Who rises and who drops? New technologies, workers, and skills

The case of a developed region

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In this paper, the authors study the evolution of the demand for new professional profiles and new skills in Emilia-Romagna in the decade 2008-2017, through the analysis of the SILER database (Mandatory Notifications to the Ministry of Labour). The focus of the analysis is on digital skills. The results, among the few available for Italy, are in line with those offered in the international literature. The proposed methodology provides a measure, built on employment balances, that allows to identify `winners and losers' in a small open economy and is a useful tool to monitor business choices and public policies.

In questo saggio si studia l'evoluzione della domanda di nuovi profili professionali e nuove competenze in Emilia-Romagna nel decennio 2008-2017, attraverso l'analisi del database SILER (Comunicazioni obbligatorie al Ministero del Lavoro). Il focus dell'analisi riguarda le competenze digitali. I risultati, tra i pochi disponibili per l'Italia, sono in linea con quelli proposti nella letteratura internazionale. La metodologia proposta fornisce una misura, costruita sui saldi occupazionali, che permette di identificare `vincitori e vinti' in una piccola economia aperta ed è un utile strumento per monitorare le scelte aziendali e le politiche pubbliche.

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Introduction

New technologies, new paradigms, new skills. An industrial revolution entails a radical change in socio-economic and political systems, driven by the introduction of new technologies usually (but not necessarily) associated with a significant increase in efficiency and productivity (Tarry 2019). From the beginning of the First Industrial Revolution, modern capitalism has been based on a knowledge economy, since the true value was produced, in large part, by the propagation of the uses of available knowledge. In other words, cognitive work, unlike human work, does not transform any raw material; it instead generates innovative knowledge (Rullani 2004). The latter is used to transform what already exists, indirectly creating utility, increasing efficiency, designing new products, or customising old services (ibidem). For this reason, in an innovation-based economy, the interdependencies of learning and innovations are crucial (Grillitsch *et al.* 2018). What was previously stated is ever more relevant with regards to digitisation and Industry 4.0[1].

With specific regards to the effects of Industry 4.0 on the labour market, several schools of thought exist. Many of the topics (and interpretative hypotheses) typical of the comparison on the effects of technical progress among social scientists since the First Industrial Revolution are now being brought up again, both in terms of employment levels and in relation to the conditions and quality of work.

On one hand, automated systems, the backbone of the 4.0 paradigm, are considered a threat: since the First Industrial Revolution, machines and technologies have been developed to replace human labour, reduce wage costs, and generate more profit (Pianta 2018). In the Fourth Industrial Revolution, some professions may be at risk of replacement by machines and algorithms. This is driven by the increase of artificial intelligence and big data, which are providing machines with greater human abilities (Rotman 2013). The work of Frey and Osborne (2017) is a typical example of research focused on the likelihood of workers being replaced by machines: they estimated that around 47% of jobs were in the high-risk category, especially those with routine activities. Brynjolfsson and McAfee (2014) reinforce this negative perspective by addressing the automation of cognitive tasks and arguing that humans and machines are perfect substitutes for one another and do not complement each other.

In a radically different perspective, Caruso (2017) states that instead of replacing work, technological innovation is creating new opportunities through increased process efficiencies. Similarly, Rosenberg (2009) sees automation not as a threat but as an opportunity: if workers were replaced by machines in routine and low-value activities, they could be free to express their talents. As a result, new technologies could have a positive impact on employment: in particular, 3D printing, the Internet of Things, augmented reality, and big data analysis require significant amounts of new skills for proper management (Freddi 2017), leading to demand for new professions. Similarly, Leigh *et al.* (2020) highlights a positive contribution of robots to manufacturing employment in the USA. Also Zysman and Kenney (2018) argued that several dynamics, like the innovation process, can never be totally 'automated' and remains for the foreseeable future a domain of human creativity and initiative. Likewise, MacCrory *et al.* (2014) assumes three main consequences of technological innovation: a significant reduction in the skills where competition with automation is more prevalent; a significant increase in skills which complement machines, and an increase in the strategic nature of skills which cannot be replicated by machines. Similar conclusions are reached by Autor (2015).

Although within different visions, the speed of the current processes, their wide scope across domains and the very unpredictability of the directions of change – the characteristics of the Fourth Industrial Revolution – pose unavoidable questions about the expected evolution of labour demand, both in terms of quantity and quality. More than half a century ago, the pioneering work carried out by the United States Bureau of Labour Statistics (BLS) strongly emphasised the need to pay attention to the evolution of the demand for new skills associated with the transformation of technologies and production processes (Wilson 2013). Today, the proactive adaptation induced by the processes of change includes the need not only to predict the 'new', but also to manage the 'old' skills and to plan for retraining. From a managerial point of view, the presence of a wrong mix of skills determines poor business performance (Grugulis and Vincent 2009; Lorentz *et al.* 2013): human capital represents the most valuable asset for an organisation (Fulmer and Ployhart 2013), and thus, firms need to focus on cultivating it (Barney 1991; Becker and Gerhart 1996; Lado and Wilson 1994). Moreover, the complex nature of organisations makes identifying the right mix of skills for a business a very difficult task (Abbott 1993), especially because workers will end up performing ever more heterogeneous activities within a regulated process (Cirillo *et al.* 2020). However, what seems evident is that robotisation is growing faster than the capacity of workers to acquire new skills; for this reason, there is the urgent need to design learning paths to prepare workers to master technologies (Gentili *et al.* 2020; Branca

1 The literature contains many and often differing definitions, derived from different interpretations of this concept. What they have in common is the idea that its impact cuts across the social, economic, and political, with boundaries that are not yet clearly defined (Last 2017).

et al. 2020), as well as to create new tasks where labour can interact with technologies in a productive and synergic way (Acemoglu and Restrepo 2020). To this end, Artificial Intelligence (and associated technologies) could be used to positively transform education (Clifton *et al.* 2020).

As a result of the above, several researchers have established a goal of defining the characteristics that could make a professional profile resilient to change (Chryssolouris *et al.* 2013; Gorecky *et al.*, 2014; Weber 2016). In recent years, scholars, managers, and operators, starting out from the same questions, have shown growing interest in cross-cutting skills. The focus of scholars and professionals on this topic has grown for many reasons. The main one is, perhaps, digitisation. The impact of digitisation is pervasive, diversified and articulated across multiple levels of skills and capabilities (Van Laar *et al.* 2017; Galati *et al.* 2019), which highlights the importance of acquiring cross-cutting and heterogeneous skills to face it (Chryssolouris *et al.* 2013; Gorecky *et al.* 2014; Weber 2016; Fonseca *et al.* 2018; Lalé 2020). Despite the lack of agreement on the domain in which soft skills operate, seminal essays on the impact of digitisation on skills (Acemoglu and Autor 2010; Author 2015; Frey and Osborne 2017; Levy and Murnane 2004; de Vries *et al.* 2020) show that the machines and algorithms that govern them are only able to replicate what is codifiable. Cross-cutting skills, in this area, are the real bottleneck of digitisation.

In this context, international competence frameworks are usually considered the main data source for studying digitalisation impact on job profiles and skills. Some of those works belong to the field of econometrics (Frey and Osborne 2017; Arntz *et al.* 2017; Autor and Dorn 2009; Acemoglu and Autor 2010; MacCrory *et al.* 2014), i.e.: trying to measure the susceptibility of workers to automation; others are mainly based on data mining techniques, focusing on the development of further skills taxonomies or entity extraction (Boselli *et al.* 2018; Karakatsanis *et al.* 2017; Alabdulkareem *et al.* 2018; Colombo *et al.* 2019), data comparison (Thompson *et al.* 2010) and data linking (Mirski *et al.* 2017; Alfonso-Hermelo *et al.* 2019, Pryima *et al.* 2018).

The possibility to link the classification systems to external data sources, such as labour market administrative data, could allow the identification of the success drivers of a job profile.

The literature provides a rich body of research analysing the Excelsior Informative System[2] as a primary source of labour market data (Antonelli and Nosvelli 2008; Autiero *et al.* 2020). Whereas in this work, the authors propose SILER (and similar administrative databases) as a primary source of information to explore the phenomenon from a different point of view. SILER is a dataset of mandatory notifications sent to regional employment centres. As will be detailed in the following pages, the dataset includes employee's personal data (age and education), information on the employment contract (including the date of recruitment and dismissal − if and when it takes place), and information on the tasks for which the worker is employed.

This information − combined with that relating to the enterprise (size, ATECO sector of activity) – are a powerful tool for understanding not what the enterprises' presumed intentions are (as in the Excelsior surveys), but what their actual behaviour has been over a given period of time. In this sense, mandatory communications are important for studying the evolution of labour demand, grasping the emergence of new professional figures, and grasping the change in the composition of the skills required of workers.

