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Skills Composition of the Cultural and Creative Industries and Regional Specialisation Opportunities

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Abstract

Despite the growing literature on the cultural and creative industries (CCIs) within the last decades, the understanding of the actual human capital that characterises these industries is still limited. The need for a framework to unfold the CCIs' human capital increases when considering their long-attributed role in knowledge spillovers, cross-fertilisation, and innovation processes in the larger economy. In this regard, the present study provides the first conceptual and empirical framework to identify and evaluate the CCIs' skill compositions by utilising the revealed skill requirements method based on the relative skill advantage, relatedness and complexity measures. Based on this framework, essential and complementary skills for the CCIs are identified and discussed in terms of the implications for regional specialisation.

Keywords: cultural and creative industries, skill relatedness, skill complexity, regional specialisation.
JEL Classification: R39, Z100

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1 Introduction

More than 20 years have passed since Richard Florida (2002, p. xiii) claimed that *human creativity is the ultimate economic resource*. Since then, concepts like *the creative class* and *the cultural and creative industries* (CCIs) have become a popular and determining vector of regional branching and urban competitiveness policies (Cooke and Lazzeretti, 2008; Throsby, 2008; NESTA et al., 2008; DCMS, 2016; OECD, 2022).

In the economic geography literature, the focus is primarily put on the location patterns of the CCIs (Comunian et al., 2010; Boix et al., 2015; Coll-Martínez et al., 2019b), the impact of CCIs clusters on firm creation and performance (De Jong et al., 2007; Piergiovanni et al., 2012; Coll-Martínez and Arauzo-Carod, 2017; Coll-Martínez, 2019a; Cruz and Teixeira, 2021; Cruz and Teixeira, 2023), and innovation and growth (Bakhshi and McVittie, 2009; Lee and Rodríguez-Pose, 2014; Innocenti and Lazzeretti, 2019). Most of these contributions agree that there are strong inter-industry linkages between creative and non-creative industries that enhance the positive effects of the former over the latter. Nevertheless, the concept of the CCIs does not come without controversy (Potts and Cunningham, 2008; Lazzeretti and Capone, 2015; Bakhshi and Cunningham, 2016; Comunian et al., 2021) as the exploitation of creative inputs –i.e. human capital, knowledge and skills– is also highly present in other industries and occupations that are not considered within the CCIs. The common practice in the related literature relies on the pre-defined industrial and occupational classifications while the empirical evidence on the actual creative inputs required by their production activities is limited. Based on this motivation, the present study takes up the challenge of broadening the understanding of the skills embedded in the CCIs by focusing on their relative skill compositions. As the complexity and digitisation of the economy continuously increase, the emergence of hybrid occupations and industries may not be adequately reflected in the standard classifications of the CCIs. In this regard, unpacking, illustrating, and analysing skill compositions of the CCIs is crucial for at least two purposes. Firstly, the exploitation of workplace skills data for the CCIs provides new insights and paves the way for the potential attempts to evaluate the actual relevance of *creativity* for the CCIs. By doing so, the well-emphasised transformative power of the CCIs in shaping regional development strategies may be better analysed. Secondly, the respective methodology to unfold the CCIs' skill compositions enables the identification and assessment of potential interdependencies and complementarities between the CCIs and the wider economy (Cunningham and Potts, 2015; Bakhshi et al., 2013).

Motivated by the aspects mentioned above, the present study uses a conceptual and empirical framework to improve our understanding of the CCIs' skills compositions. Concretely, it employs the revealed skill requirements method (Buyukyazici and Quatraro, 2024) which relies on the comparative advantage, relatedness, and complexity concepts that are extensively used in the regional economics literature (Boschma, 2017). By exploiting workplace skills data from the Italian Sample Survey on Professions (ICP), this study draws on the 161 workplace skills' intensities to construct relative skill advantage (RSA), skill relatedness and skill complexity measures for 574 industries for each of the 107 Italian NUTS-3 regions over the period 2013-2019. Afterwards, these granular metrics are used to document and analyse the essential and complementary skills required by the CCIs as well as the skill interdependencies among them. In addition, the skill complexity levels of the CCIs with a comparison to other industries are examined. Regional variations of the CCI skills and regional specialisation potential based on them are analysed.

The present study contributes to several research avenues by bridging the CCIs and EEG literature. The main contribution of the paper is to provide a framework to empirically identify and analyse the skill composition of CCIs and the subsectors that compose them. Providing such a framework that enables a skills-based approach for CCI research is particularly valuable as it might be empirically integrated into several crucial debates on the potential that CCIs have for fostering creativity and innovation at the regional level. First, a skills-based approach may help to improve the measurement of spillovers arising from the agglomeration of the CCIs and their co-location with other key sectors (STAM) (Cunningham and Potts, 2015; Coll-Martínez et al., 2019b; Rodríguez-Pose and Lee, 2020) given that cognitive distance among industries is reflected on the skills and knowledge of their workforce. Second, since the production activities of the CCIs seem to require diverse and specialised skill sets and knowledge (Turok, 2003), this approach may help to identify the skill composition of the CCIs in regional labour markets that contribute to the set-up of regional diversification strategies (Clifton et al., 2015; Cooke and De Propris, 2014). Third, a data-driven skills-based framework may be useful for the design of reskill, upskill, and education policies by identifying the missing skills that may be crucial to adapt to technological change in the forthcoming years (Bakhshi et al., 2015; Comunian et al., 2021; Lazzeretti et al., 2022).

The remaining of the paper is constructed as follows. Section 2 gives a brief overview of the related literature. Section 3 describes the data sources and introduces the methodology and research design. Section 4 identifies the essential and complementary skills for the CCIs by constructing the skill space for the CCIs, and analyses the skill interdependencies among the CCIs along with their skill complexity. Section 5 presents a regional analysis of the CCI skills and the regional potential for specialisation in the CCIs. Finally, Section 6 concludes and discusses the implications for regional policy.

2 Background: The skills of the CCIs and their geography

The fuzzy concept of creativity has become a major topic of research in a wide variety of fields over the last twenty years. The origins of this literature can be traced back to the analysis of cultural industries (Throsby, 2001; Towse, 2003) which was subsequently redirected to creative industries (Cunningham, 2002). The Cultural and Creative Industries (CCIs) are those that produce and commercialise creative services and products. Several international organisations (DCMS, 1998; Department for Culture Media and Sport, 2013; UNCTAD, 2010; OECD, 2022) and academics (Caves, 2000; Florida, 2002; Markusen et al., 2008) have contributed to establishing a definition of the CCIs. One of the most widely used definitions is the model proposed by the UK Department of Culture, Media and Sport (DCMS) in the pioneering report *Creative Industries Mapping Document* (2011, p.6) according to which the CCIs are:

those industries which have their origin in individual creativity, skill and talent and which have a potential for wealth and job creation through the generation and exploitation of intellectual property.

More specifically, the CCIs include activities such as advertising, architecture, art and antiques market, crafts, design, fashion, film and video, music, performing arts, publishing, television and radio, and video and computer games. However, the definition of the CCIs is still a matter of debate in the literature on what activities should be regarded as CCIs (Potts and Cunningham, 2008; Lazzeretti and Capone, 2015; Bakhshi and Cunningham, 2016). Some authors claim that the nature of work in these kinds of industries is not necessarily creative. The ambiguity of classifications arises from the complexity of defining and conceptualising creativity and its representations (European Commission, 2015).

Creative occupations encompass a diverse array of professions spanning sectors such as arts, design, media, technology, and innovation. What distinguishes these occupations are the specific characteristics of the required skills, knowledge, and working conditions. Unlike traditional occupations, creative professions often necessitate a high degree of imagination, originality, and problem-solving abilities. Individuals working in these fields typically possess a blend of technical expertise and artistic flair, allowing them to generate novel ideas and solutions. Moreover, creativity thrives in environments that foster experimentation and collaboration, leading to dynamic working conditions characterised by flexibility, autonomy, and interdisciplinary interactions. Whether in the realms of graphic design, software development, or cultural production, creative workers often engage in non-linear and iterative processes, where experimentation and failure are integral to the creative endeavour. As such, the nature of work in creative occupations is often project-based requiring the coordination between a diverse set of talents (Caves, 2000), which leads to a less structured and more fluid production process, emphasising adaptability and openness to innovation.

Furthermore, the knowledge base required for success in creative occupations extends beyond formal education to encompass tacit, experimental, and domain-specific expertise. While technical skills are undoubtedly important, creative professionals also draw from a broad range of influences, including cultural trends, historical contexts, and personal experiences. In the literature, we can find some works that attempted to classify creative occupations by their blend of tacit and codified knowledge, the nuances of knowledge codification, and the competencies and skills essential for their practice (Asheim and Hansen, 2009). According to these works, creative occupations can be associated with three distinct knowledge bases:

analytical, synthetic, and symbolic. The analytical knowledge base is present in activities where knowledge is extensively codified, necessitating less tacit interaction (e.g., research and development, engineering). The synthetic knowledge base encompasses activities with partial codification, requiring greater reliance on tacit knowledge and contextual factors (e.g., architecture, and software development). Lastly, the symbolic knowledge base is linked to the generation of novel ideas, characterised by high levels of tacit knowledge and context specificity (e.g., advertising, arts, cinema, fashion design, publishing, and TV and radio).

This multidimensional knowledge landscape underscores the interconnectedness of creativity with broader societal, cultural, and economic dynamics. Moreover, the digitalisation of the CCIs has transformed the nature of work, enabling remote collaboration, online networking, and the democratisation of creative tools and platforms (Li, 2020). However, it has also introduced new challenges such as digital piracy, intellectual property rights, and the commodification of creative labour. Thus, understanding the specific characteristics of skills, knowledge, and working conditions within creative activities is essential for devising effective policies and strategies to support innovation, entrepreneurship, and sustainable growth in the creative economy.

The study of the CCIs and their impact on the wider economy requires also to be presented from an evolutionary economic geography (EEG) framework. In this regard, EEG notions such as path dependence, relatedness, and co-evolution are essential to local and regional development to help understand the spatial dynamics of the CCIs (Berg and Hassink, 2014).

In the case of Italy, since the publication of the seminal work of Santagata (2009), many papers have focused on explaining the location patterns of creative firms and employment across Italian regions. Drawing on insights from various studies, including Lazzeretti et al. (2008, 2015), Bertacchini and Borrione (2013) and Boix et al. (2015), it becomes evident that the CCIs concentrate in large metropolitan areas. However, the presence of creative clusters seems to be more diffused across Italy in comparison to other Mediterranean countries. Cities like Milano, Firenze, and Roma stand out as magnets for creative talent, offering vibrant cultural scenes, access to networks, and a cosmopolitan environment for innovation and entrepreneurship (Cerisola, 2018; Cerisola and Panzera, 2022). These regions benefit from agglomeration effects, where the clustering of creative firms and professionals fosters knowledge spillovers, and firm creation (Piergiovanni et al., 2012). Nevertheless, the geography of creative employment in Italy also reveals disparities among regions, with peripheral areas often facing challenges in nurturing and retaining creative talent (Porta et al., 2022; Crociata et al., 2024).

Despite relatively larger literature on the geography of the CCIs, only a few studies have considered the role of relatedness and complexity when studying the role of the CCIs on regional dynamics. For example, Innocenti and Lazzeretti (2019) apply the related and unrelated diversification concepts to explain the growth of creative employment. Burlina et al. (2023) reveal that only the complexity of CCIs matters for CCIs firm performance. In the case of European regions, Pinheiro et al. (2022) find that CCIs, such as Motion Picture or Advertising, are among the most highly complex activities in European Regions.

Albeit the need to understand the skill composition of the CCIs, empirical evidence on the skill composition within the CCIs at the global and regional levels is still scarce. An exception is the work of the Creative Skills Monitor (2019/20) (Giles et al., 2020 - NESTA) that evaluates the skills of the CCIs within the UK economy by applying descriptive and cluster analysis.

In addition to the aspects underlined above, prior research has also shown that the agglomeration of the CCIs significantly varies across regions (Lazzeretti et al., 2008). Therefore, a regional perspective on industry-level skills is crucial to shed light on the local inter-industry linkages and industrial diversification processes to design place-specific and adequate innovation policies (Buyukyazici et al., 2024; Buyukyazici, 2023ab). It is particularly important for the CCIs since they function as a source of creativity with implications for local knowledge spillovers and cross-fertilisation processes.

Under the light of the background briefly overviewed above, the aim of the present study is twofold. First, we aim to illustrate the skill composition of the CCIs with global and regional aspects. Secondly, we aim to identify the potential of Italian regions to reinforce and diversify their creative economy. By using the relatedness and complexity frameworks, we examine whether the ability of Italian regions to create new specialisations associated with the CCIs depends on the presence, intensity and diversity of key creative skills embedded in the regional economy.

