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Visualizing the Evolving Fit of Education and Economy: The Case of ICT Education in Norway

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Visualizing the Evolving Fit of Education and Economy: The Case of ICT Education in Norway

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Abstract

Our study suggests a pattern of methodological steps aimed at an efficient visualization of the fit between an education and an economy. The steps help to detect cross-sectoral skills, originating in a given education path, and to connect them to the evolution of the labour market. Our procedure utilizes statistics derived from labour flows and builds upon the recent scientific literature on skill-relatedness. As an empirical application, we analyse the fit of ICT higher education with the Norwegian economy, using data on intersectoral labour flows (years 2009–2017). Our procedure is then used to analyze the Norwegian job market for ICT-educated people, suggesting the existence of cross-sectoral ICT skill-relatedness which could explain the ongoing dynamics. With the methodological steps we identify sectors linked to the "ICT-sector" as being a skill hub, but also find links to public sector, suggesting the public sector being attractive to ICT-educated people, and links to other skill-related communities containing higher education and R&D as well as data analysis and processing. Finally, the methodology identifies skill-related communities, such as finance and offshore, which are isolated, in terms of skill-relatedness, from the rest of the economy and appear to be islands in the Norwegian economy.

Keywords: Labour flows, Skill relatedness, Economic complexity, Capabilities, Industrial dynamics.

JEL Classification: D85, I21, J21, J24, J62.

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1. Introduction

Economies are complex systems, functioning through the interactions of a large number of different agents (Schweitzer et al., 2009). Interactions allow the combination of different capabilities, adding to a country's economic complexity (Hidalgo & Hausmann, 2009). Skills are a capability, and specific labour skills available within a country are among the determinants of a country's export mix; they also define the paths on which the export mix can be extended (Hausmann & Hidalgo, 2011; Hidalgo, Klinger, Barabási, & Hausmann, 2007). Analogously, a country's industry tends to extend its production mix, by adding products that belong to the production mix of "skill-related" industries (Neffke & Henning, 2013). The implication we draw, and on which we base our paper, is: if the same skill can be used in different industries, and if the same education can contribute to different skills, then it is possible to associate a particular education to different sets of industries, each one constituting an outlet for the given education path. Such association would in turn allow a deeper understanding of the evolving labour market, available to people having a given education.

We suggest a pattern of methodological steps aimed at answering a question: how can we best visualize the evolving fit between an education and an economy? We refer here to a specific type of education, providing a specific set of skills whose range of application varies across different economic sectors. While the economic agents interact in many different settings, and the economy can be disaggregated at different levels for study, considering sectors as units of analysis is an established and fruitful practice to understand the knowledge evolution within an economy (Castellacci, 2008; Pavitt, 1984). However, while innovation studies have often analysed the economy as a network of knowledge relations across sectors, tools originating in network theory have often been directed towards other types of analyses (Costa et al., 2011). In particular, visualization tools grounded in network theory and employed for input-output economic analyses (see, e.g., Xu & Liang, 2019) can provide additional intuitions to the visualization of knowledge relations among sectors.

Our study focuses on the visualization of knowledge relations that are rooted in a given type of education. In particular, we suggest a sequence of methodological steps which can identify cross-sectoral skills, originating in a given education path, and connect them to the observed evolution of a labour market. Our procedure utilizes statistics derived from labour flows, and builds upon the seminal work by Neffke and Henning (2013) on skill relatedness. As an empirical application, we analyse the fit of ICT higher education with the Norwegian economy. The progressive digitalization of the Norwegian economy has not been accompanied by a corresponding increase in job opportunities for ICT-educated workers, indicating sectoral as well as geographical barriers. Our procedure is then applied to dig into the Norwegian job market for ICT-educated people, and to detect the existence of cross-sectoral ICT skills which could explain the ongoing dynamics.

Section 2 provides an overview of the relevant literature. Section 3 details the methodology. Section 4 describes the data used for our empirical example, while Section 5 shows the results. Section 6 concludes.

2. Literature

The methodological steps we suggest relate to the increasing availability of microdata from the national statistical offices. During the last decade, new types of microdata have started to be available to social researchers, making thus possible to adopt different methodologies to answer research questions in social sciences. An important development has been registered in the acquisition of individual-level data connecting employers to employees. This type of datasets allows to track the careers of every resident in a given country, and especially its movement across firms, often even across establishments. The association between workers and establishments makes it possible to understand the match between skills at the individual level and the sets of skills available altogether within an establishment, thus creating the possibility of a complementation of skills which will translate into a good produced or a service provided. Most importantly, this type of employer-employee data show the evolution of careers over time, as well as the evolution of the sets of skills within establishments. The establishments are often defined by an industry code (for instance a NACE code), usually made available by the same statistical office which provides the invidual-level data. Then, a connection between people and sectors can be defined. Moreover, by looking, in the aggregate, at the movements of people between economic sectors, also a connection between sectors themselves can be defined.

The construction of a “skill-relatedness” index by Neffke and Henning (2013) has been made possible by such data availability: by observing labour flows between industries, a measure of industry “skill-relatedness” was inferred. Given that skill-relatedness can be estimated for any pair of economic sectors, and be marked as a particular connection between sectors, then a whole economy can be seen as a network, where each sector is a node and skill-relatedness is a link. This intuition has given rise to an entire strand of literature, which, during the last decade, has crystallized into a specific methodologic approach to evolutionary economic geography. In particular, industry skill-relatedness has connected with the concept of related variety (Frenken, Van Oort, & Verburg, 2007), which, at regional level, can affect diversification (Boschma & Frenken, 2011) and resilience (Boschma, 2015). The same methodology has then been applied in other national context, like in Germany (Neffke, Otto, & Weyh, 2017) and Norway (Fitjar & Timmermans, 2017). While we keep the detailed description of the methodology for a specific section below of this paper, we want now to point out the fact that individual-level education data have often been left out of the picture by this same scientific literature. We then take the opportunity of refining the idea, particularly stressed by Hidalgo and Hausmann (2009) in a macro-setting, that specific capabilities are needed to complement physical capital (as well as other capabilities), in order to produce a given good or service. Considering, instead, generic measures of human capital (e.g., measured in years of schooling) might limit the analysis's depth (Hidalgo & Hausmann, 2009).

The framework by Neffke and Henning (2013) is inspired by similar convictions and has already proved to be a fruitful tool to infer the capability base within economic sectors. However, its enrichment through the exploitation of other micro-data sources, providing observed variables related to the workers's skills, could further extend its domain of application. Alabdulkareem et al. (2018) have indeed shown that occupation-related data can set the basis for extensions of the Neffke and Henning (2013) framework, which can build skill taxonomies and explain job polarization phenomena. While we recognise that occupation data have opened promising empirical avenues for understanding employment dynamics (Burger, Stavropoulos, Ramkumar, Dufourmont, & van Oort, 2019; Consoli, Marin, Rentocchini, & Vona, 2019; Vona & Consoli, 2015), also in connection with the concept of skill-relatedness (although with different methdological approaches, see Barbieri & Consoli, 2019), we argue that education data have not been sufficiently exploited (a notable exception being Fitjar & Timmermans, 2018, who consider broad education categories). This is mostly due to the fact that education data alone do not inform sufficiently about the construction and acquisition of specific skills. Therefore, we complement education data with linked employer-employee data, within a skill-relatedness framework. In particular, we suggest a data-driven procedure which can summarize all the potential fields of application of a particular type of education, and can be connected to a country's observed employment dynamics.