After having linked SILER with ESCO[3], the authors identified the most requested job profiles in Italy's Emilia-Romagna region, with reference to the skills associated with the individual professions over the last decade and obtained through the use of data mining techniques. Thus, the characteristics that could make a job resilient to digitalisation and attractive for the labour market were identified. The dataset that was constructed contains over three million observations and covers the period December 2008 to December 2017, a period long enough to capture some of the structural changes underway.

This paper is organised as follows. Paragraph 1 describes the data sources and sets out the methodological aspects of the analysis. Paragraph

2 <https://excelsior.unioncamere.net/>.

3 ESCO (European Skill/Competence Qualification and Occupation) is a multilingual classification system for Europe: it ranks skills, expertise, and qualifications in Europe relevant to the labour market.

2 presents an analysis of the aggregate labour demand for the whole region, compared between the different clusters. Paragraph 3 examines, in a comparison by cluster, the development of professions and skills, highlighting those which have been most positive and most negative over the course of the decade. Paragraph 4 offers an analysis of the impact of Industry 4.0 technologies on professions and skills, highlighting the most relevant for each cluster. Paragraph 5 provides a conclusion.

1. The data

Mandatory notifications

The collaboration of ART-ER, in-house company of the Emilia-Romagna Region, and the Emilia-Romagna Labour Agency made it possible to build a suitable dataset to analyse the evolution of labour demand for the period 2008-2017[4]. The dataset contains data on mandatory notifications sent to regional employment centres. Mandatory notifications on employment relationships are communications from employers (both public and private) which contain detailed information on each employment relationship and must be submitted for all new hires and on transformation, extension, and termination of the employment relationship. In addition to subordinated employment relationships, self-employment relationships of a coordinated and continuous form must be notified, including project-based work, cooperative workers, associates with job-based contributions, traineeships, and any other type of similar work experience. In particular, the hiring notification must provide the employee's personal data, the date of hire, the end date (when the employment relationship expires), the type of contract, the professional qualification, and the financial and regulatory conditions applied. We obtained a record for each employment relationship: the date of recruitment, the numbers of any transformation or extension and, in case of a completed relationship, the date of termination. In this sense, the notion of employment relationship coincides with that of employment spell. The total number of employment relationships thus obtained was 3,123,108, of which 2,547,762 were terminated, while 575,346 were still active at the end of the analysed period (December 2017).

Particular attention should be paid to the specific classification of economic activities that has been adopted to analyse and compare the behaviour and results of companies belonging to the individual sectors. The criteria adopted are those defined by the Emilia-Romagna region in the Smart Specialisation Strategy, deeply described in the following section. In this way, seven categories of economic activities considered to be technologically related are identified as the main reference for guiding regional industrial and development policies. Categories are: Agrifood; Building and construction (Build); Culture and creativity (Create); Energy and sustainability (Greentech); Health and wellbeing (Health); Innovation in service (Innovate); Mechatronics and motor engineering (Mech)[5]. The clusters of industries thus identified are neither industrial districts, nor supply chains nor vertically integrated sectors. The implication is that all well-known limits apply in the ability to account for the relationship between companies that cross the boundaries between the individual sectors. However, they are functional to give an account of ongoing structural transformations and of the possible effects of labour policies in the clusters of industries considered strategic by the regional government.

The Smart Specialisation Strategy[6] and Clust-ER[7]

The European Commission required the adoption of the smart specialisation analytical system (Smart Specialisation) and the development of a strategy to assemble it as a condition for the development of cohesion policies of the Regions and Member States, to be financed with the Structural and Investment Funds for the period 2014-2020. The concept of smart specialisation provides consistency to certain requirements for the effectiveness of structural policies through their focus, including considering the results of previous programming and their critical issues through policy learning. Specifically, the Cohesion Policy 2014-2020 programming cycle

4 No more recent data are available at the time of writing this paper.

5 The full list of codes (5 and 6-digit ATECO-2007) that have been included in each of the clusters can be provided on request to the authors.

6 Main sources: https://bit.ly/3lRQW0d e https://bit.ly/3ucctoa.

7 Main sources: https://bit.ly/39BKTqG.

provides, as an ex-ante condition for the use of EC resources, for national and/or regional authorities to develop research and innovation strategies for 'smart specialisation', to allow more efficient use of Structural Funds and an increase in synergies between EC, national and regional policies.

Following the preliminary work of the S3 Forums, Clust-ERs made their debut in 2018, becoming one of the main elements of the Smart Strategy. Clust-ERs are associations – one for each area of the regional S3 – of public and private bodies: research laboratories, companies, training institutions, innovation centres of the High Technology Network. Each Clust-ER is a community structured to share ideas, skills, tools, and resources to support the competitiveness of S3 areas of the regional production system: Agrifood, Building and construction, Mechatronics and motor engineering (which make up Priority A of the S3), Culture and creativity[8], Health and well-being (Priority B), Energy and sustainability (Priority C) and Innovation in services (Priority D). The Clust-ER project received support from POR FESR 2014-2020.

The region government asked the Clust-ERs to identify the priority goals for each area of specialisation of the S3 and with reference to the sectors/supply chains of greatest value for the regional economy (in terms of turnover, employment, and competitive positioning in the international context). These objectives allow the definition of, among other things, the priorities on which to focus regional interventions for the last three years of the 2014-2020 schedule, and the Clust-ERs are configured as the brain of the production chains behind the regional production system.

Within this system, solid information on the industrial clusters and production chains, considered crucial for local development and of their evolution, also in terms of labour demand trends, takes on primary importance in the design of regional policies. In the following pages, these sets of economic activities and sectors will be referred to simply as 'clusters' or 'S3 clusters'.

Professions and skills in international statistics

The precise definition of 'skill' is subject to a huge debate and is deeply affected by the polysemy of the term itself (Benadusi and Molina 2018). According to some authors, the first distinction to outline is the one between skill and performance (Chomsky 1965), where the former refers to an individual potential, innate and universal. For others, instead of mere personal attributes, skills are a mix of actions and relationships intertwined with organisational and social dimensions (Benadusi and Molina 2018). This is how professional knowledge can be created, transmitted, interpreted. Therefore, according to the socio-constructivistic perspective (Jonnaert 2009; Benadusi and Molina 2018), skills are generated and developed but can also be impoverished, degraded, and renewed depending on educational, training and work experiences, throughout the life and across different contexts. Although the polysemy is undoubted, skills can be categorised as resources to act, as devices that allow actions and are formed in action (Benadusi and Molina 2018). Moreover, skills can be learned by immersive practice, and through family, educational and professional socialisation (Dubar 1991). Thus, they can be gained in the process of forming individual and social identities (Ajello 2003; Pontecorvo *et al.* 1995).

In this work, when citing the term skill, the authors are aligned to the ESCO and EQF definition (i.e., "skill means the ability to apply knowledge and use know-how to complete tasks and solve problems"), where the term skill typically refers to the use of methods and instruments in relation to defined tasks (European Commission 2020). Moreover, the main source of data used in the present work is represented by ESCO itself. ESCO (European Skill/Competence Qualification and Occupation) is a multilingual classification system for Europe: it ranks skills, expertise, and qualifications in Europe that are relevant to the labour market. ESCO's goal is to bridge the gap between universities and industry across Europe, through a triangular relationship between skills, profiles, and qualifications. The classification code for professions is ISCO-08, which is the International Standard Classification of

8 The scope of this sector may be defined primarily by the following activities: publishing industries; cinematographic and musical productions (audio-visual); activities related to the management, conservation, restoration and use of cultural heritage; creative and interactive digital industries; production of games and musical instruments; amusement parks; entertainment, show-business and cultural activities; design and communication services; creative services related to fashion and furniture; tourism linked to culture, entertainment and entertainment https://fesr.regione.emilia-romagna.it/s3.

Occupations (International Labour Organisation 2008).

The database is the starting point for the aggregate study of skills and professional profiles in complex economic systems (regions, nations, groups of enterprises, etc.). However, being a static representation (and strongly affected by the time required to translate observation of production and training processes into a shared classification system), it is only minimally able to capture a highly dynamic phenomenon such as the evolution of the demand for skills and abilities in the labour market.

What seems interesting to study, and could represent a possible step forward, is linking the skills in the classification systems described above with the professions present in the labour market, which is considered through the connection between the IASCO-08 international classification and the professional units of the 2011 Classification of Professions (Istat). This latter classification is the latest in a long tradition of studies, with which the Italian National Institute of Statistics has sought to meet the needs for renewal emerging from many sides, particularly the institutions which work most for and on the labour market. Since 1861, updates to the classification of professions have, indeed, followed the deadlines of the general population census – the last of which was held in 2011 – to take account of changes in the labour market. Innovation in production processes and their organisation, new aspects in the qualifications required to exercise professions, and changes in demand for goods and services are just some of the factors that affect the nature, content and manner in which the different occupations are carried out. As these changes gradually become apparent, the classification needs to be adapted to reflect market trends, new occupational areas and changes in the requirements associated with the professions. The work of reviewing the taxonomy has been directed towards this point of view, in an attempt to grasp the changes in the professional structure of the country and to represent them within the new classification system (Istat 2013).

