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Analysis

The skill requirements of the circular economy

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ABSTRACT

In response to global challenges related to resource scarcity and environmental concerns, the circular economy (CE) has emerged as a transformative model focused on resource efficiency and waste reduction. As the discourse around the CE intensifies, understanding the skill requirements of the CE becomes imperative for effective policy-making, workforce development, and regional competitiveness. This paper addresses the scarcity of quantitative methods on this aspect and proposes a conceptual and empirical framework to identify, analyse, and monitor the skill requirements of the CE through a comprehensive and reproducible approach based on relative skill advantage, skill relatedness, and skill complexity measures. Accordingly, it identifies the essential and complementary skills within the CE by constructing unique skill spaces and documents their regional variation.

1. Introduction

In a world facing resource scarcity and environmental challenges, the developing concept of the circular economy (CE) represents a vital paradigm shift towards resource efficiency and reduced waste to design a more sustainable and resilient future. Despite the ongoing discourses and debates regarding the definition, objectives, classification, and implementation of the CE (Kirchherr et al., 2017; Korhonen et al., 2018), the academic interest in the CE has been exponentially increasing (Calisto Friant et al., 2020).

The transition from the current linear economy model – extract, manufacture, use, and discard – to a CE – produce, use, service, and reuse – is expected to introduce various changes such as destroying some jobs in certain industries while creating new ones in other industries (Chateau and Mavroeidi, 2020). The circular transition aims at reducing the extraction of raw materials and producing more durable goods designed to have longer lives, therefore, implying substantial changes for resource-intensive sectors such as mining and manufacturing while increasing the demand for the service sectors related to repair, maintenance, rental and leasing (International Labour Office, 2018). In case of a circular transition that empowers such a sectoral reallocation, world employment might grow 0.1% by 2030, equivalent to 6 million more jobs (International Labour Office, 2018). A literature review by Laubinger et al. (2020) on the employment effects of a circular transition reveals that a net employment growth between 0 and 2% is expected with significant variations across sectors, regions and countries.

Based on these forecasts, a few firm-level empirical studies have provided preliminary evidence on the employment effects of the CE transition, by adopting the theoretical lens of the eco-innovation literature. Accordingly, the CE transition introduces technological and non-technological changes within and outside firms' boundaries, engendering the traditional tension between job creation and labour displacement effects. The limited empirical evidence is not conclusive, showing that the dominance of a positive or negative impact at the aggregate level may hide a more nuanced situation at the sectoral and geographical level, in which negative and positive effects may coexist (Repp et al., 2021; Moreno-Mondejar et al., 2021; Horbach et al., 2015; Horbach and Rammer, 2020).

In the face of such advancements, policymakers and firms might be subject to transforming workforce skills by employing formal and vocational education and training (VET) policies for re-skilling and upskilling of the workforce to offset the employment losses in resource-intensive industries with the employment gains in the circular industries (CIs) (Gutberlet et al., 2023). Therefore, analysing workplace skills within the CIs is not only vital in terms of maximising the job creation potential of the CE transition and the resilience of

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the workforce for potential job displacements (European Commission, 2018; International Labour Office, 2018), but also for increasing the efficiency and sustainability of the CIs, establishing regional and national competitiveness in the field (Chateau and Mavroeidi, 2020), and supporting well-informed policy-making and smart specialisation ((Marra et al., 2018); Buyukyazici, 2023b; Vona, 2023; Alexandri et al., 2024; Černý et al., 2024).

Based on these premises, the main purpose of the present study is to develop a conceptual and empirical framework to improve the understanding of the skill requirements of the CIs and further CE. Despite a growing grey literature underlying the vital role of workplace skills for the CE and CE transition (International Labour Office, 2018; Chateau and Mavroeidi, 2020; Laubinger et al., 2020), comprehensive quantitative and empirical analyses are scarce primarily because of the lack of data and adequate methods. Hence, the existing studies generally consider a part of circular activities (De los Rios and Charnley, 2017) or are based on case studies (Bassi and Guidolin, 2021; Janssens et al., 2021; Borms et al., 2023). One exception is Burger et al. (2019) which analyses the skill differences between circular and non-circular employment in the USA by using a set of 35 skills from the O*NET survey. Nevertheless, the literature still lacks a widely accepted comprehensive and reproducible method to identify, analyse, and monitor the skill requirements of the CE. This study aims to fill this gap by providing a highly granular, bottom-up, and reproducible method that can be applied to different countries, regions, and other types of industries.