The empirical example we consider throughout our paper is based on ICT education in Norway. Any type of education could in principle be under analysis, in any country which, like Norway, would make available to researchers a dataset matching, at individual level, education attained and working place registered over a sufficiently long number of years. However, the specific case we have chosen for our example provides a particularly interesting puzzle. ICT plays an import role in economies. From 2006 to 2013 ICT contributed with 26 percent of productivity growth in Norway (Eggen, Mark, & Røtnes, 2015). This is significantly more than from year 1995 to 2005, where ICT contributed with 10 percent of productivity growth in Norway, reflecting an increased digitalization of the economy. Studies show an increasing deficit of people with high-level ICT skills in the labour market (Mark, Bjørnstad, Gran, & Røtnes, 2014; Mark, Tømte, Næss, & Røsdal, 2019), whereas other studies show people with master's degrees in ICT are struggling finding a job (Støren, 2018). This has been named the ICT paradox. The digitalization of the economy and the ICT paradox raise questions as to how the ICT skills get reallocated in the economy. Our methodology will be applied to hint toward possible answers.

3. Methodology

3.1 Approach

Our question is: have there been changes, over time, in the fit of ICT education with the Norwegian economy? By "fit" we refer here to a match between the acquisition of skills through education and the application of those skills within specific sectors of the economy. Given that "skills" and "economy" are concepts which cannot be uniquely reduced to measures, an essential element for our quantitative analysis lies in the reference to "education" and "sectors" (for simplicity, we will use the word "sectors" independently of the aggregation level, including when the word "industries" could be preferred). Specifically, in our analysis we will call "ICT education" an education connected to specific NUS2000 codes (Norwegian Standard Classification of Education, see Section 4 for details) and we will call "sectors" the ones defined by NACE codes (the statistical classification of economic activities in the European Union, see Section 4 for details). A main point here is that the the relation between specific skills, on one side, and the economy as a whole, on the other side, occurs through the application of skills within specific activities, performed by workers within economic establishments. Given that a NACE code is associated, in Norway, to each economic establishment in the country, and it is possible, through data from the national statistical office, to observe the education of each employee in each establishment, then it is also possible to abstract an overall picture of what happens in the country, in terms of the fit of education and economy.

However, when employing NACE codes, the disaggregation of the whole economy in different sectors can occur at many different levels. NACE codes are in Norway available at 5-digit, so in principle the economy could be disaggregated down to a very fine level. Which level shall we choose? Our suggestion is not to choose a particular level from the beginning, but instead moving slowly from more aggregated levels to more disaggregated ones. We think that such procedure allows to keep an intuitive vision of the dynamics of the country throughout the whole analysis, allowing our research to restrict the focus while the analysis proceeds. This progressive restriction of the focus leads to the following steps of our analysis.

3.2 First step: Recent labour dynamics at macrosector level

A first step employs a higher sectoral aggregation level, for instance the A38 aggregation, which is used by Eurostat as an intermediate step between 1-digit and 2-digit NACE codes, and builds upon an aggregation of the 88 2-digit setors into 38 macrosectors (European Commission, 2010). The "A38" macrosectors provide an intuitive first disaggregation of a national economy, since they allow also a first disaggregation across manufacturing sectors, which would not be achieved by using 1-digit level disaggregations. On the other hand, this level of aggregation keeps visible the important distinction, that would exist already at 1-digit, between private and public sectors, as well as between primary, secondary and tertiary sectors.

We restrict our attention on recent changes of the match, and so we measure, in each of the 38 "A38" macrosectors, the number of people with an ICT education at the beginning and at the end of a recent period of interest; in our empirical application, such period covers the years between 2013 and 2017. This is because our object of interest, for this first step, is the ongoing dynamics in the labour market, in relation to variations in the demand for particular skills (see Section 3.4 for further details).We do the same for the whole economy: we measure how many ICT-educated people were employed in the economy at the beginning and at the end of the period of interest. If the total number of employed ICT-educated people has increased in the whole economy, through our first step of the analysis we can decompose such number as a sum of the absolute changes registered in each of the macrosectors. This may sound like a trivial step, but it is essential to provide some first intuitions on which parts of the economy are driving the employment of ICT-educated people. The intuitions are made possible by the aggregation level, since it may be easier to associate movements of more aggregated macrosectors, as the A38 macrosectors, to information we may already have about the national and international general contexts. Even if the aggregation level is high, the 2-digit sectors included within the A38 sectors may share a general common dynamics following, e.g., value chain connections, product similarities or common suppliers.

To simplify further the picture, we suggest to concentrate the attention on those A38 sectors which have contributed the most, in absolute terms, to the overall change in the economy. We must highlight the expression “in absolute terms”, since the overall change in the economy can result from a partial offset of strongly positive contributions, by some macrosectors, and of strongly negative contributions, by some other macrosectors. The strongly positive contributions and strongly negative contributions can be disentagled by looking at all macrosectors which exhibited a high change in absolute value. We could be tempted at considering a given number of positions in the ranking, say the top five “positive” contributors and the top five “negative” contributors; however, we refrain from that, since what really matters, to understand the process behind an overall change of the economy, is not the simply the ranking betwen sectors, but rather the collective push of several macrosectors in the same direction, be it toward a higher or a lower employment of ICT-educated people.

In particular, we suggest to, first, rank all the macrosectors which have increased their number of ICT-employees, according to the increase amount. Then, we compute the sums of the increases: this could be named as a positive “collective push”. Finally, we progressively sum the contributions of each macrosector to the “collective push”, starting from the macrosector having the highest increase, until we reach a given percentage of the “collective push”. For instance, if we choose a threshold of 75%, we will concentrate on the lowest number of macrosectors which can, taken altogether, provide 75% of the “collective push”; roughly speaking, these macrosectors will represent the part of the economy that mainly pushes toward an overall increase of ICT employees in the whole economy.

In statistical terms, this equates to, first, computing the empirical probability mass function of the positive absorption of ICT-employees by each macrosector; then, ordering the mass function by indexing the macrosectors with an index “x” according to their contirbution ranking; then, translating the mass function into a cumulative probability distribution $F_X(x) = P(X \leq x)$; finally, using a cutoff p-value of (1-T) (where T is our desired threshold, equal to 75% i.e. ¾ in our previous example) to isolate the highest contributing macrosectors.

The procedure is then repeated for the macrosectors which have decreased their number of ICT-educated employees during the reference period; a cumulative probability distribution function can be built following their relative contributions to such negative “collective push”, and the analysis will then focus on the minimum number of macrosectors whose total contribution is higher than 75% of the negative “collective push”. Given that this part of the analysis has focused on absolute increases, a possible influence of the number of ICT-employees at the beginning of the period can be assessed at this stage, for the macrosectors selected by the previous procedure, in order to provide an idea about which of the relevant macrosector is experiencing a high internal dynamics.

3.3 Second step: From macrosectors to 2-digit sectors

A more precise description of the internal dynamics of the macrosector involves a shift in the analysis from the A38 macrosectors to the 2-digit NACE sectors that compose them. This is our second step. First, we will look at the changes in the employment of ICT-educated people, within the period of interest, for each of the 2-digit sectors composing the macrosectors previously selected. If we had previously observed that a particular macrosectors, e.g. connected to media publishing, has drastically increased the employment of ICT-educated people, we can now check whether one or more of the macrosector 2-digit components, for instance broadcasting activities or motion picture production, have increased or decreased the employment of ICT-educated people. In other words, we can see whether it is the whole macrosector which has contributed to the "collective push" described before, or if instead only some components of it are internal drivers of the macrosector's dynamics.