The following scheme shows which information has been selected and which additions have been made in order to obtain the final result. Every observation of the SILER database described above represents an employment movement associated with the individual's 5-digit Istat professional classification, adopted in 2011 and aligned with the European ISCO-08 standard. Specifically, the Istat professions variable consists of 5 digits, each corresponding to a grouping level (Figure 1).

Figure 1. Profession's classification tree structure

Source: <https://www.istat.it/it/archivio/1832>

The legend for the Istat Big Groups is given below:

- Legislators, entrepreneurs, and senior management
- Intellectual, scientific, and highly specialised professions
- Technical professions
- Executive professions in office work
- Qualified professions in commercial activities and services
- Craftsmen, skilled workers and farmers
- Plant operators, fixed and mobile machinery workers and vehicle drivers
- Unskilled professions

To trace the skills associated with each working relationship in the SILER[9] archive, we carried out a crosswalk with the ESCO (European Skills, Competences, Qualifications and Occupations) database which incorporates the European standard for skills, qualifications, and occupations. ESCO has a structure similar to a dictionary: it describes, identifies, and classifies relevant professions, skills and qualifications and EU education and training. Every observation of the ESCO database is identified by an ISCO-08 code. The connection table between Istat 2011 and ISCO-08[10] can similarly combine the SILER database and the ESCO database. The process is briefly outlined in Figure 2.

9 In the dataset created, there is no employment relationship featuring a profession of Main Group *9 – Armed Forces*.
10 Cfr. https://bit.ly/3zEysVQ.

Through the crosswalk, it was possible to express the skills characterising the different professions. The employment trend was first observed, followed by the skills characterising the occupational profiles with a markedly positive or markedly negative employment balance (by individual sector and in terms of comparison). Finally, a search was carried out for digital skills among the profiles with the most positive (negative) employment balance, which also identified how they are distributed across the different S3 clusters. This was made possible through the help of a dictionary enriched with Industry 4.0 technologies (Chiarello *et al.* 2018), which will be described in detail in the following sections.

2. A comparative analysis of the S3 clusters in Emilia-Romagna

In this paragraph, we use mandatory reporting data to analyse the workflow for the individual clusters during the period under scrutiny.

Figure 3 shows the change in employment between 2008 and 2017 by individual clusters. All clusters, except for Health, suffered the effects of the 2008 crisis, reaching their minimum peak in 2009 (2011 for Health and well-being). Although almost all clusters experienced a recovery in 2010-11, the trends fluctuated, with employment balances (net employment variations) deteriorating in 2012-13, improving from 2014-16 and then dropping again after 2016. Only Greentech recorded an increase in employment for 2017 compared to 2016.

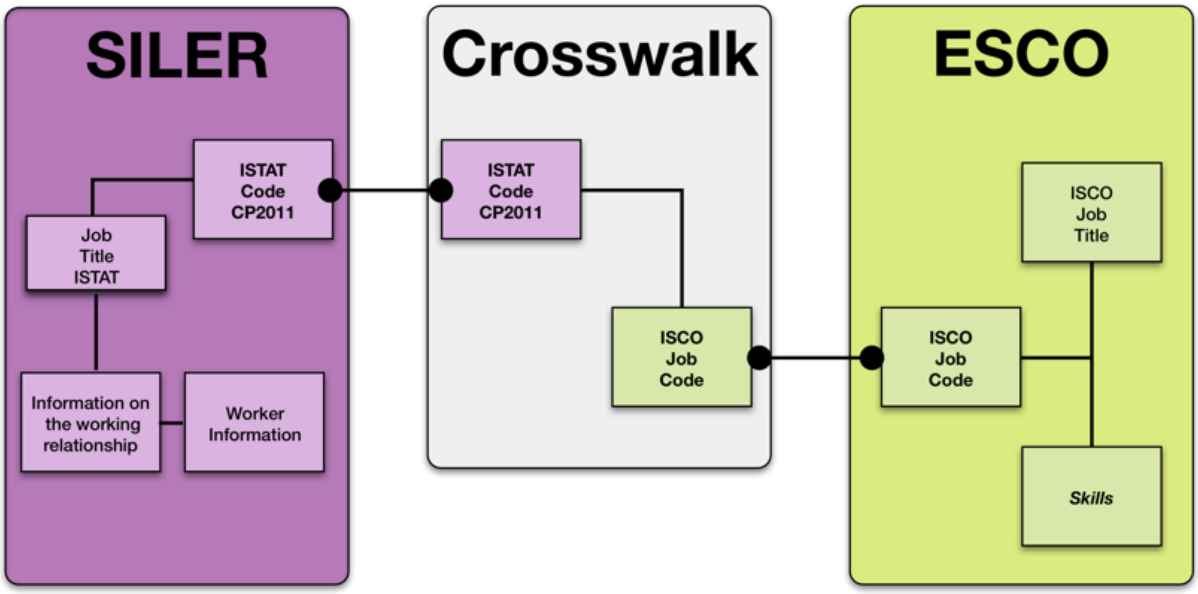
Table 1. Net employment balance by year and cluster and Total Employees (2017) by Cluster

S3 Cluster	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total	Total Employees (2017)
Agrifood	1.228	-1.731	774	1.820	435	1.134	1.366	3.981	4.215	295	13.517	431.044
Build	-4.284	-12.285	-4.609	-4.586	-7.294	-9.014	-7.715	1.106	90	-2.909	-51.500	297.757
Mech	437	-14.436	-1.464	920	-2.149	-1.441	-463	6842	5.677	4.093	-1.984	304.510
Health	-99	389	-5	-407	416	160	-56	690	1.665	961	3.714	150.710
Create	-701	-2.358	185	759	-1.321	-1.075	-932	1.751	429	-2.040	-5.303	171.879
Innovate	2.846	446	1.570	2.337	1.009	1.353	3.505	2.057	2.054	874	18.051	81.758
Greentech	959	-2.337	433	1.012	-1.759	-1.547	-290	1.410	1.478	1.680	1.039	84.900
Total	**386**	**-32.312**	**-3.116**	**1.855**	**-10.663**	**-10.430**	**-4.585**	**17.837**	**15.608**	**2.954**	**-22.466**	**1.522.558**

The Build cluster featured the worst employment balances, which were always negative except for the two-year period 2015-16. In the ten years taken into consideration, the number of workers in this cluster fell by more than 50,000. Mechanics, Mechatronics, and motor suffered a strong negative impact in 2009, followed by a period of settlement characterised by minor balances (2010-2014) and then a significant recovery after 2015 (which allowed it to limit losses in total employment to just under 2,000). As already stated, the Health and Well-being cluster shows a very peculiar dynamic compared to the others, with a significant negative balance only in 2011; there were no particular repercussions, which would have been expected, from the effects of the earthquake of May 2012, that heavily affected the regional biomedical district, among others. The Greentech, Create and Agrifood clusters did not change significantly over the period, alternating positive and negative balances, although with a general improvement after 2014 and a worsening in 2017. The Innovation cluster in services is worth a special mention: it is the only one that has never experienced negative balances; at the end of the period the total balance was 18,000 units greater than at the beginning.