The second purpose of this study is to empirically unbox the human capital of the CE to complement existing studies that look at the skill differences between circular and non-circular occupations and industries (Burger et al., 2019). In our study, we do not only consider which skill sets (i.e. basic skills, digital skills, technical skills etc.) are required in the CE, but also analyse which specific skill types (i.e. negotiation, programming, repairing etc.) are used effectively with respect to other industries by accounting for spatial differences, their relationship with other skill types, and their sophisticatedness level. In this regard, to the best of our knowledge, this study constitutes the most comprehensive and granular skill analyses of the CE available so far.

In line with the purposes mentioned above, the present study introduces the Revealed Skill Requirements (RSR) method that employs comparative advantage, relatedness, and complexity concepts which are widely used in the evolutionary economic geography (EEG) literature (Boschma, 2017). To operationalise the RSR, we focus on Italy, a country with significant endeavours towards circular transition, yet with significant regional disparities. Italy adopted a national CE strategy in 2017 and improved its CE performance in recent years although challenges remain in fully realising its potential (European Environment Agency, 2024). Italy has become one of the top circular countries in Europe in recent years, mostly due to its enhanced performance on waste management, creation of circular jobs, and circular material use rate (Italian Ministry of the Environment and Energy Security, 2017). In this regard, Italy is a suitable candidate for the present study as many CE-related policies and improvements have occurred during our time frame. By relying on a unique data set on workplace skills, the Italian Sample Survey on Professions (ICP), our study draws on the 161 workplace skills' intensities to construct the relative skill advantage (RSA), skill relatedness and skill complexity measures for 573 industries for each of the 107 Italian NUTS-3 regions over the period 2013–2019. Then, these granular metrics are exploited to document and analyse the essential and complementary skills required by the CIs as well as their sophisticatedness level, the skill interdependencies, and spatial distribution by creating industrial skill spaces.

The methodology we propose in this paper is useful and practical in several premises as it allows granular, comparable, dynamic, and relative analyses. Granularity is crucial given that the required circular skills are expected to vary across industries, locations, and the stage of the CE transition. Our methodology allows skills identification at the industry-location-time level, thus, paving the way to empirically account for the heterogeneous nature of the CE. Due to the high granularity of the method, a comparison of the skills requirements of the CIs and non-CIs located in different countries, regions and cities is possible which further enables dynamic analyses of the CE transition across time. Another crucial aspect of the RSR method is relativity. As well known, tasks, knowledge and skills required by occupations and/or industries are subject to radical change due to the global effects of technological improvement including automation and digitalisation (Brunello and Wruuck, 2021; Buyukyazici, 2024). Accordingly, some skill types, including technical and digital skills, have been becoming important for a large share of industries. In the RSR method, the skill requirements of an industry are identified by considering those skills' relative importance to other industries. In doing so, the method aims at identifying the most important skills for an industry rather than capturing the global skills trends.

The rest of the paper is organised as follows. Section 2 briefly overviews the related literature. Section 3 describes the data sources and construction of the main data set. Section 4 lays out the methodology. Section 5.1 provides descriptive insights into the skills distribution of the CIs and non-CIs. Section 5.2 identifies and analyses the essential circular skills. Section 5.3 focuses on the complementary circular skills. Section 6 discusses the main findings and their implications with a broader focus and provides some concluding remarks.

2. Literature

2.1. CE and employment dynamics

The linear organisation of production processes' has been dominating for decades. This has engendered a lock-in of economic systems in production technologies and jobs that are functional to such production modes (Unruh, 2000; Tura et al., 2019). Transitioning to the CE paradigm requires elaborating policy and business strategies, allowing for escaping such lock-in and changing how products and production processes are designed and realised. The unlocking of the linear lock-in is hence intrinsically associated with innovation dynamics. For this reason, extant literature has stressed and shown the usefulness of extending the eco-innovation conceptual and empirical framework to analyse the drivers and implications of the CE transition (De Jesus and Mendonça, 2018; Fusillo et al., 2024). Regarding the economic impacts of the innovation-driven CE transition, some studies have focused on the impact of adoption on firms' performances (Horbach and Rammer, 2020; Quatraro and Ricci, 2023) while an increasing number of studies has started focusing on the effects on labour market dynamics following the classical divide between labour displacement and labour-augmenting impacts of innovation (Montobbio et al., 2023).