If a 2-digit sector has increased the number of ICT-educated employees, such increase may be fueled either by employees that have just entered, or re-entered, the labour force, or, more often, by employees coming from other 2-digit sectors of the economy. These could be 2-digit sectors belonging to the same macrosectors, or belonging to other macrosectors of interest, or even to macrosectors that we had initially discarded as irrelevant for our analysis. This type of dynamics between sectors can be seen through a network analysis of the labour flows of ICT-educated people between 2-digit sectors. In other words, we can see the economy as a network where each 2-digit sector is a node, and the connections between nodes are given by the flow of ICT-educated employees between sectors. A representation of the network of recent labour flows can provide an idea of how the rearrangement of ICT-educated employees within the economy is happening by a reallocation of workers across sectors.

3.4 Third step: Education-specific skill-relatedness

While labour flows over the recent period of interest can explain the within- and between- macrosector dynamics, in terms of ICT-educated employees, an analysis of labour flows of a longer period can provide a vision on more permanent characteristics, in terms of skills, of economic sectors. In other words, while a short-term analysis of labour flows shows us a fine-grained description of the recent and current labour dynamics, in connection to a particular type of education, a longer-term analysis of labour flows (e.g. over ten years) suggest a view on structural characteristics of the economy.

Two theoretical comparisons can help the reader to grasp our intuition behind this distinction, wich we think can constitute the basis for a study of the matching between education and economy. A first comparison is with the difference between descriptive and inferential statistics, where the second one can aim at reconstructing a general law from the events affecting a sample. Analogously, an analysis of labour flows in the short run, during a period of interest (i.e. in more recent and current times) shows what has happened and what is happening, and allows to show the details of macro process involving the whole economy. Instead, an analysis of labour flows over a longer time span can provide an indication of deeper causes behind the labour flows, primarily about the relation, in terms of skills, between the sectors (what we will later call "skill-relatedness").

A second comparison is with the short-term versus long-term analyses in economics, where short-term movements of an economy are often associated to variation of demand (e.g. associated to consumption fluctuations), while long-term movements are associated to variations in supply (e.g. associated to technological improvements). For labour flows, we can dare a comparison by suggesting that short-term analyses would point out variations in current needs of workers of sectors, in association to demand fluctuations for the products of the same sectors; while longer-term analyses would point out skill-relatedness among sectors, meant as similarities in the skills needed by sectors as embedded in the workforce to complement fixed capital, given the sectors' technologies.

Our third step then aims at understanding how different sectors of the economy are connected in terms of education-specific skills, that is ICT skills in our empirical application. The longer time period we will consider, in this phase of the analysis, will cover the span from year 2009 until year 2017. Some particular, and unobserved, ICT skills can be used in some parts of the economy, and we can see that by observing, over such longer time period, how some sectors of the economy have been connected by labour flows; other, also unobserved, ICT skills can be used in other parts of the economy: in general, the economy can be represented as divided into several sets of sectors, each one employing a relatively defined set of ICT skills. This would suggest that, whatever the short-term variations in the national and international contexts are, ICT-educated people which have acquired a particular set of skills would tend to remain employed within the same component of the economy, even if workers might be changing sectors within that component. It is important to point out that, in line with the previous literature, we suggest to use a 4-digit sector disaggregation in this step of the procedure; a 2-digit sector disaggregation, even if sufficient for descriptive statistics of labour flows, is not sufficiently fine for using labour flows to infer skill-relatedness.

3.5 Fourth step: Education-specific employment within a general skill-relatedness network

Our fourth step will provide an additional point of view by basing upon a slightly different approach: we will analyse "skill-relatedness" between sectors without focusing on ICT-education, and see how ICT education fits in the general network of skill connections among sectors. To this purpose, we will analyse, over the longer time set 2009-2017, all the labour flows, independently of the education of the workers, and build a skill-relatedness network of sectors, in representation of the whole economy and all types of education. We will then look at the position, in this network, of sectors with a high ICT education.

Two intuitions stand behind this fourth step of our study. A first one relates to an input-output vision of the economy, where each sector uses some inputs to create outputs, and both inputs and outputs can be intangible. Apart from the knowledge that flows between sectors as embedded in the workers, and is thus directly observed as labour flows, there is also knowledge that flows across sectors independently of the worker's flows, and even of market transactions, and simply because of the co-location within the same country. Such flow of knowledge depends on the skill-relatedness between sectors, which in turn can be inferred from labour flows, observed over the longer time span (2009-2017, in our analysis). Therefore, when we represent the whole economy through its labour flows, independently of education, and then higlight the nodes which correspond to sectors with a high density of ICT-educated workers, we can get an intuition of how the ICT skills are located within the general pattern of knowledge flows in the country.

A second intuition can stem from this first one when inserting a dynamic element into it: if some parts of the economy are declining, the consequences for other parts of the economy do not come only in the sectors which are connected by market transactions to the declining sectors (e.g. in sectors that are part of the same value chains), but also in sectors which have previously benefitted only in terms of knowledge from the declining sectors (through externalities). Therefore, a look at the ICT-dense sectors of the country, in the general context of knowledge flows of the country, can be complemented by a look at "neighbouring" sectors, in terms of knowledge, in order to grasp possible future evolutions of the employment of ICT-educated people.

3.6 Measurement of skill-relatedness

In practical terms, the methods to follow for the third and fourth step are similar; however, some important differences between the two steps would lead to very different, but complementing, results. The method used in the fourth step mimics what recently done by Fitjar and Timmermans (2019), who have used labour flows between 2000 and 2007 to identify the positions of oil and gas extraction sectors within the Norwegian skill-relatedness network of sectors; the only difference set by us is the time span considered, since we use years from 2009 to 2017.

In particular, for each couple of consecutive years between year 2009 and 2017, we compare the observed flows of persons between industries to the flows which would have been expected if flows between industries were random, i.e. if no pair of industries were more tightly connected in terms of labour flows than other pairs of industries. The expected number of persons moving from industry *i* to industry *j* is calculated as the total number of persons moving out of industry *i* (to any industry) multiplied by the total number of persons entering industry *j* (from any industry), divided by the total number of movers (from any industry to any industry). In formulas, with $i \neq j$:

$\textit{expected flow}_{ij}$ = (total out of *i*) * (total entering *j*) / total number of movers

For the flow of employees between any pair of industries *i* and *j*, we may define a relatedness ratio as the ratio between observed and expected flow of employees:

$\text{Ratio}_{ij} = \textit{observed flow}_{ij} / \textit{expected flow}_{ij}$

If this ratio is above 1, the flow between the two industries is larger than what we would have expected if the labour flow among industries were random.

This ratio varies from 0 to infinity and is thus highly skewed. This may be normalised to vary between -1 and 1 through the following transformation:

$\text{SR}_{ij} = (\text{Ratio}_{ij} - 1) / (\text{Ratio}_{ij} + 1)$

The yearly indicator SR_{ij} described above is computed for each couple of industries and for each couple of consecutive years between year 2009 and 2017. We consider as “skill-related” those sectors whose average SR, across all years, lies above 0.25, and (second condition) the yearly SR lies above 0.25 for at least three of the couples of years considered within the whole time span. In this way, we are able to build an updated “skill-relatedness” network for Norway, which provides hints about knowledge flows in the countries, to which we will add information about the “ICT content” of each node, i.e. the share of ICT-educated people in the sectors.