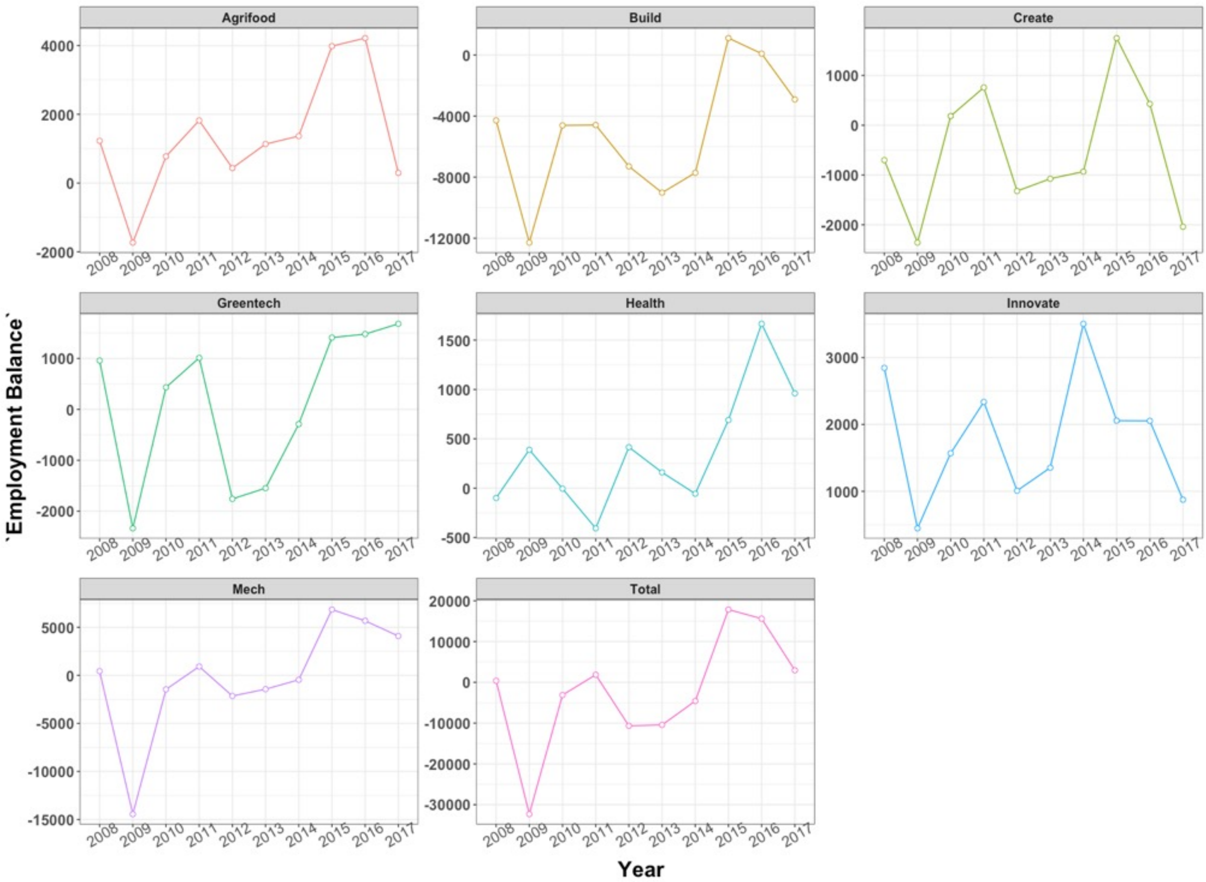
All clusters slowed down more or less markedly at the end of the period, highlighting that the regional production system, particularly manufacturing, was in difficulty even before the pandemic-induced crisis. In addition to cluster-specific problems and

Figure 2. Dataset scheme and variables used



Source: representation by Authors

Figure 3. Trends in the employment balance in individual clusters from 2008 to 2017



Source: SILER database (Mandatory Notifications to the Ministry of Labour), representation by Authors the effects of substitution with products from newly industrialised countries, it is easy to blame German manufacturing performance and the negative impact on world trade of the US-China conflict.

To sum-up. The decade under examination was a period of great structural and technological transformation. There is reason to believe that the process of digitisation, as in other highly developed areas of the country, has had no adverse effects on employment levels (Paba *et al.* 2020). Moreover, technological innovation should be seen as an opportunity, and be leveraged to support workers in their tasks, instead of replacing semi-skilled or unskilled jobs (Rodrik 2020). The latter is ever more relevant in a world affected by a dramatic pandemic phenomenon, where technology has become ever more necessary (Acemoglu 2020).

On the other hand, the period analysed came between the two worst crises that the productive system faced in the post-war period. It was also a decade in which competition from emerging and newly industrialised countries became extraordinarily intense. Therefore, a clear trend emerged of firms limiting employment and the extensive use of short-term employment contracts. Both instruments aim to streamline processes and, above all, to reduce production costs. Jobs with lower qualifications and levels of education were harmed the most by this trend. In other words, product competition in the market is undergoing change, and this has inevitable repercussions – not all positive – on the labour markets. The flip side is that the increase in university degree holders among new hires is still a relatively limited process.

In this scenario of major transformations, it is particularly important to understand how this set of factors has acted on the demand for new and old professions and on the emerging demand for trades and skills. The following two paragraphs are dedicated to this objective.

3. Winners and losers: professional profiles and skills

Using the methodology set out in the previous pages, the trends in the demand for professional figures and skills during the decade under consideration are presented below. Some of the main results are detailed in the appendix. The trend for the balances is represented using graphs showing, for each cluster, the professional profiles that have increased and the professional profiles for which demand has fallen to a greater extent. The same analysis and representation have been used for skills.

Some indications for reading the graphs follow. The occupational profiles and skills are ordered with respect to the cumulative values of the employment balance in the various clusters; the membership of one (or more) clusters can be obtained for each of the branches shown in the graphs. The thickness of the branch represents the size of the employment balance. The name of the occupational profile is derived from the international classifications.

Figure 4 shows the only professions with a positive employment balance for the period 2008-2017. In particular, the profiles with the highest employment balance were mainly associated with the Mech, Agrifood and Innovate clusters: the two clusters showing growth and the large mechanics and mechatronics cluster which is widespread in the region.

Demand is very diversified. Very briefly (the reader should refer to Appendix 1 for more detailed data), we note that there are at least four types of professional profiles for which demand has clearly increased in recent years: 1. Technical profiles with medium or high-level qualifications (software analysts and designers, technical designers, application engineers, technical programmers, installers and assemblers of industrial machinery and plants, chemists and similar professions, etc.); 2. Management administrative profiles with a broad spectrum of skills (general affairs officers, system administrators, warehouse management and similar professions); 3. Sales and marketing staff (sales distribution technicians, marketing technicians); 4. A rather varied and significant component of workers with lower levels of qualifications (machine and plant operators, series assemblers, employees in packaging machines, drivers, garment packers, freight workers and similar, retail sales people, cleaning operators, porters, etc.).

Overall, the results picture a productive system where manufacturing still holds great importance, there is a strong differentiation between different manufacturing activities, and new professions are mixed with professions and trades which have been codified for decades, also in relation to relatively newer sectors.

New elements (for which there is less evidence) emerge from the analysis of the demand for skills.

Figure 5 shows the ranking of the 30 most requested skills and abilities (summary) over the decade by S3 cluster. In line with our conclusions in the analysis of professional profiles, technical skills remain of considerable importance: from the ability to use CNC machines to the demand for data analysis skills, the latter linked to the growing number of applications for computer science and digitisation of processes. However, the clearest data point to emerge is that the top of the ranking features skills ascribed to the notions of soft skills applicable across domains: communication, problem-solving, co-ordination of working groups and staff, project management and timing, and so on, are thereby frequent. In this context, customer management skills (from communication to identifying their wishes etc.) are in particular demand at the company level. Although the Mech, Innovate and Agrifood cluster, given their relevance, continue to have a significant impact on the relevant profiles, the demand for these types of skills is increasing across all the S3 clusters.

The results for professional figures and skills with negative employment balance are shown in Figure 6 and Figure 7. More detailed information is also available for declining professional profiles in the Appendix (Appendix 2).

As with the professional profiles undergoing growth, the groups with declining professional profiles are also easily identified. Over the course of the decade, the contraction in demand affected essentially two groups: 1. Traditional trades (carpenters, masons, etc.) 2. Some highly repetitive roles in production and offices. Both were concentrated in the Build and Mech clusters.

Therefore, during this period traditional trades saw an acceleration of a process that has been going on for decades. For repetitive roles, a major process of changing and reorganising production processes and office work appears to be underway. Secretaries and secretarial workers, common to all S3 clusters, are the roles that have suffered the largest cumulative negative impact.

The skill analysis confirms the observations for professional profiles. Replacement is underway for office tasks often related to information management, duties related to operational professional profiles (maintenance and cleaning of machinery, use of machine tools etc.) or associated with traditional trades. However, it should be noted that the size of the individual flows is very small in terms of absolute values: a sign of adjustments that, although generalised, are marginal to an extent. Whole blocks of skills are not disappearing; rather, there is a progressive process of replacing old skills with new ones. Like other times of great transformation, change is the result of a slow and continuous process, modulated by the system of industrial relations and by a variety of institutional factors. The interpretation of this result will be covered in the conclusions. Here, we will simply note that, over the course of the decade, it seems to have affected the professions based on routine tasks and therefore subject to the highest risk of automation (Autor 2015; Frey and Osborne 2017); profiles with a high intensity of manual work are also gradually being replaced by technology, organisational change, and modular production. This brings us to the specific impact of the new digital paradigms associated with Industry 4.0.