3 Methodology

Each industry in the economy is a compilation of different and various jobs which are collections of different and various tasks, knowledge, and skills. Same industries and occupations might require different human capital input across regions which introduces further heterogeneity to the problem at hand. Hence, it is crucial to conduct a high-granular bottom-up analysis when evaluating the human capital requirements of economic activities. Based on this motivation, we employ a data-driven methodology, i.e., the revealed skill requirements (RSR) method introduced by Buyukyazici and Quatraro (2024), to identify the essential and complementary CCIs skills. To do so, first, we create the main data set to have a sample of 161 skills, 574 industries, 107 regions, and seven years. Second, we identify the CCIs and create the skill intensity scores of each skill type for the CCIs and other sectors at the region-time level. By following the existing practice in the literature and policy sphere that has been in use since the report DCMS (1998), the CCIs are identified based on nine broad industry groups that are considered to be creative: advertising, architecture, crafts, design (product, graphic and fashion), film, TV, video, radio and photography, music, performing and visual arts, publishing, software and computer services, and museums, galleries and libraries (Department for Culture Media and Sport, 2013; DCMS, 2016). Table A2 shows the broad CCIs to NACE codes. Third, we apply the RSA, skill relatedness, and skill complexity methods, described in detail below, to construct the skill space of CCIs which is a network that illustrates the skill requirement patterns of the CCIs. Based on this practice, we identify the essential and complementary skills required by the CCIs at the global level. Fourth, we analyse how CCI skills are distributed across the Italian regions as well as their potential to develop specialisations in the CCIs.

3.1 Data

The present paper makes use of two primary data reservoirs: namely, the Italian Sample Survey on Professions (ICP) and the Italian Labour Force Survey (ILFS). The ICP, conducted by the National Institute for Public Policies Analysis (INAPP), serves the purpose of gathering extensive insights into the various professions within the Italian labour market. To date, three waves of the ICP have been carried out in 2007, 2013, and 2019 involving interviews with 16,000 workers in each wave. These interviews represent approximately 800 different occupational categories at a detailed five-digit level[1]. In the present study, we use ICP 2013 since ICP 2007 is not compatible with our observation period and ICP 2019 has not been published yet.

The ICP data is a valuable resource as it offers in-depth information regarding the nature of work, tasks associated with occupations, the requisite knowledge and skills, as well as the organisational structures within which these jobs are situated. The survey itself is structured into seven distinct sections, covering aspects like knowledge, skills, attitudes, generalised work activities, values, working styles, and working conditions[2]. For the purposes of this study, we focus primarily on the first four sections. This choice is motivated by the compatibility of the questions in these sections, allowing us to aggregate them into a total of 161 unique skill[3] types. Within these sections, each skill type is characterised by two key dimensions: its importance and the level of skill[4] required for different occupations. We then

[1]The occupational classification is the Classificazione delle Professioni (CP) which is the Italian version of ISCO classification.

[2]The design and formulation of the ICP survey's concepts and questions draw inspiration from the Occupational Information Network (ONET), administered by the United States Bureau of Labor Statistics. Consequently, the ICP can be considered as the Italian counterpart or adaptation of the O*NET survey.

[3]Henceforth, the term *skills* is employed in a more expansive context, encompassing the content found within the initial four sections of the ICP.

[4]The importance question (*How important is this competence in carrying out your current profession?*) assesses the significance of a particular skill in the context of the current job while the level question (*Among those indicated below, at what level is this competence necessary for the development of your current profession?*) evaluates the degree to which that skill is essential for the advancement of your current profession. When it comes to importance questions, respondents use a scale that ranges from 1 (indicating low importance) to 5 (indicating high importance). In contrast, the complexity-level questions employ a scale from 1 (indicating low complexity) to 7 (indicating high complexity). Subsequently, these ratings are transformed to fit within a range of 0 to 100.

calculate skill intensity variables for each skill by multiplying the importance scores with the level scores. This multiplicative approach enhances the variation in skills across various occupations (Feser, 2003). A comprehensive list of the 161 skills examined in this study is available in Table A1, along with corresponding ICP categories, sub-categories, and concise labels, aiding readers in tracking specific skills throughout the paper.

The ILFS serves as another pivotal data source, which is subsequently merged with the ICP data at the four-digit occupational level[5]. This merging process forms the foundation of our primary data set. To compute the skill intensity score for each industry-region-year combination, we utilise matrices that detail the distribution of occupations within industries and the distribution of industries across regions, both of which are available within the ILFS. Specifically, we first identify the number of employees in each industry and their respective occupations. Next, we extract the skill intensity scores for the 161 skill types from the ICP survey, culminating in the computation of mean skill intensity scores weighted by employment numbers. This methodological approach enables us to construct a data set comprising 161 workplace skills, encompassing 574 industries at the four-digit NACE level, and spanning 107 Italian regions at the NUTS-3 level for the period 2013-2019.

Additionally, we use supplementary data source *Local Units and Persons Employed: Size Class of Persons Employed, Economic Activities, Geographical Areas* obtained from Istat to account for specialisation patterns of regions.

3.2 Revealed Skill Requirements Method

The RSR makes use of three measures alongside network techniques: RSA, skill relatedness, and skill complexity.

Relative Skill Advantage

Relative skill advantage (RSA) is a measure based on the Balassa index, also known as location quotient (LQ) and revealed comparative advantage (RCA). Differently from LQ and RCA, which use employment numbers, RSA uses the skill intensity scores as input data to determine the relative importance of a skill to an industry as defined in Alabdulkareem et al. (2018) and Buyukyazici et al. (2024).

$$RSA^{p,t}(i,s) = \frac{icp(i,s) \setminus \sum_{s' \epsilon S} icp(i,s')}{\sum_{i' \epsilon I} icp(i',s) \setminus \sum_{i' \epsilon I, s' \epsilon S} icp(i',s')} \tag{1}$$

where $icp(i,s)$ is the skill intensity score of skill s for industry i located in region p at time t that is obtained from the ICP and ILFS data sets. A higher value of RSA indicates a higher

[5]The ICP data is at the five-digit level but the highest occupational granularity available in the ILFS is the four-digit level. Therefore, the ICP data is transformed to the four-digit occupational level before the merge.

level of importance of skill s to industry i compared to the overall importance of skill s to all other industries. Skill $s \in S$ is effectively used by industry $i \in I$, or industry i requires skill s, if its RSA is greater than 1.

We use the RSA formula for two main objectives. First, we create effective use matrices to use them as input matrices to compute skill relatedness and skill complexity measures. Second, we identify the essential skill sets of industries based on their binary and non-binary RSA scores. In doing so, we first create industry-to-skill matrices for each region and year whose each cell indicates the skill intensity score of skill s for industry i located in region p at time t, summing up to 749 input matrices. Second, we compute the effective use matrices, $\mathbf{M}$, by applying the RSA formula to those input matrices. For the global level analyses, the 749 industry-to-skill input matrices are reduced to one global input matrix by taking the element-wise averages.

Skill Relatedness

The relatedness concept quantifies the interdependences between entities –which can be industries, jobs, technologies, or skills– based on their co-occurrence patterns. In the present study, we use the skill relatedness concept (Alabdulkareem et al., 2018; Buyukyazici et al., 2024; Buyukyazici, 2023b) (1) to unpack the skill interdependencies within the skill sets of the CCIs, and (2) to define the complementary CCI skills. In doing so, the skill relatedness between each pair of skills is defined as the minimum conditional probability of their co-occurrences in industry classes as formulated below.

$$R^{p,t}(s, s^{'}) = \frac{\sum_{i\epsilon I} e(i,s).e(i,s^{'})}{max(\sum_{i\epsilon I} e(i,s), \sum_{i\epsilon I} e(i,s^{'}))} \tag{2}$$

where p is region, t is time, and effective use of skills is denoted as $e(i,s) = 1$ if $RSA > 1$, $e(i,s) = 0$ otherwise. The effective use patterns are calculated with the RSA formula above. After applying the skill relatedness formula to the effective use matrices, $\mathbf{M}$, the resulting matrix is the skill relatedness index (SxS) of N industries which contain proximities between skill types s and $s^{'}$. Each cell $(s, s^{'})$ represents the probability that a random industry effectively uses skill $s(s^{'})$ effectively uses skill $s^{'}(s)$ as well.

Skill Complexity

The economic complexity approach introduced by Hidalgo and Hausmann (2009) quantifies the sophisticatedness level of economies and/or economic activities by employing dimension reduction techniques to large data inputs. Since the introduction of the method, scholars defined many varieties of economic complexity indices by using different data sources including trade flows, patents, employment numbers, and skills. In the present study, we use *the method of reflections* (MOR), introduced in the pioneering work of Hidalgo and Hausmann (2009), to quantify the sophisticatedness level of skills. MOR sequentially combines two measures: diversity and ubiquity. In our case, diversity ($K_{i,0}$) is the number of skills effectively used ($RSA > 1$) by industry i, in region p at time t. Ubiquity ($K_{s,0}$) is the number of industries that effectively use a particular skill s in region p at time t.

$$Diversity^{p,t} = k_{i,0} = \sum_{s} M_{i,s} \tag{3}$$

$$Ubiquity^{p,t} = k_{s,0} = \sum_{i} M_{i,s} \tag{4}$$

After sequentially combining diversity and ubiquity measures for $N \geq 1$ steps, MOR is defined as iterative linear equations that are theoretically infinite. Accordingly, skills that are effectively used by relatively fewer industries that effectively use a diverse set of rare skills are considered complex.

The skill complexity measure is used for two main objectives in this study: (1) to evaluate the sophisticatedness level of the CCIs and CCI skills and (2) to quantify the skill complexity level of regions.

4 Skill Composition of the CCIs: Skill Space

In this section, we analyse the skill composition of the CCIs by constructing their skill space which provides a compact visualisation of their skill usage patterns.

The skill space is built on skill relatedness and skill complexity measures (Alabdulkareem et al., 2018; Buyukyazici et al., 2024; Buyukyazici, 2023b). As defined above, skill relatedness helps us gauge how skills complement each other by considering their effective usage within industries. On the other hand, skill complexity employs dimension reduction methods to quantify the sophisticatedness level of a skill based on its utilisation across industries. These two metrics can be represented as a one-mode skills network, which we refer to as a skill space. Figure 1 visualises the skill space of the CCIs. In the figure, each node represents a specific skill type and is labelled accordingly. These nodes are colour-coded based on the ICP descriptors, as detailed in Table A1. The lengths of the edges between nodes signify the degree of skill relatedness. Accordingly, nodes that are closer to each other on the graph indicate a stronger connection between those skills, meaning that those skills are generally used together by the CCIs. To make the network visually enhanced, we applied a threshold, retaining only the edges with weights greater than or equal to 0.55. The size of each node corresponds to the complexity level of the associated skill. Smaller nodes indicate lower skill complexity, while larger nodes represent higher skill complexity. According to this setting, Figure 1 displays a couple of skill clusters. On the right-hand side, psychomotor, physical, and sensory skills are located as one cluster together with fine arts knowledge (B26) meaning that those skills are generally used for fine arts. This cluster connects with a small cluster of technical skills used together with telecommunications knowledge (B31) in the middle of the graph. The left-hand side of the graph displays a more connected structure signalling that the CCIs use a large share of knowledge types together with cognitive, mental process, interacting and some technical skills.

