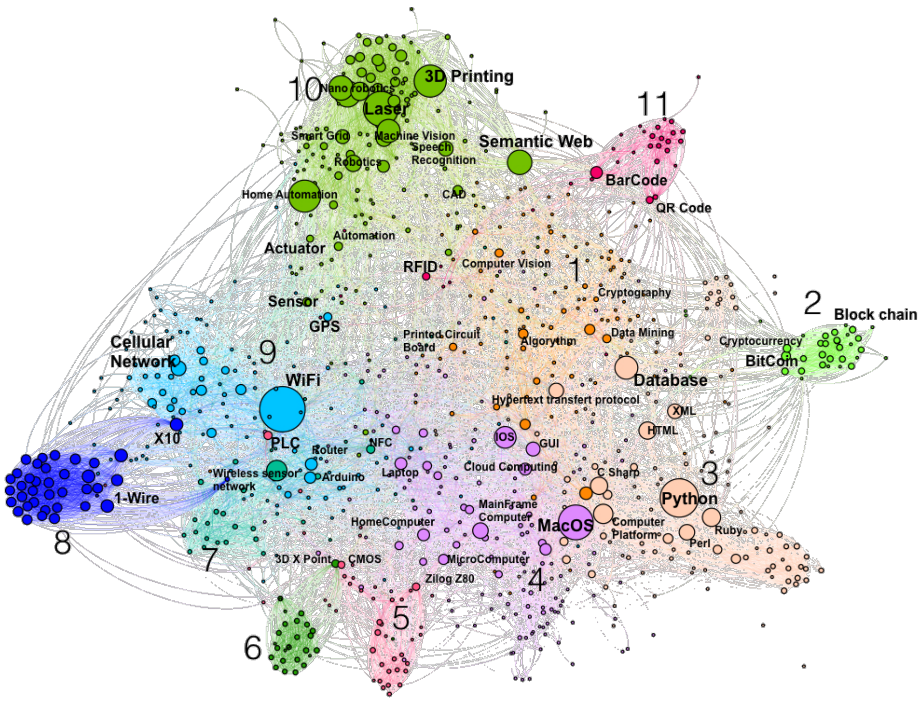
[12] Bessen, J. (2015) Learning by Doing: The Real Connection Between Innovation, Wages and Wealth. New Haven and London: Yale University Press.

[13] See https://www.cedefop.europa.eu/en/data-visualisations/skills-online-vacancies.

skill demand than that available from other forms of data analysis[14]. It thus provides policy makers with up-to-the-minute information. As longitudinal data become available from the big data analysis of vacancy data, trends and patterns will emerge, with the potential to contribute to forecasting exercises.

Big data analysis is not limited to the analysis of vacancy data. It can be used to analyse trends in new technology diffusion and the skills attached to those new technologies. For instance, one can analyse data on the number of scientific papers which mention a particular technology or the technologies for which there has been a patent application. This is important because technological change is seen to be the principal driver of skills change. An example of an approach that analyses technology trends and then links these to skill change is Technimetro[15], which analyses patent and scientific databases to identify emerging technologies, clustering those that are mentioned in relation to one another, and then identifies from various sources, such as training courses related to a technology, the skills associated with those technologies. Figure 3 below demonstrates the types of technology which can be identified from using text mining algorithms to ascertain the technologies associated with the Industry 4.0 paradigm. The larger the text in Figure 3, the more mentions made of the technology in the various databases. The advantage of this type of approach is that it identifies emerging technologies – i.e. those which are approaching a take-off phase where they are becoming more widely taken up by business versus those which are still in a developmental change. In this way, it is possible to see what is likely to lie ahead.

Figure 3: Industry 4.0 technologies identified using text mining techniques



Source: Technimetro (FGB/University of Pisa)

The above-mentioned examples of big data applications in the field of skills demonstrate how they can be used to supplement analyses of emerging skill needs. But they are able

[14] For example, the results from surveys can take several months to emerge.

[15] Technimetro has been developed by FGB in cooperation with the University of Pisa – see http://www.fondazionebrodolini.it/sites/default/files/tecnimetro_en_web.pdf.

to go only so far – an issue which is explored in more detail in the next section – in that they can begin to identify various technologies and the skills associated with them, but are less able to give an indication of the scale or importance of an emerging skill or the extent to which skill demands are likely to be met given current trends. Moreover, they are still largely dependent upon data from the past (albeit the very recent past given the real-time nature of much big data analysis).

From the above, it is evident that there are a wide range of methodologies and data collections that are able to shed light on emerging skill needs. In many respects it is a case of synthesising the wealth of evidence becoming available. One means of achieving this – though by no means the only one – is foresight. Foresight incorporates a wide range of techniques, often utilising expert knowledge in particular fields, to identify key trends and their likely impact upon the demand for skills. It provides a critical perspective which is able to build upon, amongst other things, the forecasts and big data analyses outlined above to provide a critical perspective on likely future trends. Sometimes explicit within foresight is the idea of what needs to happen if certain desired ends are to be reached. In this respect, it can be seen as a process designed to shape the future as well as reflecting upon likely trends. The key point here, however, is not so much the need to use foresight (though it has much to recommend it) but finding an appropriate means to synthesise the broad range of skills anticipation data now available.