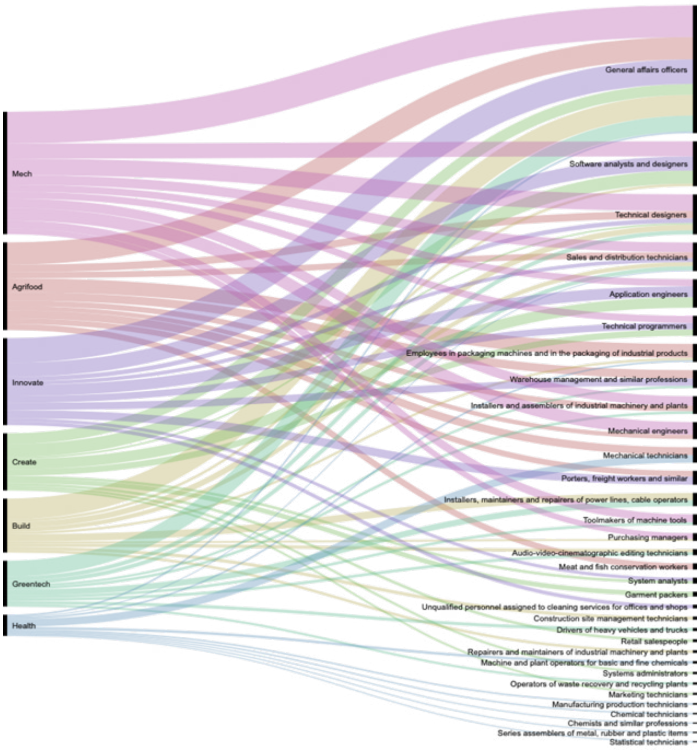
4. The demand for digital skills

For the regional production system, like for other advanced economies, the Fourth Industrial Revolution, i.e. the automation and interconnection of production processes and the management of information flows, is perhaps the biggest challenge. The new flow affects production systems and processes, organisational dimensions, professional systems and, more generally, approaches to work. The new 'Smart factory' will have to control and manage production processes using new digital and automated tools. The key technologies forming the base of the technological revolution concern areas such as cyber security, big data, cloud computing, augmented reality, robotics, rapid prototyping, radio frequency identification and tracking, super-connection of plants and 3D printing, as well as new approaches to work, process management and human resources management.

Changes of such magnitude will influence trades, professions and, with them, the knowledge, skills, and tasks required of the worker, triggering both adaptation and – even substantial – modification of individual jobs and work positions.

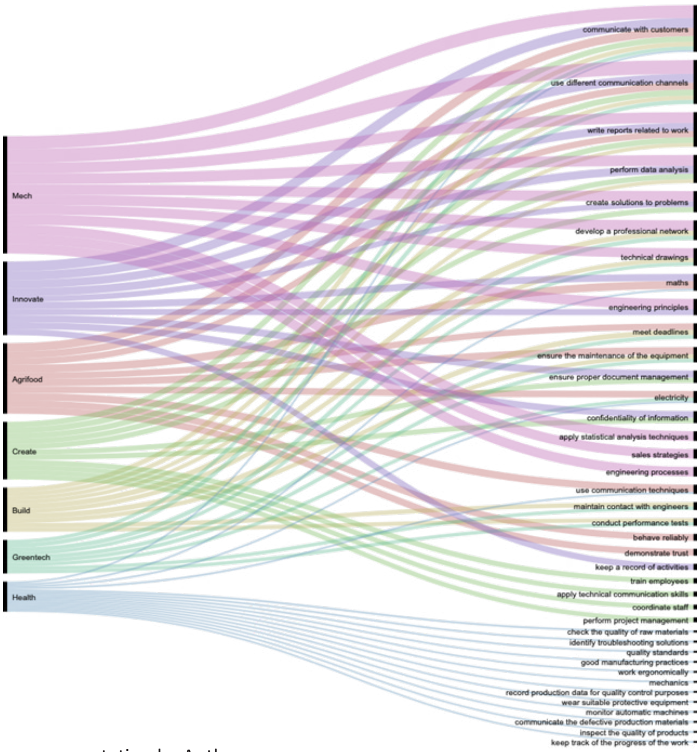
The main players in these processes are, on one hand, companies, who not only acquire the new profiles but also contribute to training them, and on

Figure 4. Professions with positive employment balance in the period 2008-2017



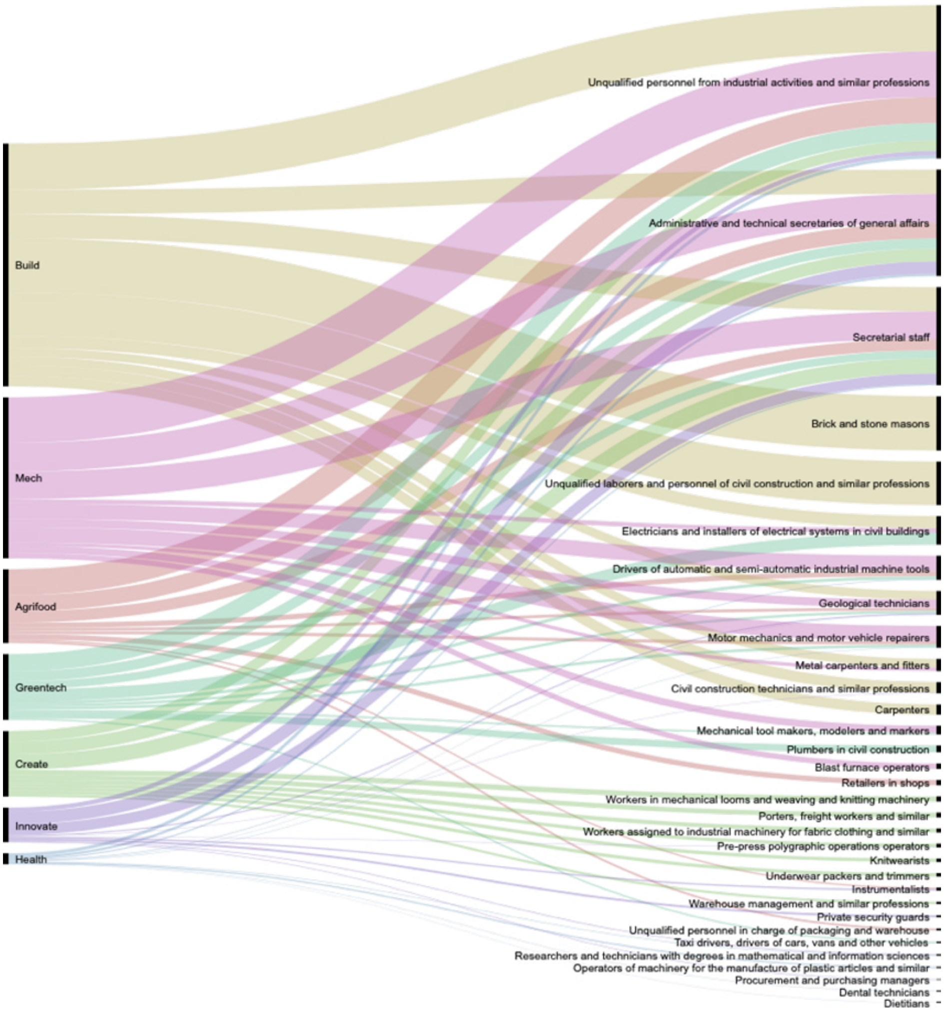
Source: ESCO & SILER database, representation by Authors

Figure 5. Extract of skills associated with profiles with positive employment balance in the period 2008-2017



Source: ESCO & SILER database, representation by Authors

Figure 6. Professions with negative employment balance in the period 2008-2017



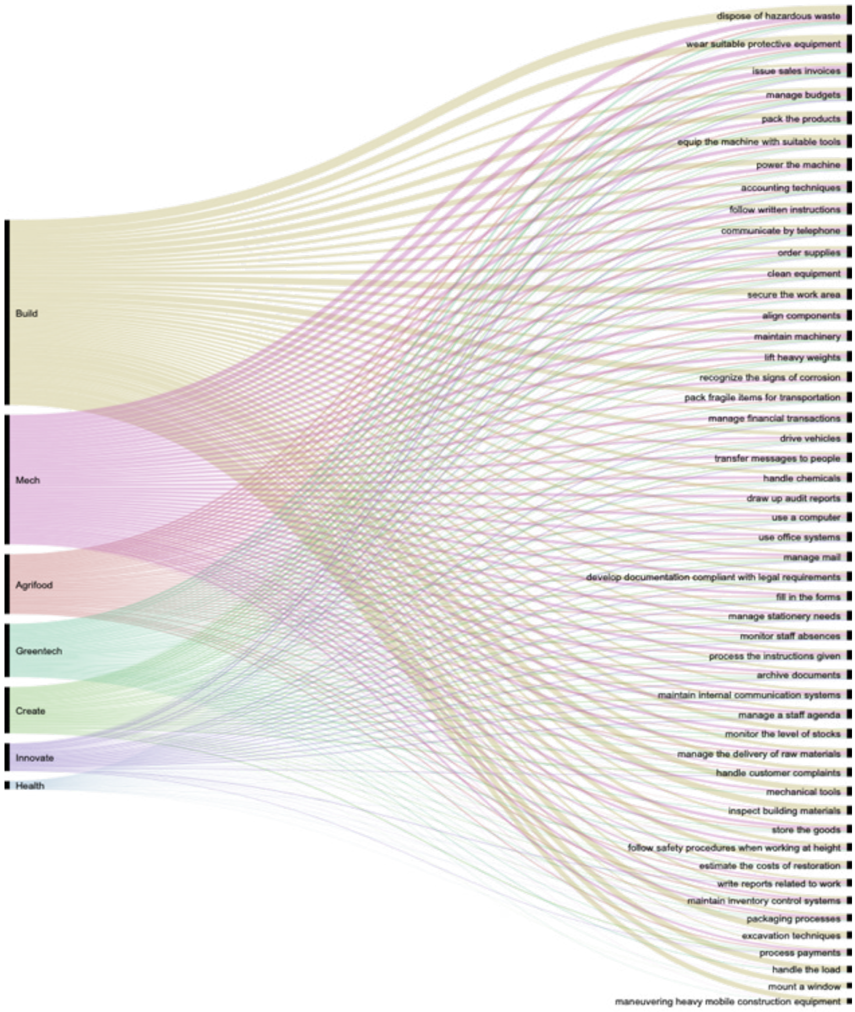
Source: ESCO & SILER database, representation by Authors

the other, the whole training system: schools of all levels and universities.