For the third step of our procedure, instead, we suggest a novel approach to skill-relateness networks, where the microdata on employees education are used not only to qualify nodes (i.e. sectors) in the network, but also to build the network itself. Indeed, the labour flows used to compute indicators, and thus to infer the connections in the network, will be measured considering only ICT-educated employees.

4. Data

We use data on employment from Statistics Norway, made available to us by means of two different datasets. A first dataset (Statistics Norway, 2019c) contains data at the individual employee level covering all persons in Norway between the age of 15 and the age of 75, and covering (in the data form available to us) each year from 2009 to 2017 included. The data include an employer variable in the form of a unique firm identifier where the employee works; the firm identifier is available at establishment level. If a person is employed by more than one firm, the person is registered as employed by the firm where he or she works most hours a week. For the years between 2009 and 2014, the employment has been registered in one given reference week each year; for the years between 2015 and 2017, the employment has been registered throughout the whole of each year, and we consider only the one defined as “main occupation” for the year. Firms are here defined at the individual plant or establishment level, rather than at the enterprise level. The enterprise is here the legal unit, and may comprise several establishments; each establishment is associated to a 5-digit NACE sector code.

For the purposes of our study, we do not consider all employed people, but we apply a filter to the population of each year. The filter is based on a “year of birth” variable, as obtained by matching our data with another dataset containing gender and year of birth of people in Norway (Statistics Norway, 2019a). For anonymity reasons, the “year of birth” variable is made available to us only as three-year intervals (e.g. we know whether a person is born in year 1948 or 1949 or 1950, but not exactly which year). We will consider only employed people that are “for sure” between the age of 18 and 65 years, thus excluding from our data also people that might be within the 18-65 age range but, given the three-year clustering, might also be out of it.

Instead, the “education” variables are obtained by matching our data with a third dataset containing, for each year, the NUS code of the highest degree obtained by each person in Norway (Statistics Norway, 2019b). The education is registered on the 1st October of each year. Also here, we adopt a restrictive approach: we consider an education degree as already achieved, for a given year, if this is registered as achieved on the 1st October of the previous year. Moreover, a worker will be considered as ICT-educated, in a given year, if the highest education degree achieved until the 1st October of the previous year is in an ICT subject, i.e. with a NUS education code whose first three digits compose one of the following two numbers: 654, 754 (we consider higher education but not Ph.D. studies, which are associated to completely different work expectations and career paths). For a worker having more than one education degrees of the same level, only the latest achieved degree will be considered.

5. Results

The following presents the results of our empirical application. To assess the fit of ICT-educated employees with Norwegian economy we focus on:

- What sectors are increasing and decreasing overall?
- What is the magnitude of increase and decrease?
- What are the significant flows to and from sectors?
- Which sectors are connected in terms of skills, and can we identify clusters of skill-related sectors?

This exercise will not provide complete answers as to the labor market situation of ICT-educated persons; yet, it will provide valueable insights as to where ICT-educated persons work, what sectors are blooming or fading in terms of work opportunities for ICT-educated people, as well as insights about restructuring processes within the economy. Also, the identification of skill-related areas of the economy (or sector “communities”, to adopt a term commonly used in network theory) will give us hints about which sectors are likely for ICT-educated persons to flow to and from.

Initially, we are focusing on what sectors are increasing and decreasing in terms of ICT-educated people. We focus on the changes between year 2013 and 2017. In total, the amount of ICT-educated people has increased by 3,342.

If we divide the figures according to the A38 macrosectors, we can identify the macrosectors contributing positively or negatively to the overall increase. In particular, Figure 1 shows the macrosectors that contributes with 75 percent of the total increase. The sectors are, in ranked order:

- Nace 62 and 63: IT and other information services
- Nace 84: Public administration and defence, compulsory social security
- Nace 86: Human health services
- Nace 58-60: Publishing, audiovisual and broadcasting activities
- Nace 69-71: Legal, accounting, management, architecture, engineering, technical testing and analysis activities

The five macrosectors add up to more than 75 percent of the total increase of high skilled ICT employees. It is not surprisingly that the traditional ICT sectors, usually associated to 2-digit sectors between 58 and 63, are included in the list, through the two A38 macrosectors 62-63 and 58-60. Even more interesting is the presence of the public sectors: both NACE 84 (public administration) and NACE 86 (health) are among the five sectors contributing the most to increased employment. This can obviously be seen as deriving from an increased digitalization of the public sector in Norway. It can also be seen as a consequence of an overall increase in the number of employees in these sectors.

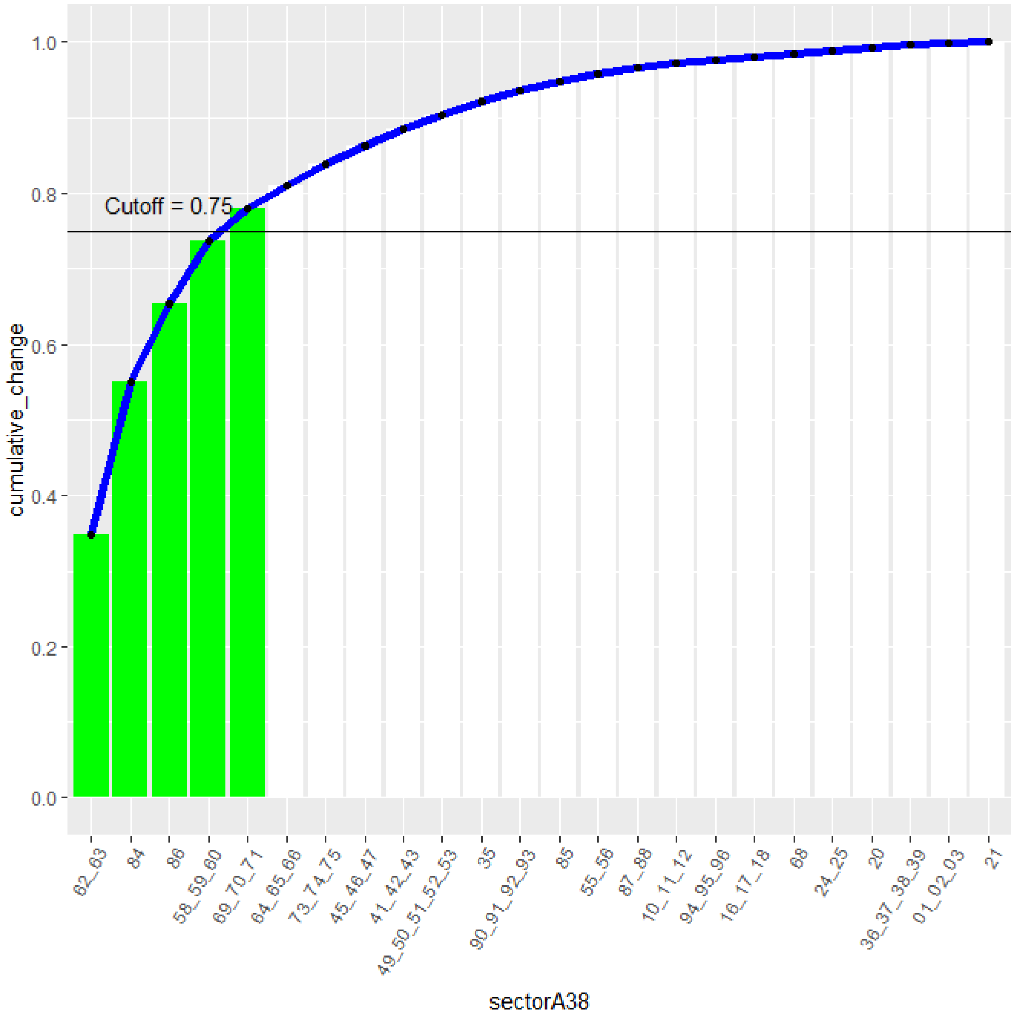

Figure 1. A38 macrosectors which have contributed positively to the employment of ICT-educated people in Norway (years 2013-2017; cumulative contribution on the y-axis).