Empirical studies at the firm and regional level have stressed the potential job-creation effects of the CE transition. By using administrative data, Niang et al. (2023) shows that in French regions employment growth in CE activities is higher than total employment growth, suggesting that the CE transition offers important opportunities for territorial development. Other studies stress, from the conceptual viewpoint, that the impact of CE on employment remains undetermined. On the one hand, increased resource efficiency may push labour demand downward. Moreover, the implementation of innovation-based CE strategies may require the hiring of specialised and better-qualified employees and the displacement of low-qualified ones, leaving the overall effect to the balance between these two contrasting forces (Horbach et al., 2015; Horbach and Rammer, 2020; Repp et al., 2021; Moreno-Mondejar et al., 2021). On the other hand, following the classical debate on the net employment effects of innovation, compensation mechanisms can be at stake. These can be the outcome of either demand-side dynamics associated with lower prices, product innovation and increased market penetration, which could translate into higher derived demand of labour, or supply-side dynamics following the reallocation of tasks and resources inside the firm and across the value chain (Aghion et al., 2017; Acemoglu and Autor, 2011; Piva and Vivarelli, 2018).

The above-mentioned studies provide evidence of various views and approaches to analyse the relationship between the CE transition and employment dynamics. Nevertheless, even though some studies mention a possible bias of the innovation-led CE transition towards the specialised or qualified workforce, the qualitative dimensions of the CE employment, i.e. its skill and knowledge composition, have been substantially disregarded by the extant academic literature, despite a relatively large grey literature emphasising the importance of workplace skills for the CE and CE transition (International Labour Office, 2018; Chateau and Mavroeidi, 2020; Laubinger et al., 2020) and emerging literature stressing that the lack of required knowledge and skills is considered crucial barriers to the CE transition (Rizos et al., 2015; Govindan and Hasanagic, 2018; Pigosso and McAloone, 2021; Tapia et al., 2021).

Delving into the skills-specificity associated with the CE transition is therefore of interest from the policy viewpoint, as it can provide useful inputs to design effective policy mixes. Moreover, it is of interest to innovation scholars focusing on the understanding of the multifaceted relationship between innovation and new technologies, the ecological transition and skills reconfiguration in labour markets. In the next section, we first discuss the few existing attempts to study the skill content of the CE transition and then we provide the rationale supporting our methodological approach.

2.2. The skill content of the CE

The literature on the skill requirements of the CE, in terms of circular occupations and/or industries, can be divided into two mainstream paths: case studies based on small sample surveys or interviews and general analyses based on large-scale workplace skills data. However, the first path is richer. Among others, De los Rios and Charnley (2017) focuses on the required design capabilities for the CE transitions by using secondary data on eight big companies. Borms et al. (2023) conducts interviews to analyse the relationship between circular strategies and different types of skills in start-ups located in Flanders, Belgium. The results show that circular strategy *design to lower material use* increases the need for transport and logistics skills, *digitalisation* increases the need for R&D and IT skills, and *recuperation of waste* requires technical knowledge.

Regarding the second path, the only example is Burger et al. (2019) that compares circular and non-circular-oriented occupations in terms of education and skills based on 35 pre-defined skills from the O*NET database in the USA by elaborating on the closely related literature on the skill differences between green and non-green jobs (Vona et al., 2015; Consoli et al., 2016). Firstly, they identify the CIs and circular employment by drawing on circular strategies known as the *R framework*, i.e. recycle, reuse, recover, repair, and remanufacture, to distinguish between the core and enabling CIs. After analysing the education requirements of circular occupations, they use weighted least squares regression to compare the CIs and non-CIs in terms of six skill categories, *Basic Skills, Complex Problem Solving Skills, Resource Management Skills, Social Skills, System Skills,* and *Technical Skills*. They find no differences in basic and social skill requirements between the CE and the rest of the economy while the remaining skill categories are required more by the CE.