Introducing new machinery is not a sufficient condition for organisations and businesses wanting to adapt to new technologies and to changing product needs and demand. Properly carrying out an activity requires not only the idiosyncratic knowledge and skills typical of new technologies, but also the ability to implement them. In the face of the profound changes induced by digitisation, the efficiency of the enterprise and its adaptability, as on other occasions of great change, requires adequate technology, organisation, and skills.

From this point of view, both for the scholar and for the public operator, being able to outline the scope of Industry 4.0 skills and define shared semantics is necessary for a greater understanding of the current transformation of production. The tool used is the aforementioned dictionary enhanced with technologies 4.0 from Chiarello *et al.* (2018). The enriched dictionary is the result of data mining work which started with the definition of a 'seed list' of technologies 4.0 collected from scientific publications and papers. Once the manual review of the list was performed, the latter was expanded using Wikipedia, collecting all the hyperlinks related to the seed elements. The output of the previous workflow was an enriched dictionary of 1211 technologies and more than 30000 relationships among them. Through the connections deduced from the links between the Wikipedia pages, the technologies were represented in a graph and clustered automatically

Figure 7. Extract of skills associated with profiles with higher negative employment balance in the period 2008-2017



Source: ESCO & SILER database, representation by Authors

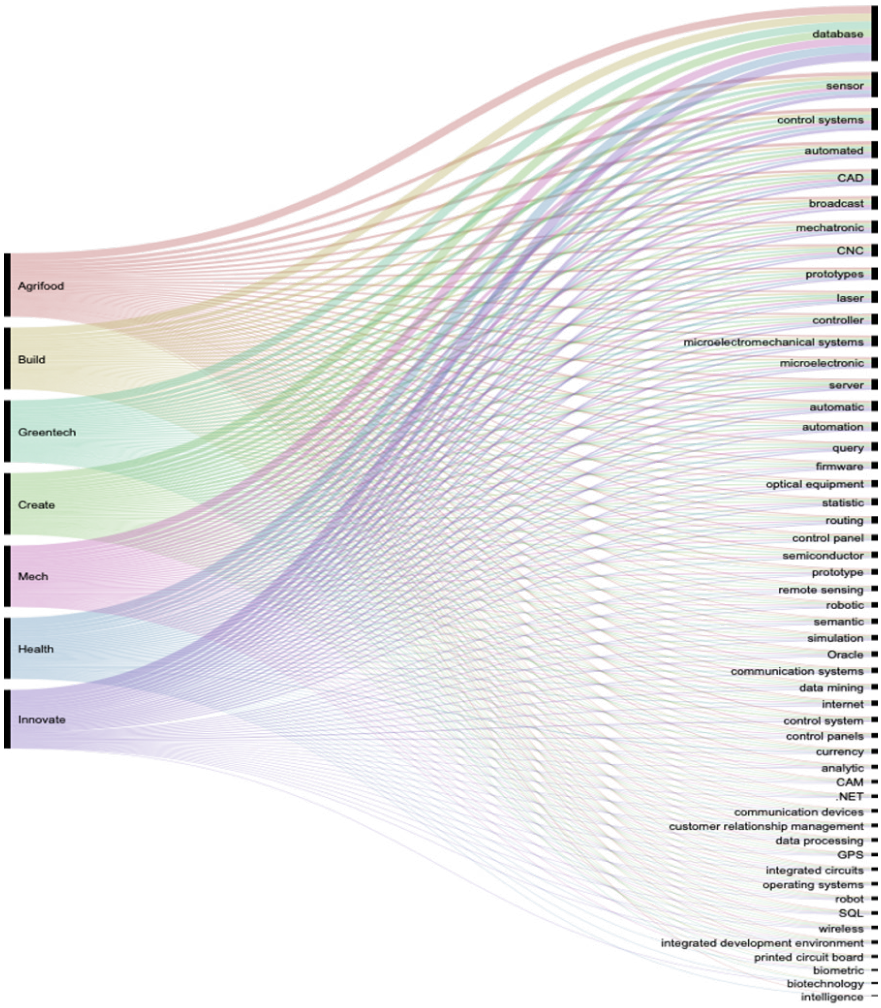
by an algorithm in homogeneous groups. More specifically, the dictionary contains lists of regular expressions[11], that is, a sequence of characters that defines a search pattern. The patterns are used by string searching algorithms for 'finding' or 'finding and replacing' operations on strings, or for input validation, and it allowed the tool to capture the different orthographic declinations in which a technology could be written.

In this paper, the analyses were performed with Software R. The dictionary was used to identify the ESCO skills that contain at least one technology, and hence, the ones that could be categorised as 4.0. The analysed skills were the only ones related to the professional profiles most requested by companies, and it allows the creation of a ranking in terms of their relevance in the regional clusters. The authors deliberately filtered the results that seem less valuable, e.g., the term 'computer' and the ones strictly related to its components ('software', 'hardware', and so on), that are ever more considered mandatory and widespread (Fareri *et al.* 2020).

Figure 8 shows the results of the projection of the 4.0 dictionary on only occupational profiles with a positive employment balance. As can be seen, the association of 4.0 technologies and skills in professional profiles undergoing growth reveals a very complex set

11 A regular expression, regex or regexp (sometimes called a rational expression).

Figure 8. Technologies associated with professional profiles with positive employment balance



Source: ESCO & SILER database, representation by Authors

of skills and abilities across a wide range of business functions and production processes.

The relevance ranking, derived from the position in the right-hand column, is calculated with reference to the number of times that a given 4.0 technology appears in a descriptive profile declaration or in a skill associated with the professional profiles[12]. In relative terms, skills related to the creation and management of databases (and therefore to the collection and structuring of 'data' in a broad sense) are especially important for all S3 Clusters. They are followed by sensor technology and signal transmission, crucial from a smart factory and Internet of Things (IoT) point of view; process automation; CAD and simulation technologies.

One of the findings to be mentioned is the crossover nature of these technologies/skills between the different industries. This result is widely expected, but important, nevertheless. One of the distinctive aspects of the Fourth Industrial Revolution, compared to the previous ones (in addition to the automation of complex functions) is the transition from 'sectoral' artificial intelligence to a general one which is widespread in the various economic activities (Bianchi 2017). This can be shown in some detail for S3 clusters.

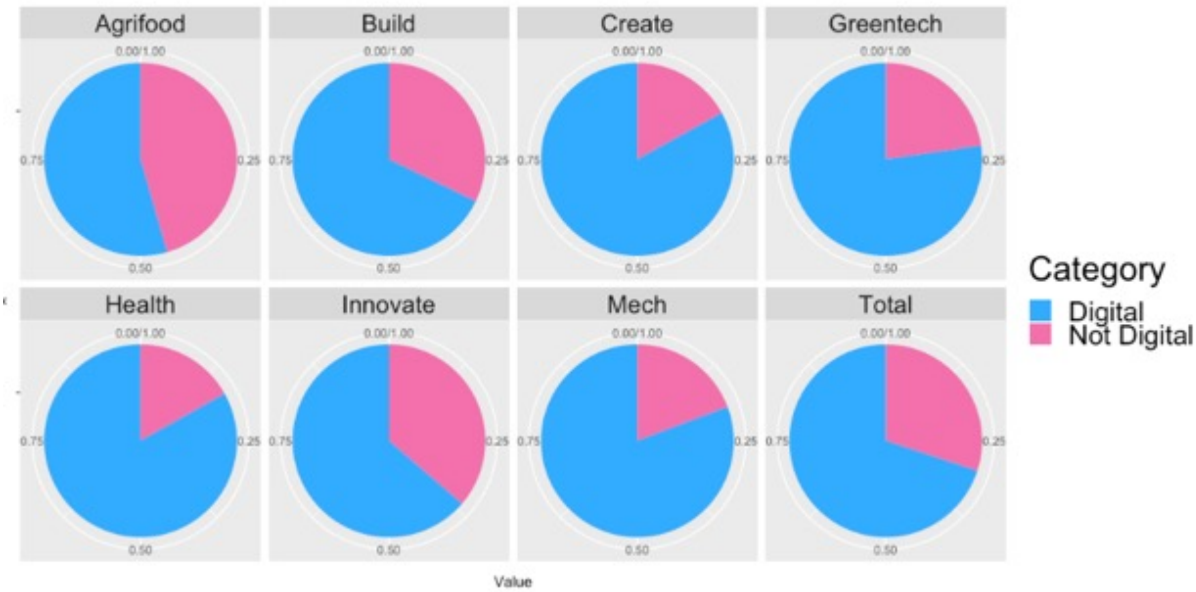
12 The dictionary also captures skills that straddle the digital and non-digital. In order to avoid assigning importance to non-digital skills, a threshold of ten recurrences has been imposed as a convention. Below this threshold, indeed, there are skills such as computer use which are now present in any job description.