We also identify the macrosectors having experienced a decrease in the number of ICT-educated employees. Again, we point at macrosectors whose cumulative contribution amounts to at least 75 percent of the overall decrease (see Figure 2). These are, in ranked order:

- Nace: 77-82: Administrative and support service activities
- Nace 05-09: Mining and quarrying
- Nace 29-30: Manufacture of transport equipment
- Nace 28: Manufacture of machinery and equipment n.e.c.

One should bear in mind that the decrease in ICT-educated people in the “negatively pushing” macrosectors is limited compared to the increase in the “positively pushing” macrosectors. In total, the positive contribution from macrosectors having an increase amounts to 3,754, while the negative contribution from macrosectors having a decrease amounts to 412. The latter is a much smaller number and thus more sensitive to idiosyncratic fluctuations. Still, we can see that lower-skilled services, along with medium-high tech industries and mining and oil, are sectors with an outflow of ICT-educated people. For the lower-skilled service sectors, this could be expected, since the potential need for ICT-educated people is presumably becoming lower. On the other hand, the decrease registered for medium-high tech industries, as well as for mining and oil, is somewhat surprising. These are sectors presumably strengthening their ICT capabilities. Yet, the decrease might be a consequence of an overall decrease in the number of employees and thus a consequence of a broader restructuring of the Norwegian economy.

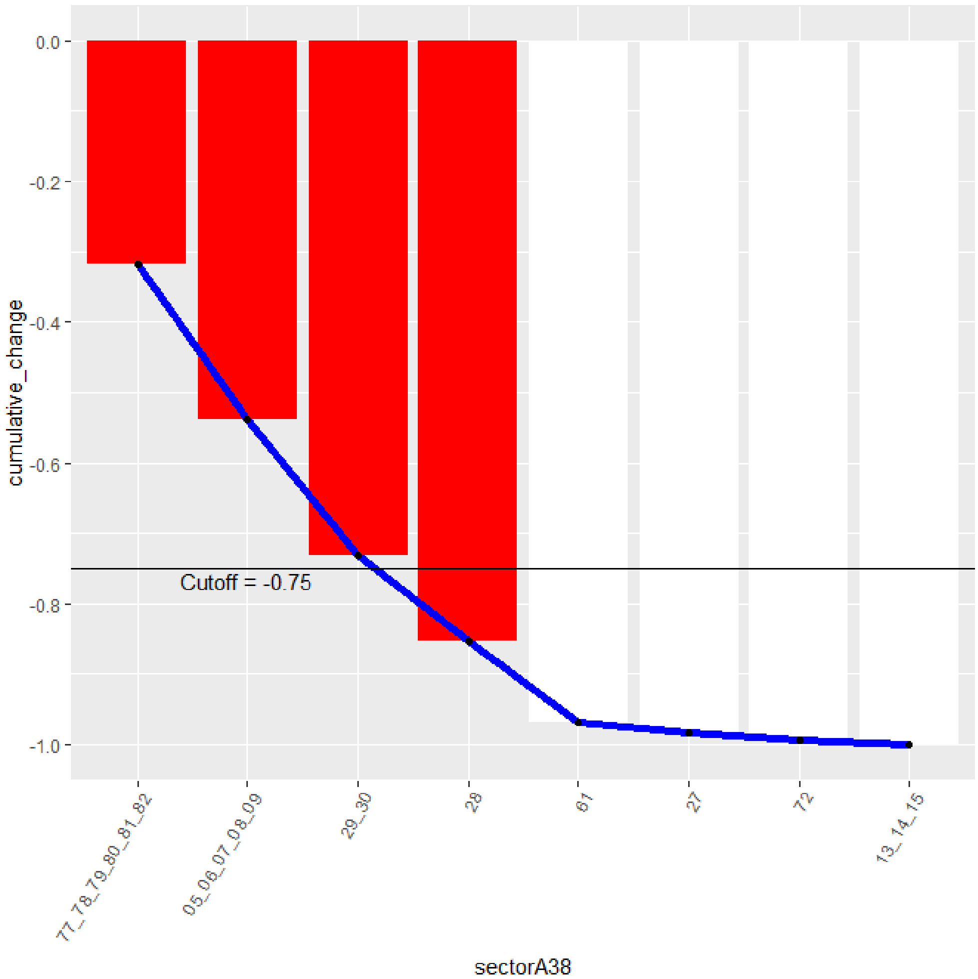

Figure 2. A38 macrosectors which have contributed negatively to the employment of ICT-educated people in Norway (years 2013-2017; cumulative contribution on the y-axis).

Figure 3 provides us with information as to whether, for each macrosector, the absolute change in ICT-educated employees derives from a high offset, in terms of initial high number of ICT employees, or from a significant change in the workforce composition. We can see, for instance, that the change for NACE 62-63 is coming from a high initial number of ICT-educated employees, so, although the registered increase is the largest in absolute terms, it does not signal the same compositional change as for NACE 86.

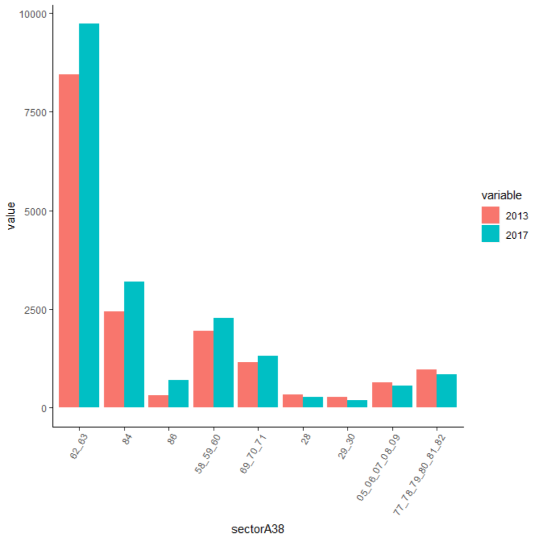

Figure 3. Initial and final number of ICT-educated employees per A38 macrosector (years 2013-2017).