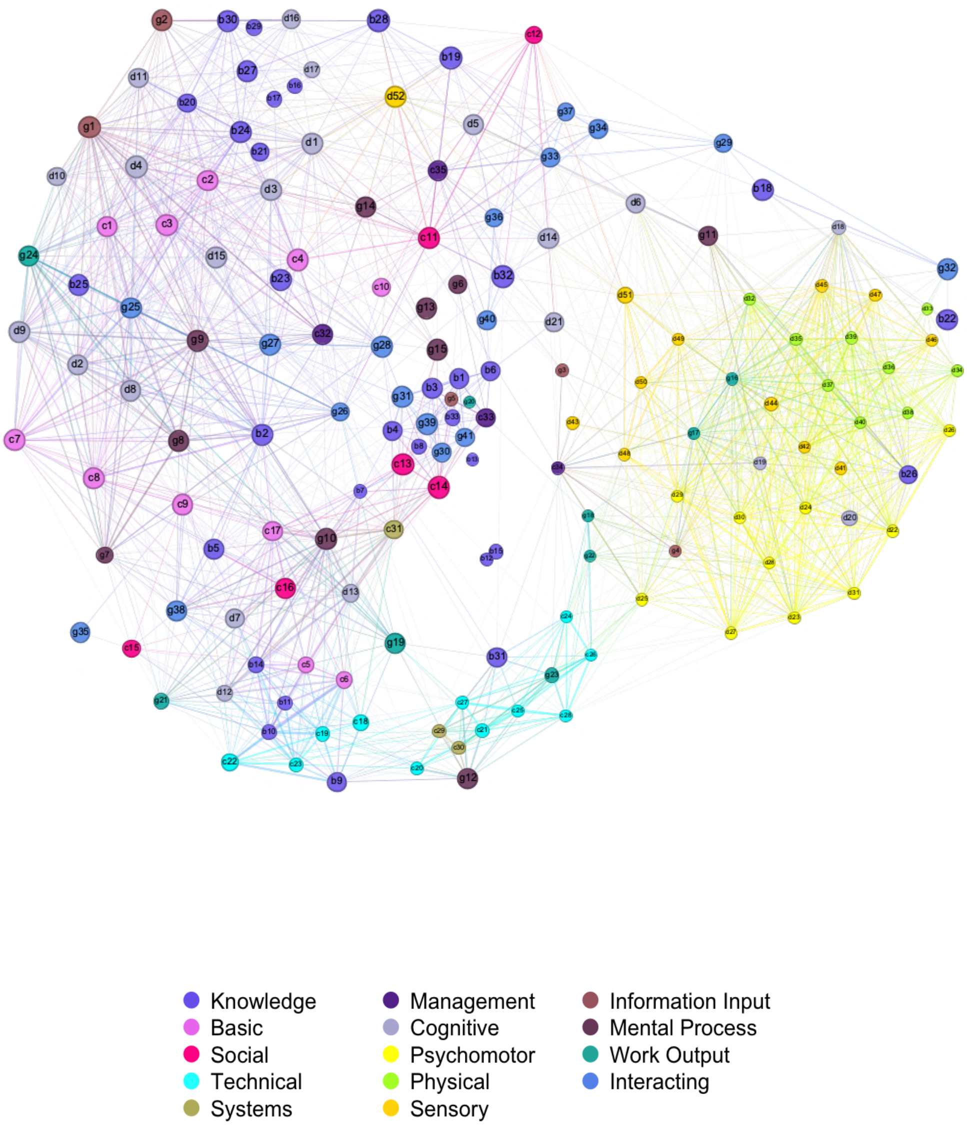


Figure 1. The Skill Space of CCIs (2013-2019). Each node represents a particular skill type and is labelled accordingly. Node size is proportional to the complexity level of the skill the node represents. Edge lengths indicate the degree of skill relatedness between skill pairs. Nodes are coloured according to the skill descriptors.

4.1 Identifying Skills for CCIs

The skill spaces formalise the skill usage patterns of industries by considering all skill types available which are the compilation of essential, non-essential, and complementary skills for the industry for which the skill space is built. Essential skills can be defined as those the industry in question requires more than other skills to conduct its production activities. Based on this definition, we identify the essential skills for the CCIs by using the RSA concept as described in Section 3. Consequently, we identify the skill types in which the CCIs have RSA, i.e. $RSA > 1$, as essential skills. Figure 2 maps the essential skills required by the CCIs on the skill space by using a blue palette. The essential skills are gradually coloured from light blue to dark blue based on their non-binary RSA scores, with darker colours indicating a higher RSA score. Non-essential skills, $RSA < 1$, are coloured beige. The figure shows that the CCIs require skills that are mostly located on the left side of the skill space.

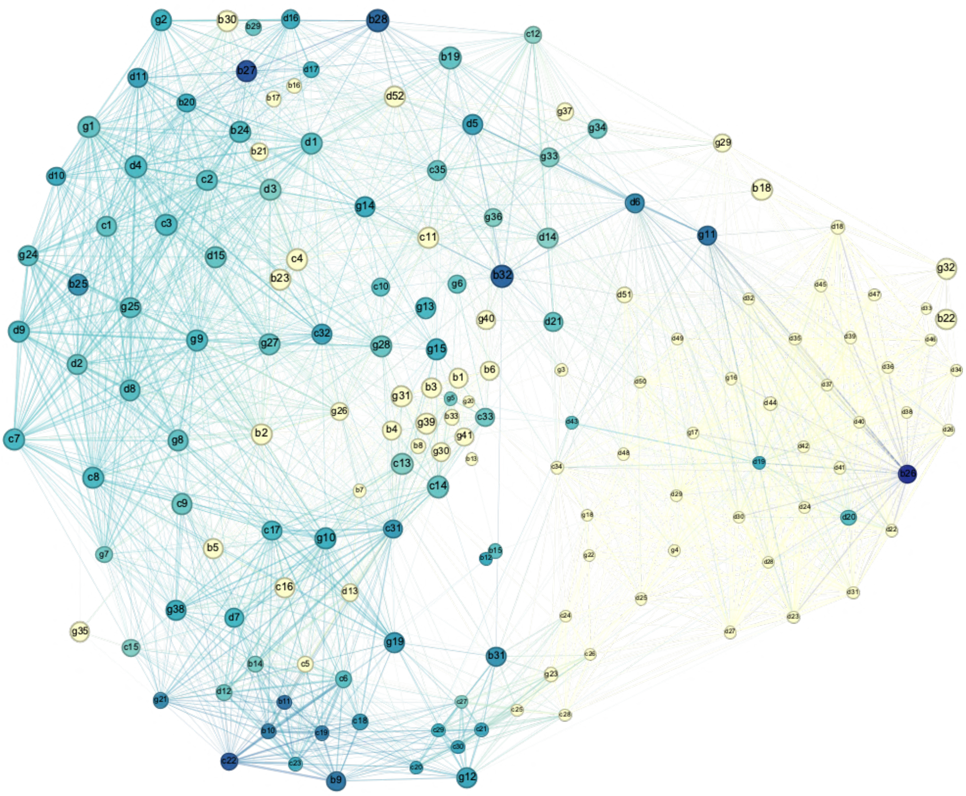
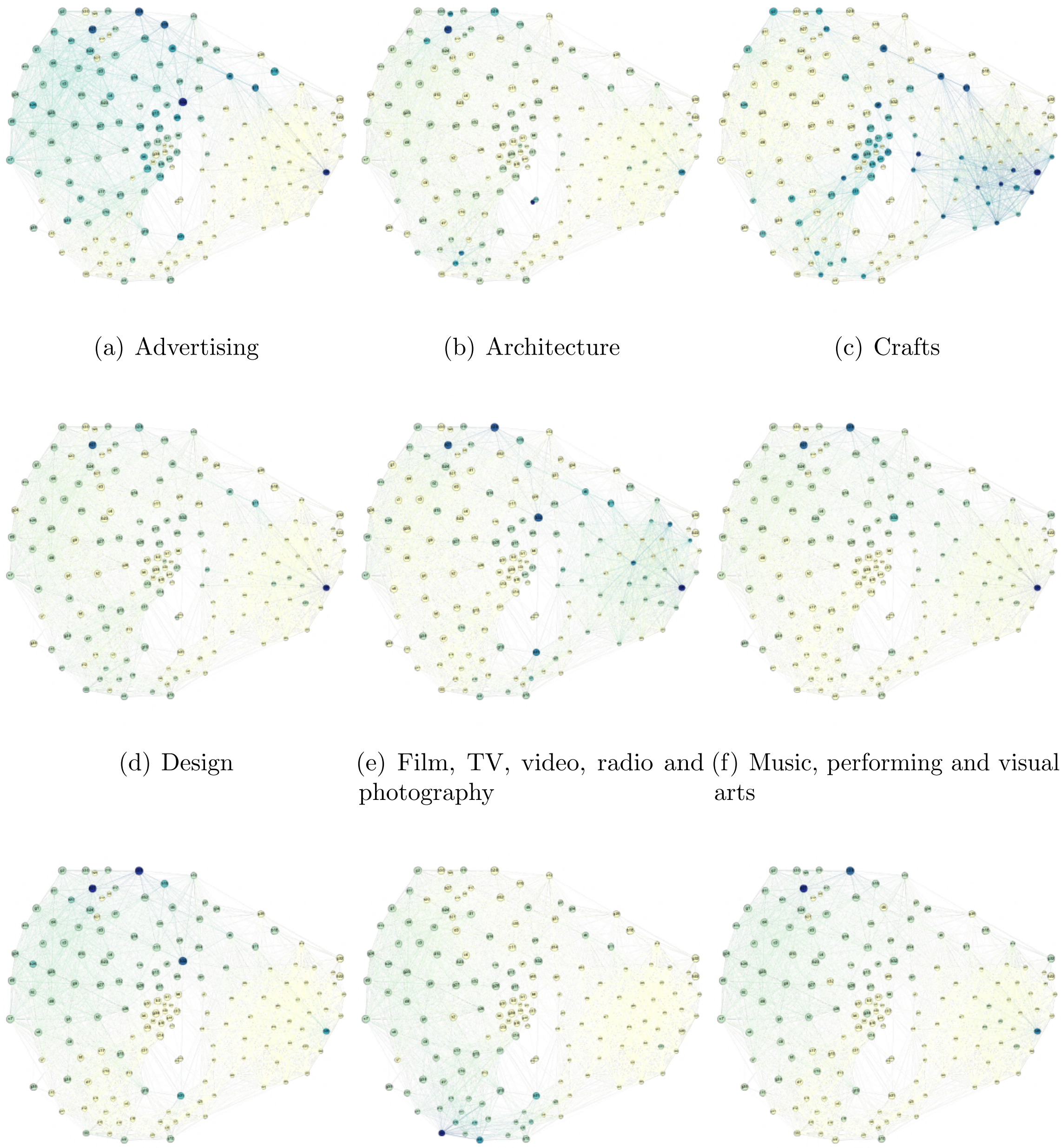


Figure 2. The Essential Skills of CCIs. The skills in which Cultural and Creative Industries (CCIs) have relative skill advantage ($RSA > 1$) are projected into the skill space by using a blue palette with lighter colours indicating lower and darker colours showing higher RSA scores.



(a) Advertising (b) Architecture (c) Crafts

(d) Design (e) Film, TV, video, radio and photography (f) Music, performing and visual arts

(g) Publishing (h) Software and computer (i) Museums, galleries and libraries

Figure 3. The Essential Skills for each Cultural and Creative Industry (CCI). Skills in which the CCIs have relative skill advantage ($RSA > 1$) are projected onto the skill space by using a blue palette with lighter colours indicating lower and darker colours showing higher RSA scores.

Despite the skill space providing a concise analysis of rich connections, it also hints at the heterogeneous skill requirements of the CCIs as they consist of a variety of different sectors as unfolded in Table A2. In this regard, we separately analyse the skill requirements of each CCI. Figure 3 displays the skills in which each CCI has RSA by projecting those skills into the skill space by using a gradient blue palette. The figure shows that each sector has a unique skill spectrum while some commonalities are evident. For instance, the skill

Table 1. Most Important Skills for the CCIs by RSA

CCIs	Skills
All	(B26) Fine Arts (4.53), (B27) History and Archaeology (3.32), (C22) Programming (3.02), (B32) Communication and Media (2.68), (B28) Philosophy and Theology (2.46), (B11) Technical Design (2.28), (G11) Thinking Creatively (2.14), (B9) IT and Electronics (2.06), (C19) Technology Design (2.03), (B10) Engineering and Technology (2.01), (G21) Drafting, Laying Out and Specifying Technical Devices, Parts, and Equipment (1.86), (D6) Originality (1.85), (B25) Foreign Language (1.74), (B31) Telecommunications (1.74), (C18) Operations Analysis (1.67), (C31) Judgement and Decision Making (1.65), (G19) Interacting With Computers (1.63), (D5) Fluency of Ideas (1.59), (D11) Category Flexibility (1.58), (C32) Time Management (1.57).
Advertising	(B32) Communication and Media (6.20), (B26) Fine Arts (5.71), (B28) Philosophy and Theology (3.66), (B27) History and Archaeology (3.62), (B19) Sociology and Anthropology (3.40), (G11) Thinking Creatively (2.49), (D6) Originality (2.37), (D5) Fluency of Ideas (2.05), (G40) Staffing Organisational Units (1.97), (B31) Telecommunications (1.93).
Architecture	(B12) Building and Construction (17.20), (B27) History and Archaeology (12.78), (B11) Technical Design (6.96), (B26) Fine Arts (6.30), (B29) Civil Protection and Public Safety (6.17), (B10) Engineering and Technology (5.29), (B20) Geography (4.57), (B28) Philosophy and Theology (4.47), (B15) Physics (4.21), (B19) Sociology and Anthropology (3.35).
Crafts	(B26) Fine Arts (4.33), (D24) Finger Dexterity (3.55), (D43) Visual Colour Discrimination (3.27), (D41) Near Vision (2.99), (D22) Arms-Hand Steadiness (2.95), (G11) Thinking Creatively (2.63), (D30) Wrist-Finger Speed (2.50), (D6) Originality (2.27), (G6) Judging the Qualities of Things, Services or People (2.14), (D5) Fluency of Ideas (2.11).
Design	(B26) Fine Arts (14.21), (B27) History and Archaeology (7.45), (G11) Thinking Creatively (3.48), (B28) Philosophy and Theology (3.11), (D43) Visual Colour Discrimination (2.99), (D6) Originality (2.83), (B32) Communication and Media (2.47) (B11) Technical Design (2.46), (D19) Visualisation (2.34), (C22) Programming (2.15).
Film, TV, video, radio and photography	(B26) Fine Arts (9.30), (B28) Philosophy and Theology (5.90), (B32) Communication and Media (5.72), (B27) History and Archaeology (5.22), (B31) Telecommunications (3.83), (D47) Glare Sensitivity (3.70), (D44) Night Vision (3.66), (D46) Depth Perception (2.67), (G11) Thinking Creatively (2.49), (D6) Originality (2.37).
Music, performing and visual arts	(B26) Fine Arts (19.60), (B27) History and Archaeology (10.61), (B28) Philosophy and Theology (9.77), (B32) Communication and Media (5.01), (B19) Sociology and Anthropology (3.47), (G11) Thinking Creatively (2.90), (D48) Hearing Sensitivity (2.58), (D6) Originality (2.53), (B23) Education and Training (2.16), (D49) Auditory Attention (2.15).
Publishing	(B27) History and Archaeology (12.07), (B28) Philosophy and Theology (11.64), (B32) Communication and Media (7.26), (B26) Fine Arts (3.82), (B31) Telecommunications (3.23), (B19) Sociology and Anthropology (3.15), (B25) Foreign Language (2.70), (B20) Geography (2.62), (B24) Italian Language (2.39), (G11) Thinking Creatively (2.15).
Software and Computer	(C22) Programming (14.52), (B9) IT and Electronics (5.23), (B31) Telecommunications (3.67), (C19) Technology Design (3.43), (B10) Engineering and Technology (3.23), (C21) Installation (3.06), (G19) Interacting With Computers (2.45), (C30) Systems Evaluation (2.19), (B11) Technical Design (2.05), (C23) Quality Control Analysis (2.00).
Museums, galleries and libraries	(B27) History and Archaeology (16.43), (B28) Philosophy and Theology (9.24), (B26) Fine Arts (6.84), (B32) Communication and Media (2.37), (B20) Geography (2.29), (B19) Sociology and Anthropology (2.22), (D11) Category Flexibility (2.02), (G24) Documenting/Recording Information (1.91), (B24) Italian Language (1.90), (G2) Identifying Objects (1.89).