It is important to underline that our study draws on Burger et al. (2019) by using their definition of the CIs (Table A1 in the Appendix). However, our work differs and adds to it in several aspects. Firstly, we propose a bottom-up methodology to reveal the required skills by identifying essential and complementary skills of the core and enabling CIs. Hence, we empirically define specific skill types for the CIs rather than comparing the skill scores of the circular and non-circular jobs. Secondly, we construct the skill spaces to analyse the interdependencies among the required skills to unveil the skill bundles within the CIs. By doing so, we are able to document not only which skills are important for the CIs but also how they interact with other skills. Thirdly, we analyse the complexity of skills required within the CIs, shedding some light on the sophisticatedness level of the circular human capital. Fourthly, our method is more granular and provides a regional perspective by paving the way for the regional-level analyses of circular skills.

The work of Burger et al. (2019) and the broader green skills literature (Vona et al., 2015; Consoli et al., 2016) are based on the task-based approach (Autor et al., 2003; Autor and Dorn, 2013) that evaluates occupations according to the connection between task content and the associated cognitive endowment. The introduction of such a framework has marked a step forward in understanding the profound transformations that labour markets are undergoing due to major technological revolutions, offering a rich framework of analysis to scholars at the intersection between innovation studies and economic geography. Nevertheless, we propose that the grafting of the resource-based view (RBV) of the firm onto the analysis of the skills content of occupations can also be far-reaching. According to the RBV, firms' resources represent the main factor constraining the direction of growth and diversification strategies (Penrose, 1959). The Natural Resource-Based view (NRBV) has further stressed that firms can strategically manage their resources to implement environmentally proactive plans and develop a competitive advantage (Hart, 1995; Ghisetti and Rennings, 2014). Resources are partly idiosyncratic to firms' activities, and so are workers' skills. Yet, the fact that resources may be likely exploited to diversify into new activities implies that they also are, to some extent, fungible (Teece, 1982). The concept of *skills relatedness* has been introduced as an empirical framework for the analysis of human capital fungibility across industries and occupations (Neffke and Henning, 2013).

Based on these arguments, we provide a highly granular – at the skill-industry-region-time level – methodology (RSR) to empirically analyse the skill requirements of the CIs which can be extended and reproduced for other countries, regions and other types of industries. We argue that the mapping of the skills requirements of specific occupations, like those featuring the CIs, might benefit from the implementation of a methodological approach, though grounded on relevance scores of skills in industries, that uses this information first to describe the relative intensity of each skill in each industry and then to derive metrics of relatedness among skills to measure their interdependence and of skills' complexity to account for their sophisticatedness. By doing so, one can address not only the basic question as to what extent the CIs require specific human capital and skills but also more challenging questions as to what the usage patterns of skills across different CIs are, in terms of effectiveness, complementarity and complexity.

The framework and empirical analyses presented in this study contribute to the CE and larger sustainability literature by paving the way for the addressing of various theoretical, empirical, and policy-related aspects that are non-mutually exclusive and intertwined. Firstly, it allows understanding of the specific skill types and sets required within the CIs which is crucial to ensure that job creation efforts align with the skill demands given that the transition to a more CE is expected to create additional jobs (International Labour Office, 2018; Laubinger et al., 2020). In this regard, by identifying the necessary skills for the CE, training programs and education can be tailored to produce a workforce that meets these sectors' needs. Correspondingly, the labour force might more smoothly move to the sectors with employment growth, increasing the immunity of the economy to potential job displacements, unemployment and income losses, thus, diminishing the negative effects of the CE transition (Chateau and Mavroeidi, 2020).

Secondly, our framework can be used to identify the skill deficits and mismatches in the CIs which may prompt investment in R&D, fostering advancements in technology and methodologies (International Labour Organization, 2010; Cainelli et al., 2020; Fusillo et al., 2023). This practice not only creates new job opportunities but also enhances the efficiency and sustainability of circular and other industries by reducing the risk of skill mismatch or unemployment, creating more stable and long-term employment prospects (Brunello and Wruuck, 2021). Moreover, the analysis of skills helps the workforce adapt to technological advancements. As technologies evolve within circular and green domains, skill requirements may change. Analysing and updating skill sets accordingly ensures that the workforce remains adaptable and competent.

Thirdly, our method allows dynamic skill analyses at a very high granular level which is essential to establish and maintain a global competitiveness in the CE. A workforce equipped with the relevant skills enhances the comparative advantage of countries and regions in the CE (Chateau and Mavroeidi, 2020). As the world increasingly embraces sustainability, having a skilled workforce would attract investments, and potentially create more jobs through increased market demand for circular products and services, paving the path for the CI clusters (Domenech et al., 2019).