To further analyse the dynamics, we now split the macrosectors into their 2-digit sector components. While the level of information detail increases, we also need to keep in mind that also the relative importance of noise, and thus the uncertainty related to the interpretation of the figures, increases. Table 1 shows, with a breakdown at 2-digit level, the macrosectors previously identified in Figures 1 and 2. The table shows the total number of employees, the number of ICT employees and the share of ICT employees in years 2013 and 2017. Even though NACE 62 has experienced the highest increase in ICT employees, the corresponding share of ICT employees does not change from 2013 to 2017. On the other hand, for NACE 63 the increase of ICT employees, in absolute terms, is rather low, while the share of ICT employees increases from 2013 to 2017. Both NACE 84 and 86 have increased their share of ICT employees, even if the initial share was rather low: for NACE 84 the increase has been from 1.7 percent to 2.0 percent, while for NACE 86 the share has doubled from 0.2 percent to 0.4 percent.

Table 1 also shows that some 2-digit sectors have experienced an increase in the number of ICT employees in spite of a decrease in the total number of employees. This is the case for NACE 58, 60 and 63 as well as NACE 80 and 81. Finally, we can focus on the sectors having a decrease in ICT-educated employees, and notice that the decrease is in line with a general decrease in employees, rather than indicating a lower need of high skilled ICT employees.

Sector		**All employees**			**ICT employees**			**Share of ICT empl.**	
Code	Name	2013	2017	Diff	2013	2017	Diff	2013	2017
62	Computer programming, consultancy and related activities	34006	39348	5342	7859	9087	1228	23.1 %	23.1 %
63	Information service activities	4869	4689	-180	579	654	75	11.9 %	13.9 %
84	Public administration and defence; compulsory social security	144524	156551	12027	2435	3198	763	1.7 %	2.0 %
86	Human health activities	182648	191179	8531	310	697	387	0.2 %	0.4 %
58	Publishing activities	20271	17339	-2932	1747	2022	275	8.6 %	11.7 %
59	Motion picture, video and television programme production, sound recording and music publishing activities	3644	4851	1207	47	73	26	1.3 %	1.5 %
60	Programming and broadcasting activities	6218	5122	-1096	159	171	12	2.6 %	3.3 %
69	Legal and accounting activities	25703	27347	1644	171	210	39	0.7 %	0.8 %
70	Activities of head offices; management consultancy activities	8955	10522	1567	210	344	134	2.3 %	3.3 %

71	Architectural and engineering activities; technical testing and analysis	46379	44483	-1896	771	761	-10	1.7 %	1.7 %
77	Rental and leasing activities	6253	6133	-120	38	36	-2	0.6 %	0.6 %
78	Employment activities	43204	33702	-9502	497	361	-136	1.2 %	1.1 %
79	Travel agency, tour operator and other reservation service and related activities	4651	4692	41	39	39	0	0.8 %	0.8 %
80	Security and investigation activities	11673	11048	-625	79	89	10	0.7 %	0.8 %
81	Services to buildings and landscape activities	38788	37220	-1568	74	79	5	0.2 %	0.2 %
82	Office administrative, office support and other business support activities	12654	12551	-103	245	237	-8	1.9 %	1.9 %
6	Extraction of crude petroleum and natural gas	25067	22400	-2667	441	400	-41	1.8 %	1.8 %
9	Mining support service activities	31479	24744	-6735	198	150	-48	0.6 %	0.6 %
29	Manufacture of motor vehicles, trailers and semi-trailers	3047	2424	-623	10	8	-2	0.3 %	0.3 %
30	Manufacture of other transport equipment	20092	14554	-5538	254	177	-77	1.3 %	1.2 %
28	Manufacture of machinery and equipment n.e.c.	19528	15597	-3931	319	269	-50	1.6 %	1.7 %

Table 1. Initial and final number of ICT-educated employees per 2-digit sector (years 2013-2017).

The data also provides us with the possibility to see how the ICT-educated employees flow between economic sectors: Figure 4 shows all the flows involving at least 50 ICT-educated people between year 2013 and 2017. The green color is used to highlight nodes, i.e. 2-digit economic sectors, where the number of ICT-educated employees has increased, while the red colour signals a decrease. The figure shows that NACE 62 has absorbed from many different sectors, but it has also experienced an ouflow towards NACE 86, 70 and 64 (whose intakes are only from NACE 62). The public administration (NACE 84) absorbs from NACE 62 and 85, the latter corresponding to education activities and signalling an increasingly important attractor for ICT-educated employees. Other sectoral novelties in the ICT labour market are brought by NACE 46 (Wholesale trade, except of motor vehicles and motorcycles) and 47 (Retail trade, except of motor vehicles and motorcycles). NACE 46 experiences both an outward and an inward flow of ICT-educated employees in connection to NACE 62; instead, for NACE 47 there is only a flow towards NACE 62. The presence of NACE 46 and 47 might seem surprising at a first glance, but we need to point out that both sectors contain sub-sectors which are closely related to ICT: NACE 46.5 covers “Wholesale of information and communication equipment”, whereas NACE 47.4 convers “Retail sale of information and communication equipment in specialised stores”. From the overall picture, it appears that NACE 62 constitutes a labour flow hub for ICT-educated people.

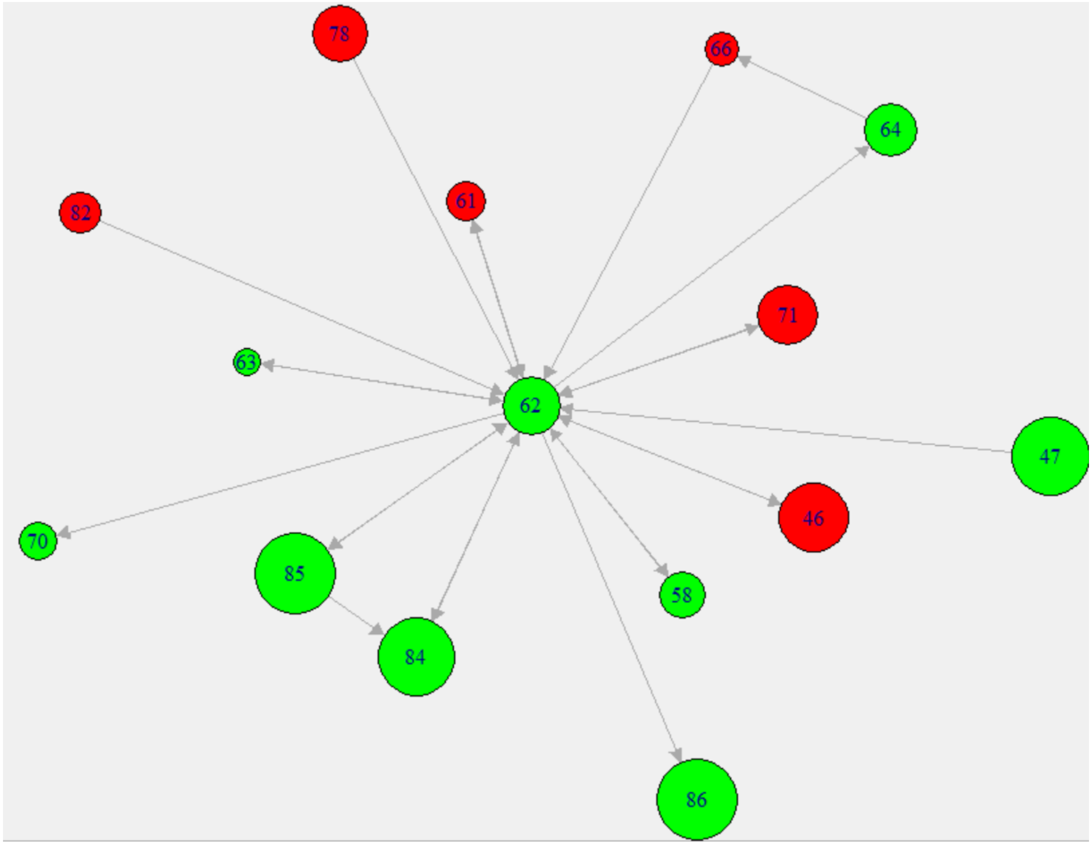

Figure 4. Flows of ICT-educated employees between years 2013 and 2017 (only flows of at least 50 employees are shown). The green and red colour indicate respetively an increase or a decrease in ICT-educated employees in the corresponding 2-digit economic sector.