Notes: The most important skills by CCIs are ranked by non-binary RSA scores reported in parentheses after each skill type.

requirements of the majority of CCIs, such as Advertising, Architecture, Design, Music, performing and visual arts, Publishing, and Museums, galleries and libraries, are similar. Those CCIs generally require the skills located on the top-left part of the skill space, which is mostly knowledge in humanities alongside some cognitive skills, while they do not require many psychical, psychomotor and sensory skills located on the right-hand part of the skill space apart from knowledge in *(B26) Fine Arts*. Two CCIs, namely Crafts and Film, TV, video, radio and photography, differ from others as they require a larger share of psychical, psychomotor and sensory skills.

In order to better portray the human capital requirements specific to the production activities of each CCI, we identify the 20 most important skills for all CCIs and the 10 most important skills for each CCI. We do so by ranking the non-binary RSA values of skills for CCIs. Table 1 documents the results. The first column indicates CCIs while the second column ranks the most important skills by the RSA scores. First, we consider the most important 20 skills for the CCIs as a whole, as indicated in the first row of the table, to provide a holistic perspective. Accordingly, the required human capital for the CCIs generally consists of knowledge in humanities, i.e. *(B26) Fine Arts, (B27) History and Archaeology, (B28) Philosophy and Theology*, and technical fields, i.e. *(B11) Technical Design, (B9) IT and Electronics, (B10) Engineering and Technology, and (B31) Telecommunications*, supported by technical skills, i.e. *(C22) Programming, (C19) Technology Design, (C18) Operations Analysis*, and cognitive skills, i.e. *(G11) Thinking Creatively, (D6) Originality, (D5) Fluency of Ideas*. Moreover, knowledge in *(B32) Communication and Media* and *(B25) Foreign Language* is crucial for the CCIs. These results expectedly reflect the diverse sectoral composition of the CCIs. We, therefore, consider the most important skills for each CCI to provide a more granular analysis. The following rows of Table 1 unfold sector-specific human capital requirements for each CCI. The results indicate that some CCIs require a unique combination of knowledge and skills that is different from other CCIs. For instance, the most important skills for *Software and Computer* sector are fully technical. On the other hand the *Crafts* sector mostly requires psychomotor and sensory skills. A general pattern found in the skill composition of each CCI, except for *Crafts*, is high knowledge-intensiveness indicated by the large shares of B-labelled skills.

As underlined above, the skill spaces convey rich information on the skill usage patterns of industries. For instance, one can observe the skills that are primarily used together with the most important CCI skills by evaluating the skill relatedness values among them. We perform such an analysis to shed some light on the skill complementarities within the CCIs. In this regard, we identify the top five skills with the highest skill relatedness to each of the 20 most important CCI skills that are presented in Table 1. By doing so, we unfold the complementarities among different skill types that are required by the CCIs as presented in Table 2. For instance, the complementary skills for *(B26) Fine Arts* knowledge, the most essential skill for the CCIs, are mostly psychomotor and physical skills that reflect the needs

Table 2. CCI Skills and Most Related Skills

CCI Skill	Most Related Skills
(B26) Fine Arts	(D22) Arms-Hand Steadiness; (D37) Extent Flexibility; (D40) Gross Balance Body Equilibrium; (D18) Spatial Orientation; (D23) Manual Dexterity.
(B27) History and Archaeology	(B28) Philosophy and Theology; (B30) Legislation and Institutions; (B20) Geography; (B24) Italian Language; (D11) Category Flexibility.
(C22) Programming	(B9) IT and Electronics; (C6) Science; (B10) Engineering and Technology; (C23) Quality Control Analysis; (C19) Technology Design.
(B32) Communication and Media	(G14) Scheduling Work and Activities; (D5) Fluency of Ideas; (D6) Originality; (C12) Coordination; (C35) Management of Personnel Resources.
(B28) Philosophy and Theology	(B27) History and Archaeology; (D52) Speech Clarity; (B19) Sociology and Anthropology; (D14) Memorisation; (D1) Oral Comprehension.
(B11) Technical Design	(C6) Science; (C23) Quality Control Analysis; (C19) Technology Design; (D12) Math Reasoning; (B14) Mathematics.
(G11) Thinking Creatively	(D6) Originality; (D22) Arms-Hand Steadiness; (D19) Visualisation; (D32) Static Strength; (D24) Finger Dexterity.
(B9) IT and Electronics	(C22) Programming; (C19) Technology Design; (C6) Science; (B10) Engineering and Technology; (C23) Quality Control Analysis.
(C19) Technology Design	(C6) Science; (B10) Engineering and Technology; (B9) IT and Electronics; (C22) Programming; (C23) Quality Control Analysis.
(B10) Engineering and Technology	(C6) Science; (C19) Technology Design; (C22) Programming; (C23) Quality Control Analysis; (B11) Technical Design.
(G21) Drafting, Laying Out and Specifying Technical Devices, Parts, and Equipment	(C31) Judgement and Decision Making; (C17) Complex Problem Solving; (G10) Making Decisions and Solving Problems; (C6) Science; (B10) Engineering and Technology.
(D6) Originality	(G11) Thinking Creatively; (D5) Fluency of Ideas; (D23) Manual Dexterity; (B19) Sociology and Anthropology; (B32) Communication and Media.
(B25) Foreign Language	(D2) Written Comprehension; (G25) Interpreting the Meaning of the Information for Others; (D9) Inductive Reasoning; (C1) Reading Comprehension; (G24) Documenting/Recording Information.
(B31) Telecommunications	(C30) Systems Evaluation; (C29) Systems Analysis; (G23) Repairing and Maintaining Electronic Equipment; (C24) Operation Monitoring; (C21) Installation.
(C18) Operations Analysis	(C31) Judgement and Decision Making; (C19) Technology Design; (B9) IT and Electronics; (B10) Engineering and Technology; (C6) Science.
(C31) Judgement and Decision Making	(C17) Complex Problem Solving; (G10) Making Decisions and Solving Problems; (D13) Number Facility; (D7) Problem Sensitivity; (D12) Math Reasoning.
(G19) Interacting With Computers	(G24) Documenting/Recording Information; (D8) Deductive Reasoning; (G25) Interpreting the Meaning of the Information for Others; (C7) Critical Thinking; (D9) Inductive Reasoning.
(D5) Fluency of Ideas	(D6) Originality; (B32) Communication and Media; (G11) Thinking Creatively; (B19) Sociology and Anthropology; (D1) Oral Comprehension.
(D11) Category Flexibility	(B20) Geography; (G1) Getting Information; (B24) Italian Language; (D4) Written Expression; (C3) Writing.
(C32) Time Management	(G1) Getting Information; (C3) Writing; (D4) Written Expression; (G27) Communicating with Persons Outside Organisation; (D3) Oral Expression.

Notes: The first column (CCI Skill) reports the most important CCI skills, i.e., the ones with the highest non-binary RSA scores. The second column presents the most related, i.e. the ones with the highest skill relatedness scores, five skills to each CCI skill.

of artistic production given that fine arts primarily consist of painting, sculpture, music, and dance which require strong psychomotor and physical skills. Similarly, *(G11) Thinking Creatively* is complemented by psychomotor and physical skills. The complementarity patterns of the rest of the CCI skills seem to reflect the production heterogeneity between traditional cultural sectors and knowledge-intensive sectors in the CCIs. The skills that are mainly required by creative sectors like *Architecture* and *Software and computer* including *(C22) Programming, (B9) IT and Electronics* and *(B10) Engineering and Technology* are complemented by technical knowledge and skills alongside system skills. On the other hand, the skills that are primarily required by cultural sectors, such as *Music, performing and visual arts, Publishing*, and *Museums, galleries and libraries*, including *(B27) History and Archaeology, (B28) Philosophy and Theology* are complemented by knowledge in humanities and related disciplines alongside cognitive skills.

It is important to underline that the complementarity patterns are available and embedded in the CCIs skill space (Figure 1). Given that the edges indicate skill relatedness scores between skill types, the complementarity pattern of each skill can be traced by inspecting the surrounding nodes.

Overall, the results above underline that the CCIs not only require an abundance of skills related to creativity and originality but also demand a large set of technical knowledge and skills. This empirically-identified observation supports the argument that there has been an increasing demand for *createch* skills in the CCIs and wider economy (Carey et al., 2019). Prior research has also shown that the CCIs experience skill shortages of technical skills as the demand for technical skills increases across all sectors (Creative and Cultural Skills, 2018). In this regard, policymakers should not overlook the importance of STEM fields in arts and humanities education.

4.2 Skill Complexity of the CCIs

Figures 1, 2, and 3 reveal that the CCIs use a large share of complex skills. In this section, we provide further discussion on the skill complexity level of CCIs.

Table 3 shows that the rich and diverse human capital requirements of the CCIs place them in the top three most skill-complex industries in line with the findings of (Pinheiro et al., 2022). After *Finance, Insurance and Real Estate* (92.41) and *Information and Communication* (81.00) industries, the CCIs come third with an average skill complexity score of 76.43. Given that complexity is defined based on ubiquity and diversity components, a non-common combination of a variety of skills –including knowledge in humanities, fine arts, IT, engineering and telecommunications combined with cognitive skills such as originality and creativity alongside some technical skills– underpins the high complexity level of the CCIs. For instance, a group of CCIs, such as *Architecture, Design, Film, TV, video, radio and photography,* and *Publishing* require a combination of technical knowledge alongside humanities and fine arts knowledge which is one of the primary aspects that increases the complexity level of the CCIs. Nevertheless, the CCIs are a collection of diverse production activities which might lead to internal heterogeneity with respect to skill complexity. To shed some light on this aspect, Table 4 presents the skill complexity scores of each CCI alongside the four-digit industries that compose them. Accordingly, *Advertising, Publishing,* and *Museums, galleries and libraries* are the most skill-complex CCIs with complexity scores of 87.79, 87.71, and 85.60 respectively. On the other hand, *Crafts* is ranked as the least skill-complex CCI with a score of 51.18. The CCIs also exhibit some heterogeneity within them. For instance, the skill complexity scores of the four-digit industries that compose *Film, TV, video, radio and photography* sector vary between 41.97 for *Photographic activities* (7420) and 79.28 for *Radio broadcasting* (6010).

It should be acknowledged that the complexity scores might change across different studies depending on the complexity method used, data source, observation period, classification differences, and country in question.

Table 3. Average Skill Complexity by Industry

Industry (one-digit)	Skill Complexity
(K/L) Finance, Insurance and Real Estate	92.41
(J) Information and Communication	81.00
Cultural and Creative Industries (CCIs)	76.43
(P/Q) Education, Health and Social Work	75.25
(M-O) Professional, Scientific and Technical	70.22
(G) Wholesale and Retail Trade	64.15
(R) Arts, Entertainment and Recreation	62.18
(I) Accommodation and Food Services	51.10
(S-U) Other Services	49.52
(H) Transportation and Storage	46.98
(C-E) Manufacture	46.65
(B) Mining and Quarrying	46.05
(F) Construction	29.90

Notes: CCIs (see Table A2) are excluded from other industry categories. For instance, *(J) Information and Communication* does not include publishing and software sectors. Similarly, *(R) Arts, Entertainment and Recreation* is not inclusive of visual and performing arts.