Table 2. Hires with digital skills out of the total number of hires for the period 2008-2017. Absolute values and percentage values

	Agrifood	Build	Mech	Health	Create	Innovate	Greentech	Total
Total Hired	648.437	783.994	698.667	60.188	280.185	340.077	256.124	3.067.672
Not Digitized Hired	295.527	252.171	134.715	10.167	47.682	123.495	58.207	921.964
Digitized Hired	352.910	531.823	563.952	50.021	232.503	216.582	197.917	2.145.708
% Not Digitized Hired	46	32	19	17	17	36	23	30
% Digitized Hired	54	68	81	83	83	64	77	70

Source: ESCO & SILER database

Figure 10. Hires with digital skills out of the total number of hires for the period 2008-2017, percentage values



Source: ESCO & SILER database, representation by Authors

As stated above, the tool by Chiarello *et al.* (2018) kept trace of the technological clusters to which each technology/skill belongs. Thus, it allowed the authors to perform an additional analysis. In more detail, the previously detected technologies belong to fourteen different technology clusters, entirely covering the spectrum of enabling technologies outlined by the Boston Consulting Group (Rüßmann 2015). Once the technology clusters were defined, the authors studied their distribution among the S3 clusters to reveal the most relevant technologies for each S3 cluster. To achieve the goal, the number of technologies belonging to each cluster was calculated and normalised for the total number of technologies retrieved by S3 clusters. The latter process allowed the definition of the weight of importance of each technology for every S3 clusters. The result is shown in Figure 9 through a heat map. The greater the purple intensity, the higher the weight of the technology cluster on that S3 clusters; conversely, the greater the light blue intensity, the lower the weight of the technology cluster on the S3 cluster. The percentage is given by the total number of technologies belonging to a specific technology cluster, normalised by the total number of technologies detected on the S3 cluster analysed.

In this family of enabling technologies, those belonging to the cloud computing and remote data management cluster prevail. The presence of simulation technologies, experimental analysis tools aimed at evaluating and predicting the dynamic development of a series of events under specified constraints – typically construction of scenarios (expected demand estimates in particular markets, etc.) is also significant (Fantoni *et al.* 2017).

With regard to block chain technology and crypto currencies (meaning a representation of the value based on cryptography), these have an incidence in all S3 Clusters, particularly Health. There are two possible reasons: centralised management of medical expenses and the management of confidential data that require transferability. In general, healthcare block chains ensure that different actors share access to their networks without compromising the security and integrity of business data. Data analytics, programming languages (preparatory) and predictive tools follow at more modest concentrations.

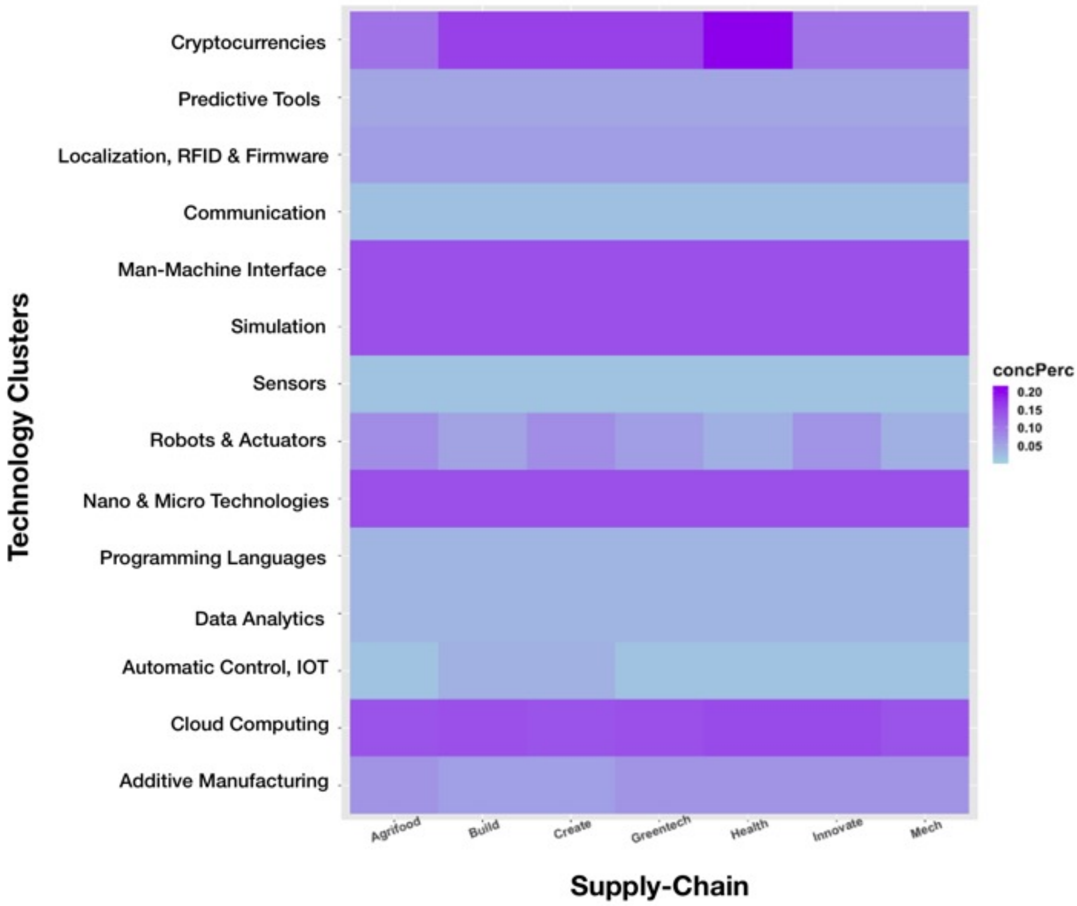
The results obtained are in line with other surveys on the adequacy and digital maturity of Emilian companies (Solinas *et al.* 2019).

The last feature to be discussed is the distribution of digital skills in Emilia-Romagna. With the aforementioned analysis tool, a simple measure of the distribution of digital skills was constructed using the ratio of hires with digital skills to the total number of employees hired during the period under consideration. The results are given in Table 2 and Figure 10. They show that, despite some variability, the vast majority of working relationships created over the course of the decade in all S3 Clusters required digital skills. This confirms that the Fourth Industrial Revolution is on the move, affecting most professional profiles.

5. Summary and conclusions

In this paper, the typical tools of the flow analysis of labour markets relate to the emerging demand for professional profiles and skills. With regard to professional profiles and skills, a methodology is

Figure 9. Impact of technology clusters on different S3 clusters, percentage values



Source: ESCO & SILER database, representation by Authors proposed to provide a measure, built on employment balances, between incoming flows and outgoing flows at the firm level. This measure makes it possible to identify the winners and losers in a small open economy exposed to all major changes in the world economy such as the Emilian. From this point of view, the focus is shifted towards the processes of replacing employment profiles and skills induced in particular by the spread of new technologies.

The results obtained confirm important findings shown by the literature about the effects of new technologies on the labour markets. Along with a downsizing of the old trades, characterised by physical effort and manual skill – a process that has been ongoing for some decades – routine factory line and office jobs appear most at risk of replacement. This is in keeping with the findings of seminal studies on the effects of digital technologies, whether they are based on professions (Frey and Osborne 2017) or on the tasks and skills associated with professional profiles (Autor 2015). Nevertheless, this does not mean that 'dropping occupations' are totally automatable or disappearing. As also highlighted in the McKinsey Report (Manyika *et al.* 2017), full automation is a process whose methods and implementation times are subject to the costs of implementing new technologies, their degree of social acceptance, labour market regulation systems, the effectiveness of training systems in retraining, and reconverting workers to the new conditions (Nedelkoska and Quintini 2018).

The top positions of the 'winning' skills ranking are held by soft skills: communication, problem-solving, coordination of working groups and staff, project management and timing and similar profiles, are the most frequent. The result is, once again, in accordance with literature: many studies stress the advantage of acquiring soft skills in order to face the digital wave (Chryssolouris *et al.* 2013; Gorecky *et al.* 2014; Weber 2016), outlining the negative impact of such a skill gap on the workforce (Frank *et al.* 2019; Bauer *et al.* 2011; Bridgstock 2011; Dobrunz *et al.* 2006; Haukka 2011; Cooper and Tang 2010). It is also important to outline the disappearance of the belief that they are innate characteristics of individuals. In the last years, many scholars have been searching for innovative ways to facilitate their development (Sanz *et al.* 2019; Tseng *et al.* 2019; Duran-Novoa *et al.* 2011), their assessment (Bohlouli *et al.* 2017), their comprehension (Chechurin and Borgianni 2016) or more specifically identifying how they impact digital jobs (Hendon *et al.* 2017).