Following the criteria set by Fitjar and Timmermans (2019), in turn based on Neffke and Henning (2013), we can now define skill-relatedness networks on the basis of labour flows. We thus expand our time series to 2009-2017 and proceed to a finer 4-digit disaggregation of economic sectors. First, we delineate a network of "ICT-skill-relatedness", built considering only labour flows of ICT-educated people. Figure 5 shows the resulting network; variations in the blue shade of a node indicates variations in the percentage, in year 2017, of ICT-educated employees among all the employees of the corresponding sector (the darker the blue color, the higher the percentage; the area of each node is proportional to the logarithm of the total number of employees; isolated nodes are not shown).

An interesting aspect of the figure is that some sectoral clusters, or "communities", seem to emerge. Alhough the main component of the network seems to cover most of the sectors, we also see that some relevant parts of the networks are totally separated: this is the case, for instance, of the NACE group 3511-3513-3514 and the NACE group 6419-6512. The main component of the network seems to be dominated by the traditional ICT sectors and public sectors, plus some additional sectors: it is worth mentioning two sectors with a relative high share of high skilled ICT employees, NACE 26.11 "Manufacture of electronic components" and NACE 72.19 "Other research and experimental development on natural sciences and engineering".

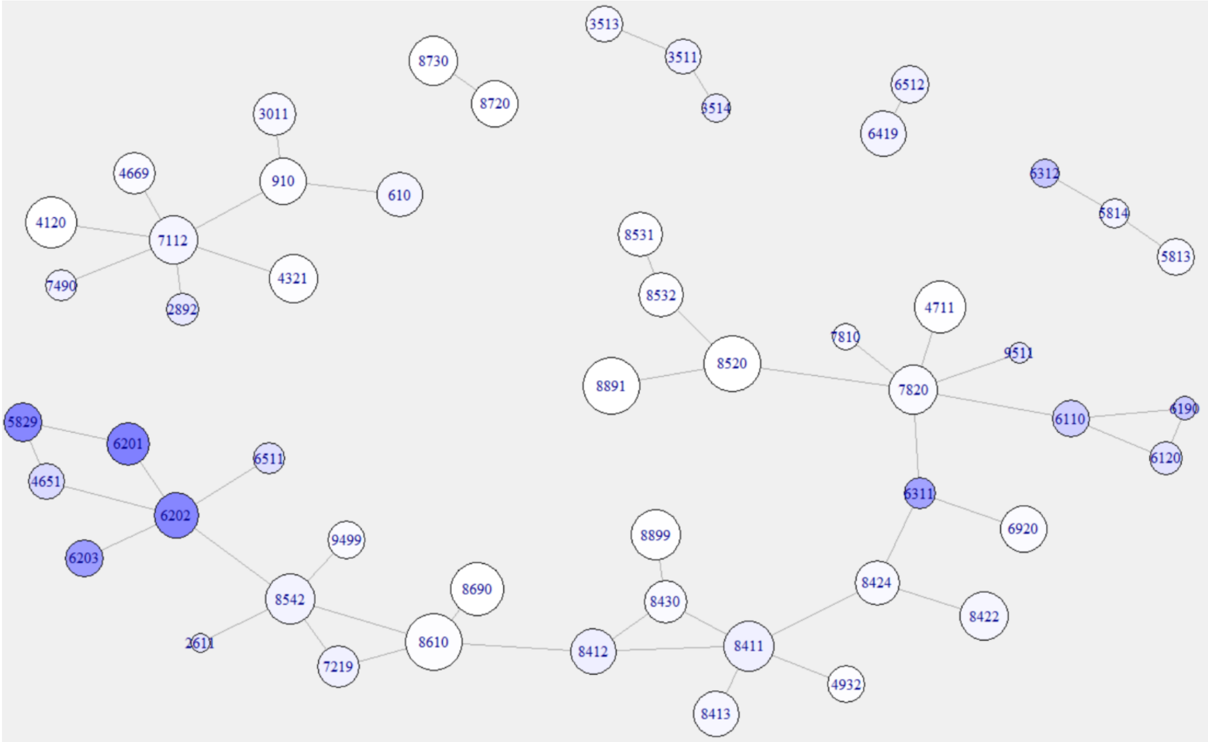

Figure 5. ICT-skill-relatedness network, built on labour flows in Norway between years 2009 and 2017.

To obtain a more objective view on a possible clusterization of the network, we apply a "leading eigenvector" algorithm for community detection, as codified in the "cluster_leading_eigen" function of the "igraph" R software package. The resulting community structure is shown in Figure 6, and we report additional information about number of employees in Table 2 (the names of the communities in Table 2 are assigned by us according to the sectors involved).[1] The ICT-skill-relatedness network can be summarized into eleven communities, some of them connected into a unique network component. Community 3 ("ICT") is by far the biggest with 11,415 ICT-educated employees, followed by Community 8 ("Public administration": 3,120 ICT-educated employees) and Community 1 ("Offshore industries and services": 1,834 ICT-educated employees).

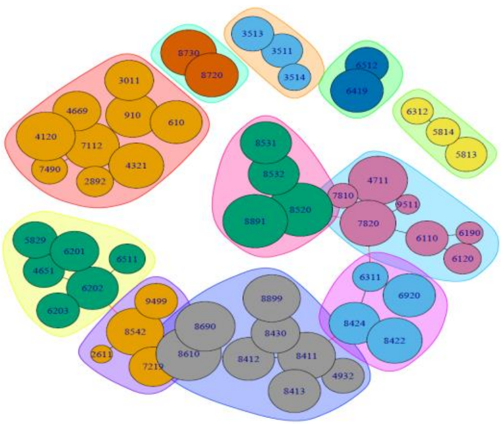

Figure 6. Community structure of the ICT-skill-relatedness network.

[1] Notice that, using different detection algorithms, the sectors 8610 and 8690 (hospital and health) could be assigned to community 9 (research) instead of community 8 (administration).

Name	Contain (4-digit nace)	Number of ICT employees	Links to other communities
1. Offshore industries and services	0610, 0910, 2892, 3011, 4120, 4321, 4669, 7112, 7490	1,834	
2. Supply industry – electricity	3511, 3513, 3514	286	
3. ICT	4651, 5829, 6201, 6202, 6203, 6511	11,415	Community 9
4. Media and publishing	5813, 5814, 6312	303	
5. Finance	6419, 6512	678	
6. Residential care	8720, 8730	64	
7. ICT operation and telecommunication	4711, 6110, 6120, 6190, 7810, 7820, 9511	1,370	Communities 10 and 11
8. Public administration	4932, 8411, 8412, 8413, 8430, 8610, 8690, 8899	3,120	Communities 9 and 10
9. R&D and higher education	2611, 7219, 8542, 9499	1,362	Communities 3 and 8
10. Data analysis and processing	6311, 6920, 8422, 8424	1,428	Communities 7 and 8
11. Primary and secondary education	8520, 8531, 8532, 8891	412	Community 7

Table 2. Number of ICT-educated employees in the ICT-skill-relatedness network communities.