Table 4. Skill Complexity of the CCIs

CCI	NACE 4	Description	Skill Comp.
Advertising			87.79
	7021	Public relations and communication activities	92.54
	7311	Advertising agencies	85.38
	7312	Media representation	85.44
Architecture			79.41
	7111	Architectural activities	79.41
Crafts			51.18
	3212	Manufacture of jewellery and related articles	51.18
Design: product, graphic and fashion design			78.34
	7410	Specialised design activities	78.34
Film, TV, video, radio and photography			64.43
	5911	Motion picture, video and television programme production activities	68.14
	5912	Motion picture, video and television programme post-production activities	50.15
	5913	Motion picture, video and television programme distribution activities	77.29
	5914	Motion picture projection activities	62.18
	6010	Radio broadcasting	79.28
	6020	Television programming and broadcasting activities	72.02
	7420	Photographic activities	41.97
Music, performing and visual arts			68.72
	5920	Sound recording and music publishing activities	61.43
	8552	Cultural education	68.63
	9001	Performing arts	66.20
	9002	Support activities to performing arts	71.40
	9003	Artistic creations	78.02
	9004	Operation of arts facilities	66.66
Publishing			87.71
	5811	Book publishing	83.36
	5812	Publishing of directories and mailing lists	84.39
	5813	Publishing of newspapers	90.83
	5814	Publishing of journals and periodicals	90.84
	5819	Other publishing activities	82.44
	7430	Translation and interpretation activities	94.45
Software and Computer Services			83.25
	5821	Publishing of computer games	84.12
	5829	Other software publishing	83.76
	6201	Computer programming activities	82.96
	6202	Computer consultancy activities	82.16
Museums, galleries and libraries			85.60
	9101	Library and archives activities	91.83
	9102	Museums activities	79.37

Notes: The values indicate the average skill complexity of cultural and creative industries (CCIs) across Italian regions for the period 2013-2019.

4.3 Skill Interdependencies among the CCIs

The analyses above regarding the essential and complementary skill requirements of the CCIs have signalled similarities as well as differences among CCIs in terms of human capital. Despite sharing a common ground on fine arts and creativity, the CCIs exhibit diverse skill requirements. Hence, analysing the human capital similarity among CCIs might yield insightful observations with potential implications for the classification of the CCIs. In this vein, we construct a skill-related industry space, Figure 4, whose each node represents a CCI at the four-digit NACE level. Nodes are coloured and labelled by the CCIs. An alternative

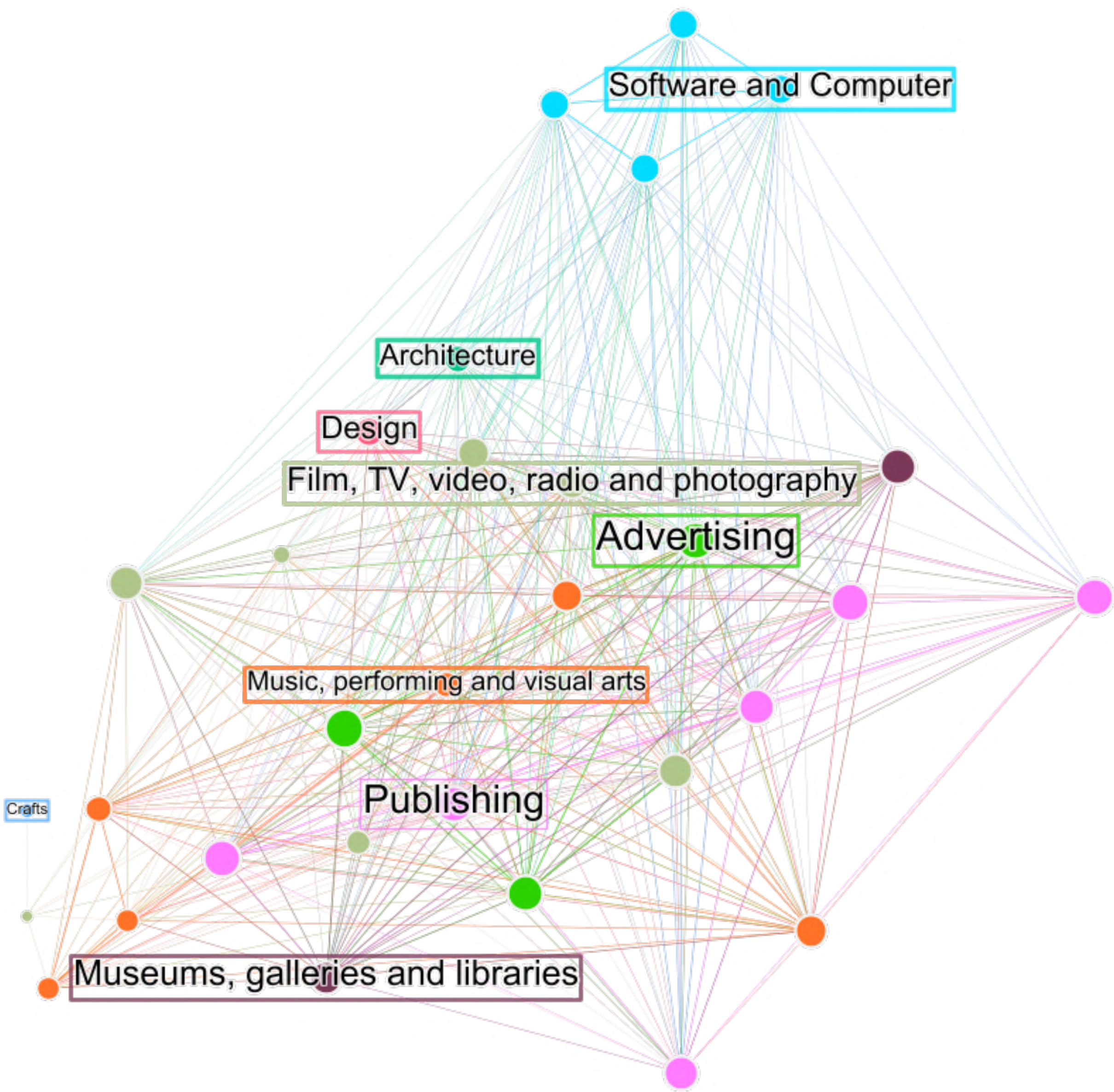


Figure 4. The Skill-Related Cultural and Creative Industry Space (2013-2019). Each node represents a particular CCI at the four-digit NACE level. Node size is proportional to the skill complexity level of the industry the node represents. Edge lengths indicate the degree of skill relatedness between industry pairs. Nodes are coloured according to the CCIs the nodes belong to.

graph (Figure A2) with the labels of four-digit industries is provided in the Appendix. Node size reflects the skill complexity level of the industry. Edges indicate the skill relatedness score between the CCIs. Accordingly, industries that are located closer to each other have similar skill requirements, i.e., human capital. In order to provide a more compact picture, Figure 5 represents the average skill relatedness values among CCIs as a similarity matrix. Lighter colours indicate low skill relatedness levels while darker colours indicate higher skill relatedness. Similarly, Figure A3 in the Appendix displays the skill relatedness among the four-digit CCIs as a similarity matrix.

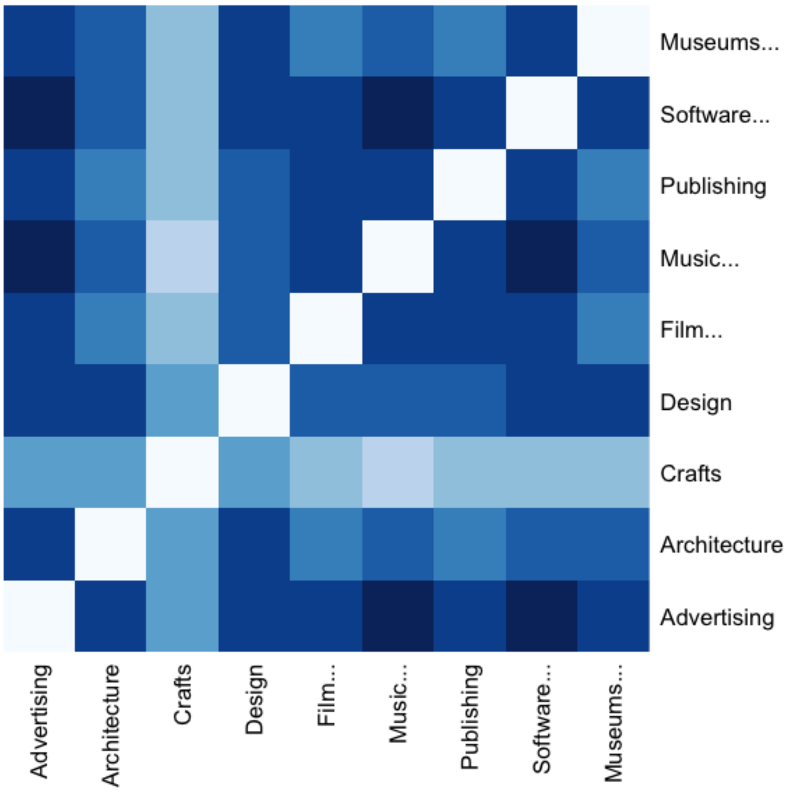


Figure 5. Skill Relatedness Among CCIs (2013-2019). The skill interdependences among CCIs are represented as a similarity matrix. Lighter colours indicate lower skill relatedness while darker colours show higher skill relatedness.

The most salient feature of the skill-related CCIs space at first glance is the divergence of the *Software and computer* sectors from other CCIs. They are located on the upper part of the network as isolated from other CCIs, implying that they have substantially higher human capital similarity within the CCI than they have with other CCIs. Nevertheless, this is not the case for the rest of the CCIs. The four-digit industries that compose *Advertising, Film, TV, video, radio and photography, Music, performing and visual arts, Publishing*, and *Museums, galleries and libraries* are not clustered together but are distributed across the skill space. In other words, for those CCIs, a four-digit industry might be more related to other four-digit industries within a different CCI than the industries within its own CCI. For instance, *Support activities to performing arts* (9002), belongs to the CCI *Music, performing* *and visual arts*, is more related to *Public relations and communication activities* (7021), which belongs to the CCI *Advertising*, than the industries within the CCI *Music, performing and visual arts*. The isolated position of the *Software and computer* sector in the industry space recalls the debate on the legitimacy of the insertion of the broad software sector into the CCIs classification (Cunningham and Potts, 2015). However, if we look at Figures 5 and A2, the *Software and computer* sector is also one of the CCIs that have the highest skill relatedness to other CCIs. Similarly, the *Advertising* sector also has very high skill relatedness to other CCIs as demonstrated by its central position in the industry space. One of the reasons behind this fact might be that, in the digital age, every industry requires some degree of computer and advertising skills which increases the skill similarity between those sectors and other CCIs. For instance, a musician in the modern era would require computer programs to record and edit songs as well as media representation and public relations to promote them. Interestingly, the *Crafts* sector has the lowest skill similarity to other CCIs that can also be inspected in Figure 3.

5 CCI Skills and Regional Aspects: Spatial Distribution, Specialisation and Opportunities

The main purpose of the present study, as aforementioned, is to unpack the skill composition of the CCIs by employing a data-driven approach. In this regard, we have defined the skills required by the CCIs. However, the related literature and analyses above imply substantial variations of the CCIs and related human capital across regions. To document the regional aspects of the CCI skills, we first illustrate the regional variation of the CCI skills across Italy. Then, the spatial analysis is complemented with the regional specialisation potential of Italian regions, in terms of human capital, in the CCIs with respect to actual specialisation patterns.

5.1 Regional Variation of the CCI Skills

The CCI skills are expected to differ significantly by region due to the uneven distribution of CCIs across space which is widely analysed by the cluster studies (Boix, 2012 ; Gong and Hassink, 2017; Coll-Martínez et al., 2019b). To briefly document the variation of the CCI skills across Italian regions, we first create a measure of the average CCI skills (*CCI_Skills*) by region (p) and time (t) as follows.

$$CCI\_Skills_{p,t} = \left(\frac{1}{n} \sum_{h} I_{h,p,t} \right) \tag{5}$$

where $n = 85$ is the total number of skills in which the CCIs have RSA (see Figure 2). $h \in H$ represents a CCI skill and H denotes the skill set of the CCIs. CCI skills are subsets of all skill types ($H \in S$) documented in Table A1. Afterwards, the CCI skills are averaged for the observation period 2013-2019 and presented in Figure 6. The figure shows that Milano, Roma, and Bologna have the highest CCI skill levels. A strict polarisation is visible between the north and south of Italy. The northern regions have significantly higher levels of CCI skills while the southern regions have lower values. The main reason for this difference is the historical, cultural, socioeconomic, and productive capabilities that differ across regions that enhance or hinder the development of knowledge-intensive and complex skills including humanities knowledge, technical, and cognitive skills that characterise the CCIs.