Regarding technical skills, and more specifically digital skills, there is as a clear emergence of those related to data management which is considered a priority to actually begin implementing the change (Roy *et al.* 2016; Colegrove and Peters 2017). Furthermore, there is a predominance of cloud computing and experimental analysis tools aimed at evaluating and predicting the dynamic development of events under specified constraints, also known as Simulation technologies, that are ever more requested by firms in Emilia-Romagna (Solinas *et al.* 2019) and deeply described by Fantoni *et al.* (2017).

The final part of the essay outlines a method to estimate how many new jobs are specifically associated with 4.0 technologies and which are now most in demand by companies. It shows that digital skills and knowledge are required in three out of four new hires. Against this background, what stands out is the fact that the management of information flows is by far the most typical element of the ongoing transformation processes. This element emerges in many industries, both in the new productions chains and in those more typical of Emilian manufacturing tradition. Connecting business processes and functions through full control of information flows is the heart of the 'smart factory', the glue holding together new and old industrial knowledge, new and old crafts, the ability to learn and the ability to do.

The research presented in this paper is to some extent exploratory, and the proposed methodology must certainly be refined. We believe, however, that it represents a useful tool to analyse labour markets, changes in the industrial structure and for the construction of informed economic policies itself.

Appendix 1. - Professions with the most Positive Employment Balance [2008-2017]

S3 Cluster	Employment Balance (+)	Job Profile CP2011
Mech	4578	General affairs officers
Innovate	3551	General affairs officers
Agrifood	3214	General affairs officers
Build	3001	General affairs officers
Mech	2389	Technical designers
Greentech	2279	General affairs officers
Mech	2172	Software analysts and designers
Innovate	2035	Software analysts and designers
Agrifood	2005	Employees in packaging machines and in the packaging of industrial products
Create	1880	Software analysts and designers
Mech	1820	Mechanical engineers
Innovate	1587	Application engineers
Create	1571	General affairs officers
Create	1509	Application engineers
Mech	1383	Sales and distribution technicians
Mech	1361	Installers and assemblers of industrial machinery and plants
Agrifood	1201	Warehouse management and similar professions
Innovate	1181	Porters, freight workers and similar
Mech	1153	Toolmakers of machine tools
Agrifood	1123	Mechanical technicians
Health	1095	Mechanical technicians
Agrifood	1079	Technical designers
Innovate	1049	Warehouse management and similar professions
Build	1039	Installers, maintainers and repairers of power lines, cable operators
Mech	1001	Application engineers
Mech	990	Technical programmers
Innovate	974	Technical programmers
Create	906	Technical programmers
Agrifood	888	Sales and distribution technicians
Agrifood	882	Meat and fish conservation workers
Greentech	865	Installers, maintainers and repairers of power lines, cable operators
Agrifood	827	Porters, freight workers and similar
Mech	820	Purchasing managers
Build	814	Technical designers
Agrifood	801	Installers and assemblers of industrial machinery and plants
Create	680	Garment packers
Innovate	643	Technical designers

S3 Cluster	Employment Balance (+)	Job Profile CP2011
Agrifood	637	Mechanical engineers
Build	601	Sales and distribution technicians
Greentech	586	Technical designers
Greentech	572	Sales and distribution technicians
Innovate	537	Sales and distribution technicians
Innovate	530	Unqualified personnel assigned to cleaning services for offices and shops
Build	478	Audio-video-cinematographic editing technicians
Build	464	Construction site management technicians
Innovate	457	System analysts
Greentech	455	Drivers of heavy vehicles and trucks
Greentech	409	Audio-video-cinematographic editing technicians
Create	402	Retail salespeople
Create	398	System analysts
Greentech	394	Toolmakers of machine tools
Greentech	385	Installers and assemblers of industrial machinery and plants
Build	384	Software analysts and designers
Build	381	Repairers and maintainers of industrial machinery and plants
Health	363	Machine and plant operators for basic and fine chemicals
Build	345	Employees in packaging machines and in the packaging of industrial products
Create	342	Systems administrators
Greentech	333	Warehouse management and similar professions
Greentech	329	Operators of waste recovery and recycling plants
Create	303	Marketing technicians
Build	283	Purchasing managers
Health	259	General affairs officers
Create	259	Technical designers
Health	256	Employees in packaging machines and in the packaging of industrial products
Health	225	Manufacturing production technicians
Health	209	Chemical technicians
Health	172	Chemists and similar professions
Health	170	Series assemblers of metal, rubber and plastic items
Health	164	Statistical technicians
Health	145	Sales and distribution technicians

Appendix 2. - Professions with the most Negative Employment Balance [2008-2017]

S3 Cluster	Employment Balance (-)	Job Profile CP2011
Build	9277	Brick and stone masons
Build	7896	Unqualified personnel from industrial activities and similar professions
Mech	7800	Unqualified personnel from industrial activities and similar professions
Build	7431	Unqualified laborers and personnel of civil construction and similar professions
Mech	4902	Administrative and technical secretaries of general affairs
Mech	4719	Secretarial staff
Agrifood	4474	Unqualified personnel from industrial activities and similar professions
Build	4146	Administrative and technical secretaries of general affairs
Build	4132	Secretarial staff
Greentech	2966	Unqualified personnel from industrial activities and similar professions
Agrifood	2723	Administrative and technical secretaries of general affairs
Create	2624	Secretarial staff
Mech	2619	Motor mechanics and motor vehicle repairers
Mech	2601	Drivers of automatic and semi-automatic industrial machine tools
Create	2218	Administrative and technical secretaries of general affairs
Innovate	2101	Administrative and technical secretaries of general affairs
Build	2082	Electricians and installers of electrical systems in civil buildings
Greentech	2030	Electricians and installers of electrical systems in civil buildings
Agrifood	1945	Secretarial staff
Build	1842	Civil construction technicians and similar professions
Create	1814	Unqualified personnel from industrial activities and similar professions
Innovate	1813	Secretarial staff
Build	1770	Carpenters
Greentech	1723	Administrative and technical secretaries of general affairs
Build	1479	Metal carpenters and fitters
Build	1466	Geological technicians
S3 Cluster	**Employment Balance (-)**	**Job Profile CP2011**
Mech	1400	Geological technicians
Greentech	1354	Secretarial staff
Mech	1196	Mechanical tool makers, modelers and markers
Greentech	1176	Plumbers in civil construction
Mech	923	Blast furnace operators
Agrifood	903	Retailers in shops
Create	888	Workers in mechanical looms and weaving and knitting machinery
Agrifood	882	Drivers of automatic and semi-automatic industrial machine tools
Create	817	Porters, freight workers and similar

S3 Cluster	Employment Balance (-)	Job Profile CP2011
Mech	766	Electricians and installers of electrical systems in civil buildings
Innovate	754	Unqualified personnel from industrial activities and similar professions
Create	700	Workers assigned to industrial machinery for fabric clothing and similar
Mech	605	Metal carpenters and fitters
Create	588	Knitwearists
Create	582	Underwear packers and trimmers
Create	576	Pre-press polygraphic operations operators
Agrifood	556	Motor mechanics and motor vehicle repairers
Health	544	Unqualified personnel from industrial activities and similar professions
Greentech	538	Drivers of automatic and semi-automatic industrial machine tools
Agrifood	505	Geological technicians
Greentech	472	Motor mechanics and motor vehicle repairers
Greentech	444	Geological technicians
Create	413	Warehouse management and similar professions
Health	400	Administrative and technical secretaries of general affairs
Innovate	361	Private security guards
Agrifood	353	Unqualified personnel in charge of packaging and warehouse
Greentech	285	Mechanical tool makers, modelers and markers
Agrifood	269	Instrumentalists
Greentech	266	Taxi drivers, drivers of cars, vans and other vehicles
Innovate	255	Instrumentalists
Health	227	Operators of machinery for the manufacture of plastic articles and similar
Innovate	207	Geological technicians
Health	202	Secretarial staff
Innovate	147	Researchers and technicians with degrees in mathematical and information sciences
Innovate	125	Procurement and purchasing managers
Health	122	Drivers of automatic and semi-automatic industrial machine tools
Health	104	Researchers and technicians with degrees in mathematical and information sciences
Health	81	Motor mechanics and motor vehicle repairers
Innovate	78	Pre-press polygraphic operations operators
Health	75	Dental technicians
Innovate	74	Civil construction technicians and similar professions
Health	68	Geological technicians
Health	51	Dietitians

Source: ESCO & SILER Database

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