The ICT-skill-relatedness community structure hints at the existence of groups of sectors with a common need for specific ICT-skills. Notably, the common need for skills crosses traditional sector boundaries and provide valuable information regarding the possibility of different sectors to absorb and utilize certain type of skills, in this case derived from higher education in ICT. Further, we see an interdependence between Communities 3, 7, 8, 9, 10 and 11. This indicates that, potentially, ICT-educated employees can still transfer from one community to another.

The last part of our analysis focuses on the “general” (i.e. not ICT-education-specific) skill-relatedness of the most ICT-intensive sectors. The skill-relatedness network is now built by using all labour flows (years 2009-2017) of all people, independently of their education. Given that showing the whole network would be confusing (there are many connections, due to the high number of relevant labour flows), Figure 7 shows only the union of the ego-networks of the ten 4-digit sectors having, in year 2017, the highest share of ICT-educated workers.[2] It is then possible to notice how the ICT-dense ICT consultancy sectors 6201 and 6202 appear close to the management consultancy sectors 7021 and 7022. This was not the case in the previous Figure 5 on ICT-skill-relatedness: the proximity would then be interpreted generally in terms of skills, but not specifically in terms of ICT skills. Notice also that the public sector does not seem to occupy a relevant position in the network of Figure 7, while it was strongly present in Figure 5: this would imply that the skills employed by both ICT intensive sectors and public sector are only the skills derived specifically from an ICT education.

[2] The ten sectors are: 2894, 6201, 5821, 6202, 5829, 3240, 6203, 6311, 6130, 6611; isolated sectors are not shown in the graph.

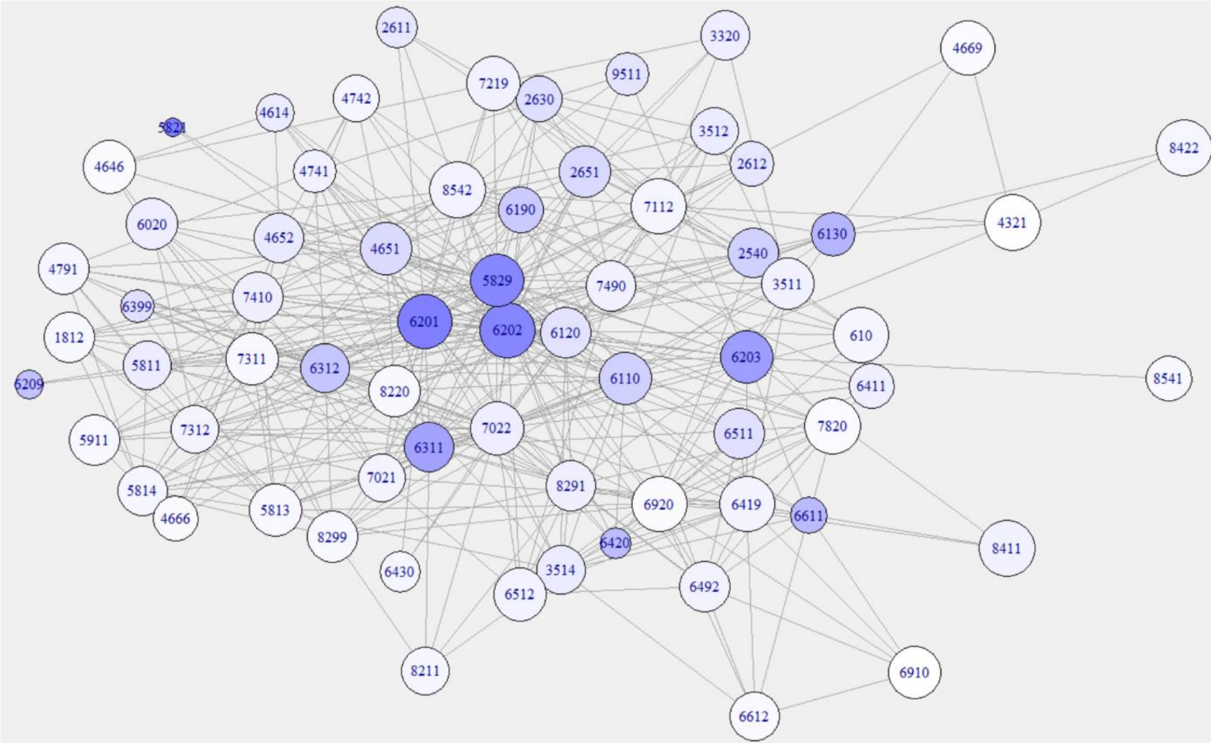

Figure 7. General skill-relatedness network, built on labour flows in Norway between years 2009 and 2017. Only the union of the ego-networks of the ten 4-digit sectors having, in year 2017, the highest share of ICT-educated workers is shown.

6. Conclusions

Our study has illustrated an efficient procedure to visualize the evolving fit of education and economy. We have suggested to connect descriptive statistics about recent labour flows to descriptions of the economy in terms of sectoral skill-relatedness. Such connection allows to contextualize fluctuations in the demand for a specific education into the structural frame of an economy, as represented by the economic sectors which composes it. The fit between education and economy can then be summarized as depending on a range of skills, which are all associated to a same education degree, but can each be applied to a subset of the economy.

For our empirical application, we have chosen to analyse the fit of the ICT education with the Norwegian economy. Recent fluctuations in the employment of ICT-educated workers have then been put into a longer term perspective, in which specific ICT skills appear, thanks to our procedure, as appliable mainly in given subsets of the economy. Some subsets comprehend sectors obviously associated to ICT, like consultancy and business services, or like telecommunication sectors. Some subsets involve sectors not directly associated to ICT, but often associated between themselves: many of the sectors within the pblic administration, or media and publishing sectors. Some subsets, however, defy the initial expectations: this is, for instance, the case of accounting and auditing activities which are associated, by a common use of ICT skills for data analysis, to defence and public order activities.

Moreover, there are subsets which look isolated from the rest of the economy, in the sense that ICT-educated people who work within those subsets have a low chance of being later employed anywhere else: this is the case of finance and offshore sectorwhich appears like big island in the Norwegian economy, in terms of ICT skills. Instead, other subsets that are only indirectly connected have, in recent years, been affected by direct labour flows: this is the case of the move of ICT-educated people from ICT firms to the public administration. Indeed, the progressive digitalization of the public administration seems to have provided attractive job position for ICT workers previously employed in the private sectors.

We envision two possible paths for further research. A first one concerns the direct applications of our methodology. For instance, it would be worth investigating the fit with the labour market for those types of education which are not explicitly designed for a specific job. Especially for humanistic study plans, e.g. for philosophy or history education, the identification of cross-sectoral skills from education, to be employed in specific parts of the economy, would be an interesting research topic. A second path for future research deals with methodological advances, to solve a related research question, about which types of education best provide a specific cross-sectoral skill. Given the increasing interest in defining skills which would help solve specific social and environmental challenges (see, for instance, the ongoing research about "green" skills), a tweak of our methodology could depart from an observation of the labour flows in the economy to suggest variations in the existing education supply.

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