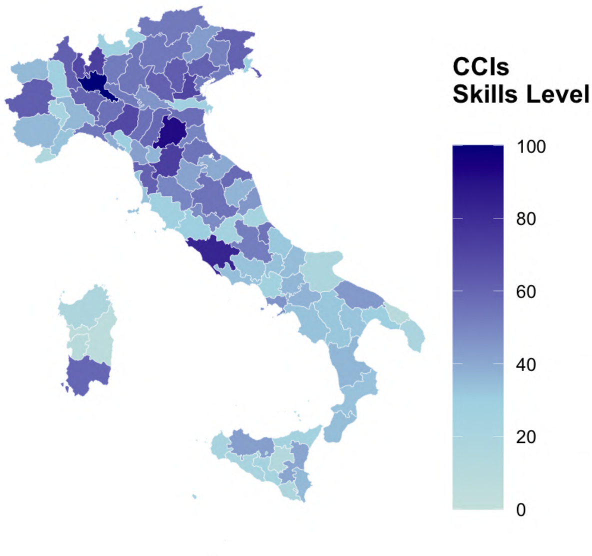


Figure 6. Average Levels of CCI Skills Across Italian Regions for the Period 2013-2019.

5.2 Regional Specialisation Patterns and Potential in the CCIs

Regional specialisation patterns and potential for economic activities can be analysed by utilising the relatedness-complexity diagram which has been widely used, especially, in the smart specialisation literature to identify the most promising and place-based regional priorities (Hausmann et al., 2014; Balland et al., 2019; Buyukyazici, 2023a). In Figure 7, we draw on this practice to unveil the potential of Italian regions, in terms of their human capital, to be specialised in the CCIs. In doing so, we employ the skill relatedness and skill complexity measures that are defined in Section 3.2. The skill complexity scores of industries are averaged by region and observation period 2013-2019 to be presented in the y-axis. Given that the skill relatedness index (equation 2) yields a skill-to-skill matrix, a density formula[6]

[6]

$$ASRD_i^{p,t} = \frac{\sum_{s\in i}\left(\frac{\sum_s \phi_{s,j} RSA_{s,i}}{\sum_s \phi_{s,j}} \times 100\right)_{s,i}}{\sum_{s\in i} s}$$

is employed by considering only the CCIs skills defined in Section 4.1 (i.e. the skills in which the CCIs have RSA) to provide the dimensions of time and region. Accordingly, the CCI skill relatedness density scores averaged on the observation period are located on the x-axis. Hence, the figure is coined as the skill relatedness and skill complexity (SRSC) diagram. The reference lines on the y and x-axis–representing the mean skill complexity and CCI skill relatedness density scores respectively– divide the diagram into four quadrants. Then, the Italian regions are placed on the diagram based on their SRSC scores and are coloured by their average specialisation level in the CCIs during the observation period.

We define the specialisation level of a region in the CCIs as an ordered categorical variable, *CCI_Specialisation*, as follows.

$$
\begin{aligned}
CCI\_Specialisation_{p,t} =& 1,\ \ if\ \ RCA_{p,t} > 0\ \ and\ \ RCA_{p,t} \leq 0.5 \\
CCI\_Specialisation_{p,t} =& 2,\ \ if\ \ RCA_{p,t} > 0.5\ \ and\ \ RCA_{p,t} \leq 1 \\
CCI\_Specialisation_{p,t} =& 3,\ \ if\ \ RCA_{p,t} > 1
\end{aligned}
$$

$$RCA_{p,t} = \frac{E_{c,p,t}/E_{p,t}}{E_{c,t}/E_t}$$

where c is the CCIs, p is region, t is year, and E is employment. RCA defines the comparative advantage level of the CCIs in each region-year in terms of the number of employed people. Accordingly, *CCI_Specialisation* accounts for three different specialisation levels: no specialisation if takes the value 1, quasi-specialisation if takes the value 2, and full specialisation if takes the value 3. Such a variable allows us to observe different levels of regional specialisation.

In Figure 7, regions that are coloured green have an average RCA less than or equal to 0.5 in the CCIs, meaning no specialisation. Blue-coloured regions have an RCA higher than 0.5 but less than or equal to 1, thus, they have quasi-specialisation. Finally, the regions that have RCA higher than 1, which is the most widely accepted cut-point for specialisation, are coloured red, presenting full specialisation. Based on this setting, the SRSC diagram not only provides a compact view of the CCIs' specialisation opportunities but also a snapshot of regions in terms of their existing specialisation patterns.

The top-left quadrant is characterised by above-mean skill complexity but below-mean CCI skill relatedness density signalling high benefits and high risk given that above-mean skill complexity values would bring sophisticated production but low levels of CCI skill

where $\phi_{s,j}$ is the relatedness score between skill s and j used by industry i located in region p at time t. $RSA_{s,i}$ indicates if industry i effectively uses skill s. Correspondingly, the formula located within the parenthesis in the numerator calculates skill-to-industry relatedness density matrix. Then the average skill relatedness density (ASRD) score for each industry is computed by considering the skills industry i uses ($s \in i$). By doing so, skill-to-industry skill relatedness density matrix is reduced to an ASRD vector of industries. After doing the same steps for every region and year, all vectors are put together to have a complete ASRD variable.

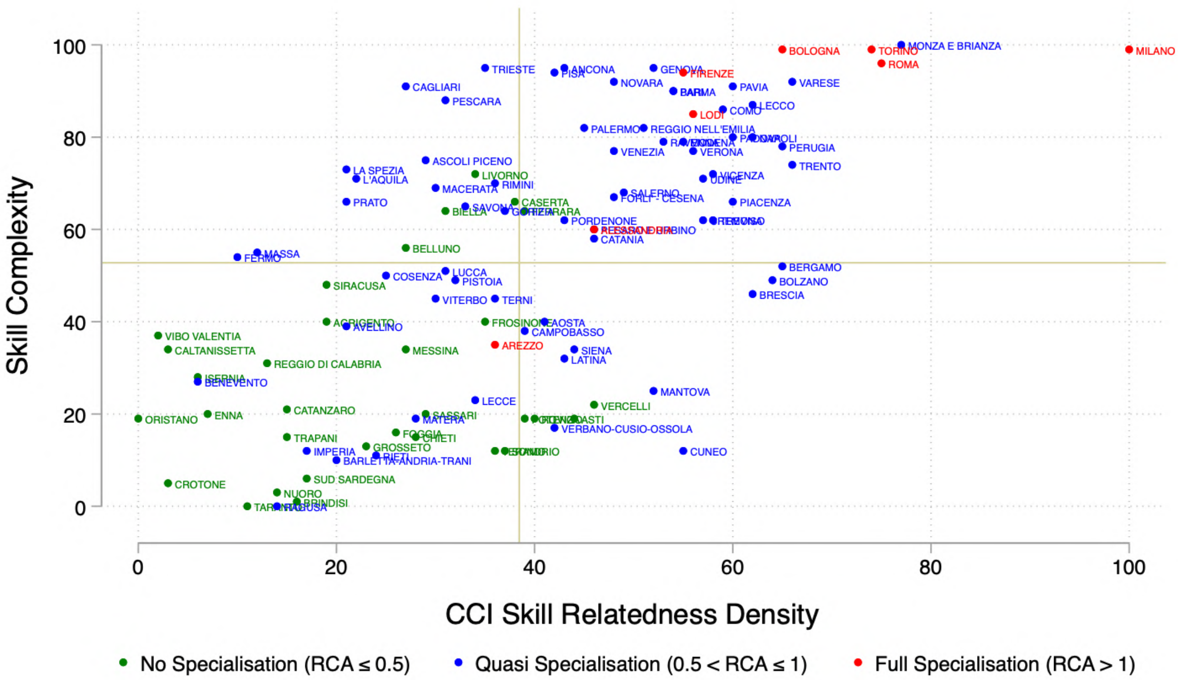


Figure 7. Regional Specialisation Potential in the CCIs based on CCI Skill Relatedness Density and Skill Complexity (2013-2019)

relatedness density indicate a lack of necessary human capital for the CCIs. The majority of regions located in this quadrant, such as Trieste, La Spezia, and Prato, have an RCA in the CCIs higher than 0.5 but lower than or equal to 1. The bottom-left quadrant locates the regions with below-mean complexity and relatedness scores, thus, they are in the worst position with low benefits and high risk. Unsurprisingly, a very high majority of the regions located in this quadrant have an RCA below or equal to 0.5 in the CCIs. The bottom-right quadrant shows the regions with low complexity but high relatedness density, i.e. low benefits and low risk such as Bergamo, Siena, and Aosta. Finally, the top-right quadrant accommodates the regions that are in the best position for specialising in the CCIs with high complexity and relatedness scores. These regions possess workforces endowed with above-average CCI-related skills and sophisticated knowledge and skills in general. Almost all the regions that already specialised in the CCIs (i.e. RCA>1) are located in the top-right quadrant. These regions are the richest and most highly-populated regions of the country, such as Milano, Roma, Torino, Firenze and Bologna, where agglomeration economies, industrial and cultural diversity, history and the infrastructures linked to the capital power facilitate the development of CCIs. An exception is Arezzo, a region in Tuscany, that is highly specialised in the CCIs but located in the bottom-left quadrant with a lower level of complexity and relatedness, representing an example of unrelated diversification. This exception to the rule can be explained by the heterogeneity of the human capital involved in cultural and creative activities. Arezzo, a region historically renowned for crafts work, including goldsmith and pottery, involves a combination of skills that is very specific and difficult to apply to the rest of the economic activities in the territory, enhancing its uniqueness but limiting the diversification opportunities of the region. Since specialisation, i.e. RCA, is defined in terms of employment, the specialisation patterns of the CCIs reflect regional employment dynamics in the CCIs that are provided in Table A3.

6 Conclusion

The present study provides a conceptual and empirical framework to better understand the skills composition of the CCIs by drawing on granular data sources and metrics. Integrating previous research on the CCIs and EEG literature, the skill space of the CCIs is conceptualised and analysed for the Italian regions. The empirical results offer evidence of the heterogeneity of skill requirements between and within CCIs, the skill complexity of the CCIs, the skill complementarities among the CCIs as well as the regional variation of the CCI skills. The results suggest that the typology of skills associated with the CCIs is quite complex and heterogeneous. In contrast to the dichotomy classification of *creative* or *non-creative* that has led most urban and regional policies over the last 20 years, the skill-based approach on the CCIs may illustrate the actual compatibility of these industries to collaborate and diffuse knowledge across all the sectors of the economy. Hence, policies for regional and urban development must reflect the particularities of the skill requirements of these industries as well as their complementarity to other sectors in the wider economy when evaluating the agglomeration and firm performance based on industrial or occupational classifications of the CCIs (Piergiovanni et al., 2012; Coll-Martínez, 2019a; Cruz and Teixeira, 2023).

The potential of the CCIs drives significant implications for the national and regional development dynamics, especially in today's knowledge and complex economy. When we put together the theoretical arguments and empirical evidence presented in this paper, we find that it is important to point out that the CCIs are more heterogeneous than expected in terms of skills and knowledge. Hence, the policies involving the CCIs should not overlook the cognitive distance neither among the CCIs nor between the CCIs and the wider economy by relying only on the predefined CCI classification based on industry codes. This study empirically demonstrates that there is a need to contextualise the underlying arguments of the CCIs' potential for growth and innovation outcomes (Bakhshi and McVittie, 2009; Sleuwaegen and Boiardi, 2014; Lee and Rodríguez-Pose, 2014; Rodríguez-Pose and Lee, 2020; Gutierrez-Posada et al., 2023) by adopting a skills-based approach alongside relative methods such as relatedness and complexity.

An additional consideration is that national, even regional, differences in the industrial and employment composition are also likely to determine the skill space of the CCIs. This study has focused on a Western European country with a longstanding tradition in the CCIs like Italy. Further validation exercises for more countries will help strengthen the understanding of the composition of the CCIs as well as their cross-fertilisation potential with other economic activities.

It is important to underline that the skill types considered in this study are limited to the skill taxonomies of the survey. Yet, it provides the first attempt to investigate the skill composition of the CCIs and open the debate on their taxonomy. Future studies may consider other data sources to measure and identify the combination of skills that are required in the online labour market –i.e., LinkedIN or UpWork (Horton, 2010). For instance, by testing what skills present in the CCIs could develop or disappear with the introduction of AI technologies (Stephany and Teutloff, 2024) or by identifying the impact of new technologies (e.g., AI, digitalisation) on the CCIs' location patterns and/or resilience (Lazzeretti et al., 2022). Further research could also link the CCIs' skill complexity to regional diversification and innovation potential (Innocenti and Lazzeretti, 2019; Burlina et al., 2023; Casadei et al., 2023).