The above provides a *tour d'horizon* of how future skill needs are identified. In the next section, attention is turned to the challenges that remain for those with a responsibility for identifying future skill needs, guiding individuals, and developing skills policy.

3. Challenges facing skills anticipation systems

Whilst many challenges remain with regard to identifying future skill needs, it should be borne in mind that substantial progress has been made over the recent past. Across the EU, a detailed picture is now available on (a) how the occupational structure of employment has changed and is likely to change over the medium-term; and (b) the particular skills (or mix of them) that comprise a job or occupation. This marks significant progress in the production of labour market skills intelligence. Nevertheless, it is perhaps worth considering those areas where further progress is required. A number of challenges can be identified:

- providing data at the right level of granularity. Data from surveys and forecasting tends to provide information on skills at a relatively high level of aggregation such that its application to policy or use in guidance can be limited;
- big data analysis continues to face issues related to the representativeness of the data analysed (i.e. does it reflect a reasonable approximation of the population under consideration?);
- more insight into skill mismatches is required, including prioritising those skills which are of most importance (however that might be defined), and the extent, characteristics, and persistence of some kinds of mismatch;
- being able to identify skill needs in new sectors or new occupations which are not currently classified using classifications such as NACE or ISCO;
- being able to disseminate information in such a way that the behaviour of a range of labour market actors is influenced.

In the past, skills demand was principally expressed with respect to occupation and level of educational attainment (highest qualification held) at a fairly aggregate level. For example, occupational data derived from surveys cannot always be disaggregated to a level where one is looking at something akin to a job (e.g. at the ISCO 4-digit level), and educational attainment has been typically expressed with reference to ISCED levels. From the discussion presented above, it is becoming increasingly apparent that more detailed data on skills is being captured (e.g. through OVATE). This is a major advance insofar as it is possible to look at the specific skills that are in demand. There is still a need to collate these data in a way that makes them consistent with existing classifications of jobs and skills. ESCO provides the basis for developing something similar to O*NET in the USA whereby there is detailed information about the skill content of an occupation at a highly disaggregated level (US-SOC is available at the 5-digit level whereas ISCO is limited to 4 digits). The importance of having information about specific skills, rather than just occupations, is that it allows policy makers to identify which courses and qualifications should be made accessible to individuals if they are to successfully make the transition from school to work or return to work. It is readily apparent that big data has a contribution to make here, as it can provide detailed information about the skills required in a job (rather than an occupation) and deliver this information rapidly. No doubt, as the process of big data analysis is further developed, it will be able to provide more representative data that is able to give an indication of the scale and importance of certain skill needs.

Provision of information is not sufficient in itself. There needs to be a way of being able to both (a) prioritise skill demands and (b) provide information that is readily accessible to individuals, guidance counsellors, and policy makers.

A way of prioritising where interventions might be required is needed. In other words, which skills demands – or the combination of skills that comprise a job – require policy interventions to ensure that they are met. Surveys of employees have sought to gauge the extent to which employees feel their skills are matched to their current job, thus providing some information on the extent to which employees feel their skills are becoming or are likely to become obsolescent over the short to medium term. Additionally, employer surveys record information about those jobs for which: (a) employers report difficulties in recruiting people because applicants lack the skills they need; and (b) the extent to which their existing employees lack proficiency. With relatively large sample sizes, it is possible to provide data that can be suitably disaggregated by occupation so that one begins to develop a detailed picture of those jobs where there may be an under- or over-supply of skills. Matched administrative data sets also provide information which can identify skill mismatches. Typically, these link the databases that record a person’s movement through the education system to those that document their position in the labour market (i.e. tax/benefit databases). These databases can reveal, at a high level of disaggregation, those qualifications that are likely to be associated with relatively good or bad employment or wage returns.

As noted above, surveys and administrative data tend to be backward-looking, i.e. they are based on how things were six months or a year ago and do not readily indicate how things might pan out in the future (especially given that they tend to report average rather than marginal returns). Moreover, they rely upon classifications of jobs which were designed some years in the past. This raises the problem of being able to identify new jobs. There has been some success in the US with respect to identifying green jobs which fall outside of existing occupational classifications of jobs[16]. For instance, with reference to renewable energy generation, the following new occupational groups were identified which were not currently in the US-SOC:

- Biofuels/Biodiesel Technology and Product Development Managers,
- Biofuels Production Managers,
- Biofuels Processing Technicians,
- Biomass Plant Engineers,
- Biomass Production Managers,

[16] Dierdorff. E. et al. (2009) Greening of the World of Work: Implications for O*NET® -SOC and New and Emerging Occupations. The National Center for O*NET Development.

- Biomass Plant Technicians.