A Additional Figures and Tables

Table A1. ICP Categories

1.Knowledge	(B1) Administration and Management, (B2) Office Work, (B3) Economics and Accounting, (B4) Sales and Marketing, (B5) Services to Customers, (B6) Human Resources Management, (B7) Production and Processing, (B8) Food Production, (B9) IT and Electronics, (B10) Engineering and Technology, (B11) Technical Design, (B12) Building and Construction, (B13) Mechanical, (B14) Mathematics, (B15) Physics, (B16) Chemistry, (B17) Biology, (B18) Psychology, (B19) Sociology and Anthropology, (B20) Geography, (B21) Medicine and Dentistry, (B22) Therapy and Counseling, (B23) Education and Training, (B24) Italian Language, (B25) Foreign Language, (B26) Fine Arts, (B27) History and Archaeology, (B28) Philosophy and Theology, (B29) Civil Protection and Public Safety, (B30) Legislation and Institutions, (B31) Telecommunications, (B32) Communication and Media, (B33) Transportation
2.Skills	
2.1 Basic Skills	(C1) Reading Comprehension, (C2) Active Listening, (C3) Writing, (C4) Speaking, (C5) Mathematics, (C6) Science, (C7) Critical Thinking, (C8) Active Learning, (C9) Learning Strategies, (C10) Monitoring
2.2 Social Skills	(C11) Social Perceptiveness, (C12) Coordination, (C13) Persuasion, (C14) Negotiation, (C15) Instructing, (C16) Service Orientation
2.3 Complex Problem	(C17) Complex Problem Solving
2.4 Technical Skills	(C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C21) Installation, (C22) Programming, (C23) Quality Control Analysis, (C24) Operation Monitoring, (C25) Operation and Control, (C26) Equipment Maintenance, (C27) Troubleshooting, (C28) Repairing
2.5 Systems Skills	(C29) Systems Analysis, (C30) Systems Evaluation, (C31) Judgement and Decision Making
2.6 Resource Management Skills	(C32) Time Management, (C33) Management of Financial Resources, (C34) Management of Material Resources, (C35) Management of Personnel Resources
3.Attitudes	
3.1 Cognitive	(D1) Oral Comprehension, (D2) Written Comprehension, (D3) Oral Expression, (D4) Written Expression, (D5) Fluency of Ideas, (D6) Originality, (D7) Problem Sensitivity, (D8) Deductive Reasoning, (D9) Inductive Reasoning, (D10) Information Ordering, (D11) Category Flexibility, (D12) Math Reasoning, (D13) Number Facility, (D14) Memorisation, (D15) Speed of Closure, (D16) Flexibility of Closure, (D17) Perceptual Speed, (D18) Spatial Orientation, (D19) Visualisation, (D20)Selective Attention, (D21) Time Sharing
3.2 Psychomotor	(D22) Arms-Hand Steadiness, (D23) Manual Dexterity, (D24) Finger Dexterity, (D25) Control Precision, (D26) Multilimb Coordination, (D27) Response Orientation, (D28) Rate Control, (D29) Reaction Time, (D30) Wrist-Finger Speed, (D31) Speed of Limb Movement
3.3 Psychical	(D32) Static Strength, (D33) Explosive Strength, (D34) Dynamic Strength, (D35) Trunk Strength, (D36) Stamina, (D37) Extent Flexibility, (D38) Dynamic Flexibility, (D39) Gross Body Coordination, (D40) Gross Balance Body Equilibrium
3.4 Sensory	(D41) Near Vision, (D42) Far Vision, (D43) Visual Colour Discrimination, (D44) Night Vision, (D45) Peripheral Vision, (D46) Depth Perception, (D47) Glare Sensitivity, (D48) Hearing Sensitivity, (D49) Auditory Attention, (D50) Sound Localisation, (D51) Speech Recognition, (D52) Speech Clarity
4.Work Activities	
4.1 Information Input	(G1) Getting Information, (G2) Identifying Objects, Actions, and Events, (G3) Monitor Processes, Materials or Surroundings, (G4) Inspecting Equipment, Structures or Material, (G5) Estimate the Quantifiable Characteristics of Products, Events, or Information
4.2 Mental Process	(G6) Judging the Qualities of Things, Services or People, (G7) Evaluating Information to Determine Compliance with Standards, (G8) Processing Information, (G9) Analysing Data or Information, (G10) Making Decisions and Solving Problems, (G11) Thinking Creatively, (G12) Updating and Using Relevant Knowledge, (G13) Developing Objectives and Strategies, (G14) Scheduling Work and Activities, (G15) Organising, Planning, and Prioritising Work
4.3 Work Output	(G16) Performing General Physical Activities, (G17) Handling and Moving Objects, (G18) Controlling Machines and Processes, (G19) Interacting With Computers, (G20) Operating Vehicles, Mechanised Devices, or Equipment, (G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment, (G22) Repairing and Maintaining Mechanical Equipment, (G23) Repairing and Maintaining Electronic Equipment, (G24) Documenting/Recording Information
4.4 Interacting with Others	(G25) Interpreting the Meaning of the Information for Others, (G26) Communicating with Supervisors, Peers, or Subordinates, (G27) Communicating with Persons Outside Organisation, (G28) Establishing and Maintaining Interpersonal Relationships, (G29) Assisting and Caring for Others, (G30) Selling or Influencing Others, (G31) Resolving Conflicts and Negotiating with Others, (G32) Performing for or Working in Directly with the Public, (G33) Coordinating the Work and Activities of Others, (G34) Developing and Building Teams, (G35) Training and Teaching Others, (G36) Guiding, Directing, and Motivating Subordinates, (G37) Train and Nurture Other People, (G38) Provide Consultation and Advice to Others, (G39) Performing Administrative Activities, (G40) Staffing Organisational Units, (G41) Monitoring and Controlling Resources

Authors' elaboration on ICP 2013 and O*NET data descriptors.

Table A2. Cultural and Creative Industries' Classification

CCI	NACE 4 digit	Description
Advertising		
	7021	Public relations and communication activities
	7311	Advertising agencies
	7312	Media representation
Architecture		
	7111	Architectural activities
Crafts		
	3212	Manufacture of jewellery and related articles
Design: product, graphic and fashion design	7410	Specialised design activities
Film, TV, video, radio and photography	5911	Motion picture, video and television programme production activities
	5912	Motion picture, video and television programme post-production activities
	5913	Motion picture, video and television programme distribution activities
	5914	Motion picture projection activities
	6010	Radio broadcasting
	6020	Television programming and broadcasting activities
	7420	Photographic activities
Music, performing and visual arts	5920	Sound recording and music publishing activities
	8552	Cultural education
	9001	Performing arts
	9002	Support activities to performing arts
	9003	Artistic creations
	9004	Operation of arts facilities
Publishing		
	5811	Book publishing
	5812	Publishing of directories and mailing lists
	5813	Publishing of newspapers
	5814	Publishing of journals and periodicals
	5819	Other publishing activities
	7430	Translation and interpretation activities
Software and Computer Services		
	5821	Publishing of computer games
	5829	Other software publishing
	6201	Computer programming activities
	6202	Computer consultancy activities
Museums, galleries and libraries		
	9101	Library and archives activities
	9102	Museums activities

Authors' elaboration on DCMS (2013) and DCMS (2016).

Table A3. Cultural and Creative Industries' Employment by Regions

Region	Employment 2013	Emp. Share 2013	Employment 2016	Emp. Share 2016	Employment 2019	Emp. Share 2019
Agrigento	773	1.21	746	1.17	706	1.10
Alessandria	7,169	5.12	7,237	5.29	7,482	5.47
Ancona	4,151	2.36	4,345	2.53	4,158	2.37
Aosta	1,544	3.30	1,300	2.89	1,143	2.49
Arezzo	9,281	7.82	9,841	8.35	9,477	7.71
Ascoli Piceno	1,226	1.86	1,412	2.15	1,640	2.31
Asti	932	1.43	942	1.50	1,070	1.65
Avellino	1,631	1.83	1,712	1.85	1,969	2.03
Bari	7,474	2.28	8,380	2.44	9,505	2.56
Barletta-Andria-Trani	1,215	1.54	1,374	1.68	1,727	2.01
Belluno	899	1.19	909	1.20	938	1.18
Benevento	1,006	1.80	1,000	1.70	1,112	1.82
Bergamo	7,877	1.87	8,232	1.94	8,906	1.99
Biella	801	1.26	864	1.36	1,402	2.13
Bologna	13,275	3.04	14,273	3.19	15,697	3.31
Bolzano	4,540	2.25	4,936	2.34	5,408	2.35
Brescia	8,529	1.80	9,054	1.89	9,683	1.90
Brindisi	896	1.14	981	1.21	1,082	1.26
Cagliari	2,838	1.88	3,268	2.45	3,971	2.78
Caltanissetta	446	0.99	445	0.96	462	1.05
Campobasso	865	1.76	885	1.75	927	1.78
Caserta	2,063	1.29	2,381	1.39	2,827	1.56
Catania	3,435	1.58	3,785	1.68	4,269	1.84
Catanzaro	886	1.30	904	1.29	1,048	1.48
Chieti	1,295	1.11	1,534	1.31	1,689	1.37
Como	4,261	2.11	4,641	2.28	4,721	2.25
Cosenza	2,420	1.97	2,524	2.00	2,729	2.15
Cremona	1,981	1.80	2,016	1.84	2,103	1.84
Crotone	516	1.78	315	1.09	523	1.77
Cuneo	3,476	1.65	3,822	1.79	4,233	1.91
Enna	308	1.26	333	1.39	305	1.25
Fermo	1,174	1.91	1,303	2.17	1,270	2.17
Ferrara	1,470	1.43	1,540	1.49	1,659	1.58
Firenze	13,297	3.26	13,751	3.17	14,184	3.14
Foggia	1,414	1.26	1,419	1.22	1,591	1.32
Forli' - Cesena	3,318	2.13	3,660	2.38	3,665	2.13
Frosinone	1,464	1.18	1,609	1.30	1,775	1.38
Genova	7,067	2.25	8,639	2.72	8,309	2.59
Gorizia	751	1.76	623	1.45	684	1.59
Grosseto	861	1.45	914	1.54	908	1.53
Imperia	925	1.63	959	1.71	1,031	1.84
Isernia	272	1.31	274	1.34	324	1.48
L'Aquila	1,274	1.58	1,463	1.91	1,634	2.08
La Spezia	1,332	1.98	1,414	2.09	1,352	1.96
Latina	2,289	1.64	2,311	1.61	2,527	1.71
Lecce	2,861	1.68	3,515	2.03	3,465	1.86
Lecco	2,478	2.05	2,710	2.28	2,653	2.14
Livorno	1,645	1.56	1,525	1.48	1,661	1.59
Lodi	2,075	3.17	2,281	3.53	2,244	3.35
Lucca	2,495	1.84	2,578	1.87	2,848	2.01
Macerata	2,543	2.33	2,533	2.38	2,706	2.43
Mantova	3,550	2.36	4,847	3.22	3,619	2.34
Massa	872	1.56	906	1.62	874	1.54
Matera	703	1.77	700	1.68	805	1.79
Messina	1,662	1.33	1,661	1.32	1,671	1.31
Milano	103,879	6.13	118,565	6.50	133,025	6.84
Modena	6,606	2.24	7,319	2.47	8,308	2.66
Monza E Brianza	8,276	2.71	9,024	2.93	10,227	3.17
Napoli	15,287	2.38	17,055	2.46	19,509	2.66
Novara	3,076	2.50	2,765	2.23	2,756	2.13
Nuoro	533	1.31	499	1.27	529	1.32
Oristano	406	1.36	421	1.43	449	1.43
Padova	10,312	2.76	11,033	2.90	13,420	3.34
Palermo	4,747	2.06	4,195	1.79	4,385	1.82
Parma	4,656	2.49	5,140	2.72	5,447	2.74
Pavia	2,690	1.80	2,945	1.95	3,379	2.14
Perugia	4,418	2.08	4,597	2.18	4,643	2.16

Table A3 continued.