By using big data techniques, there is the possibility of automating the process of identifying new or emerging jobs to some extent. Where the challenge remains is in being able to indicate the scale of demand. So whilst it is possible to identify new emerging jobs and their associated skills, there is no indication of the numbers of people who will be required to fill these jobs.

The final challenge relates to the critical issue of how to translate skills anticipation data/information into something which individuals find readily interpretable and useful with respect to choosing what to study or which lines of work to enter. Typically, this will be information that is mediated through guidance counsellors, including those in PES. This clearly indicates that data need to be presented in a way that allows counsellors to readily use it in their day-to-day jobs. It also needs to be accessible to policy professionals taking strategic decisions with respect to skills policies. The LMI for All initiative in the UK is interesting in this respect, as it provides a portal which contains a large volume of information on the state of the labour market and the likely future demand for skills. These are data collated by the government. These data are then open to anyone who wants to develop an app or programme related to careers guidance (see box). In this way, there is an opportunity for those who are most knowledgeable about communicating with particular groups in the population to effectively disseminate labour market information. In short, the data are made available to those who are experts in communication.

LMI for All

LMI for All is an online data portal which connects and standardises existing sources of high-quality, reliable labour market information (LMI) with the aim of informing careers decisions. This data is made freely available via an Application Programming Interface (API) for use in websites and applications.

The portal makes data available and encourages open use by applications and websites that can bring the data to life for a range of audiences. This is an open data project, which is supporting the wider government agenda to encourage the use and re-use of government data sets.

Source: LMI for All https://www.lmiforall.org.uk/

4. Key messages

From the discussion provided in the foregoing, it is possible to discern several key messages.

1. **There is no one single method that provides all the information required to provide a robust though nuanced view of likely future skill demands.** There are a range of methods available for analysing trends in skill needs over the recent past and how those skill needs are likely to develop over the short to medium term. It is a question of piecing together information from various sources to provide a comprehensive picture.

2. **The availability of data on the demand for particular skills in a job, coupled with that generated by big data analyses, has significantly improved the supply of information on skills demand.** Whilst there are limitations associated with many of the methods and methodological approaches described above, it is apparent at the same time that they all complement one another. It really is about finding a means to fully utilise the data which are available. There are examples from across Europe – which can be found on the Skills Panorama – of how member states have sought to achieve this particular end.

3. Finally, and perhaps most critically, collating and analysing various data takes one only halfway. It is worth reiterating that **the accessibility and communicability of data related to current and emerging skill demands are of critical importance. Communicating this type of information to a non-expert/non-researcher audience can be a challenge**, but it is one that needs to be met if the full potential for data on emerging skill needs to influence behaviour is to be realised. Data must be used by organisations and professionals which represent the key interlocutors for individuals at their key transition points – this includes PES counsellors, school careers officers, etc.

Arguably, as Europe feels its way through the Fourth Industrial Revolution and embraces Industry 4.0, it is much better placed to identify emerging skill needs compared with, say, when it was faced with the microprocessor revolution of the late 1970s/early 1980s. But for the investment in skills anticipation data to reap a return, it must find its way to those who are able to influence the behaviour of those who are thinking about which courses to study and/or thinking about their next job.

5. Suggestions for further reading

Selected publications

Bessen, J. (2015) *Learning by Doing: The Real Connection Between Innovation, Wages and Wealth*. New Haven and London: Yale University Press

Cedefop (2018*). Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey*. Luxembourg: Publications Office

Cedefop (2015) *Matching Skills and Jobs in Europe*. Luxembourg: Publications Office of the European Union

Cedefop (2014) *Macroeconomic Benefits of Vocational Education and Training*. Research Paper No.40. Luxembourg: Publications Office of the European Union

Cedefop (2011) *Vocational Education and Training is Good for You: The social benefits of VET for individuals*. Research Paper no.17

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Sudakov, D., Luksha, P., Strietska-Ilina, O., Gregg, C., Hofmann, C., Khachatryan, L. (2016) *Skills Technology Foresight Guide*. Geneva: International Labour Office.

Suta, S., Barbieri, L. and May-Gillings, M. (2018) "Future Employment and Automation" in Hogarth, T. (ed.) *Economy, Employment and Skills: European Regional and Global Perspectives in an Age of Uncertainty*. Rome: Fondazione Giacomo Brodolini

World Economic Forum (2014) *Matching Skills and Labour Market Needs Building Social Partnerships for Better Skills and Better Jobs*. Davos: World Economic Forum

Selected websites

Cedefop Skills Panorama - https://skillspanorama.cedefop.europa.eu/en

Cedefop Skills Forecasts - https://www.cedefop.europa.eu/en/events-and-projects/projects/forecasting-skill-demand-and-supply

Cedefop OVATE (Online Vacancy Analysis Tool for Europe) - https://www.cedefop.europa.eu/en/data-visualisations/skills-online-vacancies

O*NET - https://www.onetonline.org/

European Skills Competences Qualifications and Occupations - https://ec.europa.eu/esco/portal/home