Region	Employment 2013	Emp. Share 2013	Employment 2016	Emp. Share 2016	Employment 2019	Emp. Share 2019
Pesaro E Urbino	2,452	1.88	2,590	1.97	2,943	2.16
Pescara	2,138	2.32	1,988	2.16	2,536	2.63
Piacenza	2,170	2.06	2,111	2.04	2,277	2.08
Pisa	3,577	2.43	3,946	2.67	4,162	2.74
Pistoia	1,396	1.62	1,421	1.66	1,497	1.69
Pordenone	2,091	1.86	2,174	1.96	2,520	2.17
Potenza	1,106	1.29	1,099	1.19	1,239	1.30
Prato	1,788	1.77	1,875	1.70	2,001	1.69
Ragusa	975	1.57	1,018	1.57	1,174	1.74
Ravenna	2,512	1.75	2,748	1.93	2,880	1.91
Reggio Di Calabria	1,307	1.47	1,289	1.46	1,249	1.44
Reggio Nell'Emilia	3,883	1.86	4,553	2.17	5,013	2.25
Rieti	584	2.02	447	1.67	467	1.54
Rimini	3,309	2.41	3,200	2.36	3,544	2.48
Roma	83,462	5.61	83,244	5.22	88,578	5.34
Rovigo	1,073	1.43	948	1.31	960	1.29
Salerno	3,456	1.49	3,986	1.60	4,287	1.61
Sassari	1,607	1.33	1,524	1.30	1,677	1.38
Savona	1,325	1.48	1,331	1.54	1,328	1.48
Siena	2,090	2.26	2,313	2.55	2,037	2.13
Siracusa	929	1.26	928	1.26	1,041	1.34
Sondrio	699	1.12	772	1.26	861	1.40
Sud Sardegna	336	0.83	536	0.94	645	1.11
Taranto	1,364	1.11	1,230	0.99	1,554	1.22
Teramo	1,113	1.20	1,332	1.46	1,348	1.43
Terni	1,369	2.06	1,353	2.08	1,505	2.26
Torino	43,715	5.09	44,695	5.18	40,257	4.50
Trapani	945	1.25	1,001	1.29	1,177	1.52
Trento	5,217	2.59	5,185	2.62	8,191	3.84
Treviso	7,474	2.22	8,566	2.49	8,984	2.47
Trieste	2,397	3.07	2,245	2.87	2,361	2.97
Udine	3,537	1.90	3,760	2.06	4,091	2.14
Varese	6,365	2.10	6,889	2.27	7,068	2.27
Venezia	6,822	2.20	7,003	2.21	8,309	2.48
Verbano-Cusio-Ossola	886	1.93	912	2.01	895	1.95
Vercelli	794	1.42	768	1.44	761	1.40
Verona	9,012	2.55	10,667	2.92	9,855	2.58
Vibo Valentia	301	1.22	313	1.27	316	1.24
Vicenza	9,651	2.84	10,319	2.97	11,004	2.99
Viterbo	1,074	1.55	1,106	1.60	1,304	1.84

Data source: Local Units and Persons Employed: Size Class of Persons Employed, Economic Activities, Geographical Areas, Istat.

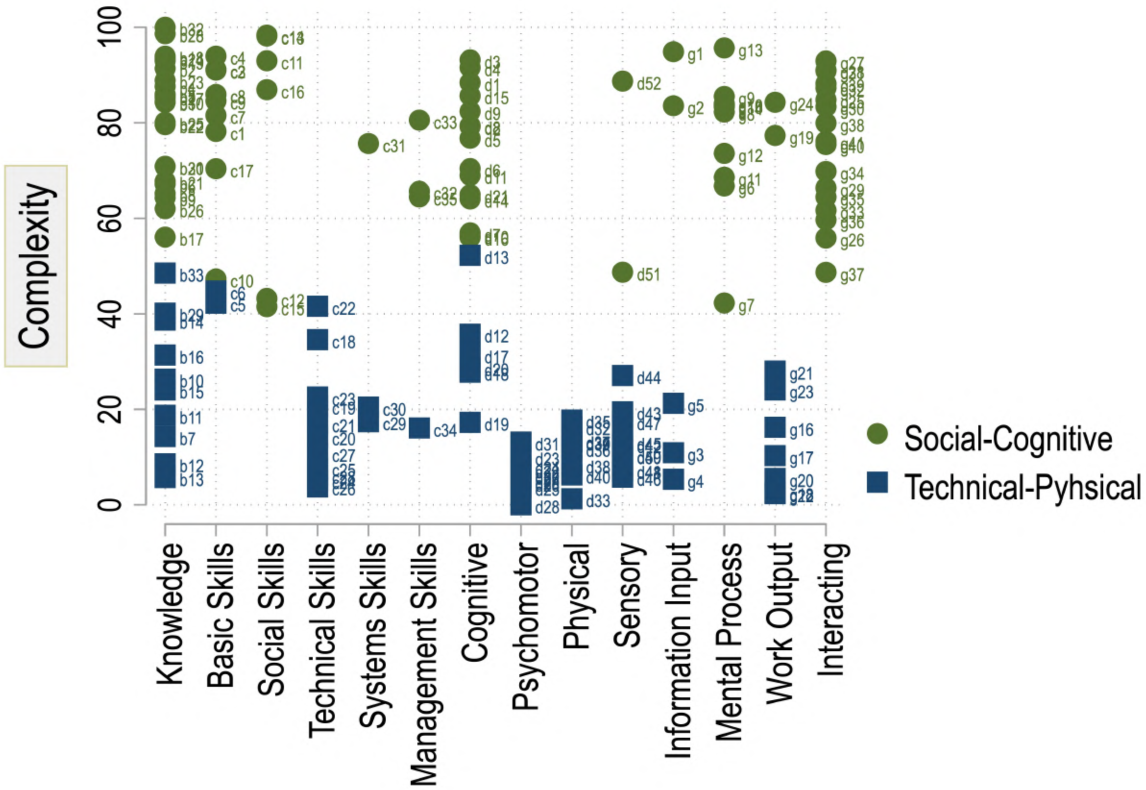


Figure A1. Complexity Scores of Skills

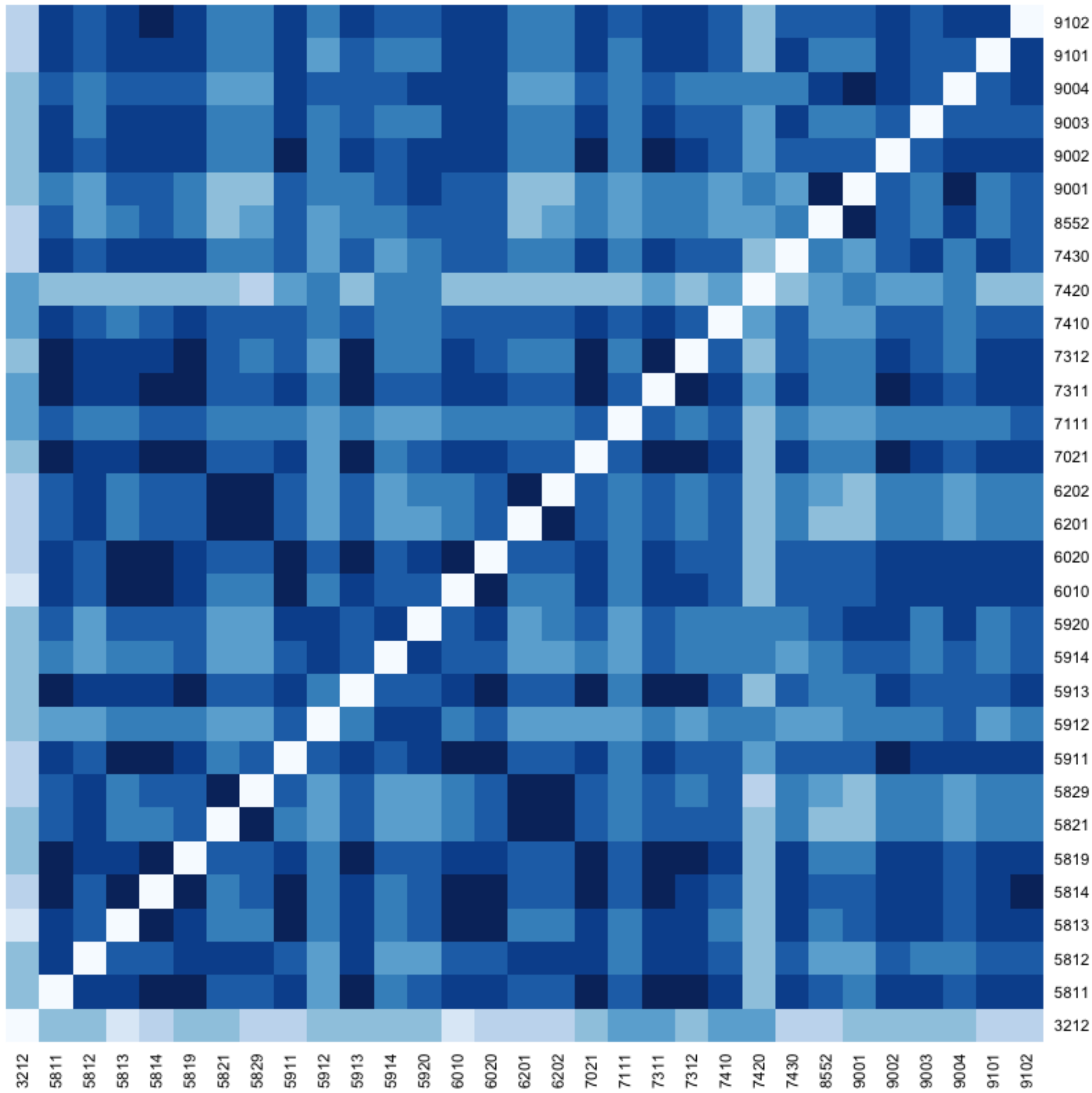


Figure A2. Skill Relatedness Among the CCIs for the period 2013-2019.

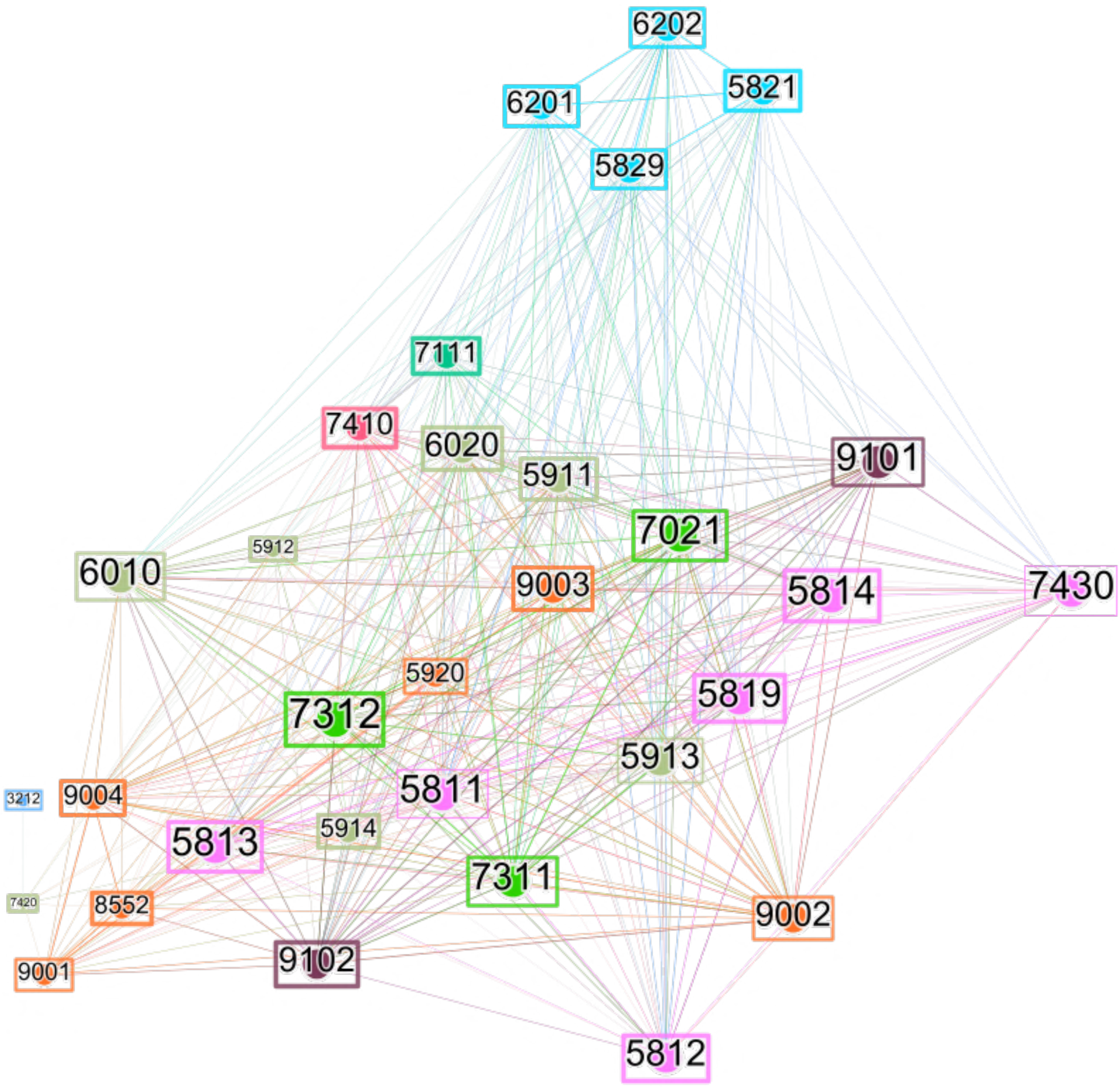


Figure A3. The Skill-Related CCIs Space (2013-2019). Each node represents a particular industry at the four-digit NACE level. Node size is proportional to the skill complexity level of the industry the node represents. Edge lengths indicate the degree of skill relatedness between industry pairs. Nodes are coloured according to the aggregated industries.

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