Fourthly, our method can be used to design realistic and achievable national and regional CE and industrial specialisation strategies (Marra et al., 2018; Buyukyazici, 2023b). Such a practice would allow policymakers to adequately identify the most promising cities and regions for various circular activities, thus, enhancing the efficient use of funds. Well-informed policy-making is crucial given that substantial amounts of national and international funds have been devoted to increasing resource efficiency, and circular and green practices in recent years.

Lastly, our method can be extended to green literature. A stream of recent studies at the intersection of workplace skills and green jobs have enhanced the understanding of the skill content of the green economy (Vona et al., 2015; Consoli et al., 2016; Vona et al., 2018). However, our study can complement these studies in two main aspects. Firstly, the existing studies mostly focus on the skill differences between green and non-green occupations by drawing on a small set of predefined skills provided by the O*NET survey. This approach has limited explanatory power regarding the skill content, specific skill types, and usage patterns. On the other hand, our approach can analyse and concisely document a larger set of skills alongside their usage patterns in terms of complementarity (skill relatedness) and sophisticatedness (skill complexity). Secondly, the existing studies are at the skill and occupation/industry level, providing a time-invariant national-level analysis. Our approach has time and region dimensions alongside skill and industry dimensions that pave the way to regional and dynamic green skills analyses.

3. Data

The present study employs two main data sources: the Italian Sample Survey on Professions (ICP) obtained from the National Institute for Public Policies Analysis (INAPP) and the Italian Labour Force Survey (ILFS) provided by the National Institute of Statistics of Italy (Istat).

The ICP is a rich data set on workplace skills resulting from a comprehensive survey of approximately 800 occupational units[1] present in the Italian labour market. The ICP survey was conducted in two waves, 2007 and 2013, and almost 16,000 workers and professionals were interviewed in each wave. Workers responded to a questionnaire – which is based on the O*NET survey in the USA – evaluating the work content, tasks, knowledge and skills of their professions alongside the organisational structure where their work takes place. The questionnaire consists of seven sections, each of which captures different aspects of occupations: knowledge (33 questions, both importance and complexity level), skills (35 questions, both importance and complexity level), attitudes (52 questions, both importance and complexity level), generalised working activities (41 questions, both importance and complexity level), values (21 questions), working styles (16 questions), working conditions (57 questions), summing up to 275 questions. The first four sections have the same question design, addressing both the importance and usage level[2] of skill types while other sections have different question designs and scales making them uncombinable with the first four sections.[3] Based on this aspect, we use the first four sections in the present study summing up to 161 different skill types presented in Table A2 in the Appendix alongside their descriptor categories. By following the studies used the O*NET survey (Feser, 2003; Gabe and Abel, 2011; Krenz, 0000), we multiply the importance score with the level score to create a skill intensity score for each skill type. This practice maximises the skill variation across occupations and allows us to combine the two aspects, i.e. importance and level, of each skill type in one score.

The ICP data specifically pertains to occupational categories, thus, we rely on the ILFS data to establish connections between workplace skills and spatial and industrial information. We create the primary data set through the following steps. Firstly, we transform the ICP data, originally at the five-digit occupational level, to match the four-digit level scheme of the ILFS. We use the second wave of the ICP survey, namely the ICP 2013, to comply with the occupational classification of the ILFS.[4] Subsequently, we calculate skill intensity variables for each workplace skill by multiplying the importance scores with the level scores. Secondly, we merge the ICP and ILFS data sets on the four-digit occupational level. Finally, we compute the average skill intensity scores for each industry. It is worth noting that the combined ICP/ILFS data set provides information on skill distributions among occupations (from the ICP), occupational distributions within industries (from the ILFS), and the industrial composition across regions for each year (also from the ILFS). Utilising these distributions, we calculate average skill intensity variables for every industry within each region and year. After excluding part-time workers and individuals outside the age range of 15-64, the resultant data set comprises 161 average skill intensity variables for 573 industries and 107 NUTS-3 regions for the period spanning from 2013 to 2019.

4. Identifying circular skills: Revealed skill requirements method

In the present study, we provide a data-driven method, which we coin as the revealed skill requirements (RSR), to analyse the skills of the CIs. The RSR is based on the relative skill advantage (RSA), skill relatedness, and skill complexity measures that are combined with network techniques. These measures, or their variations, are widely used in the EEG literature to describe the activity space in question such as product space (Hidalgo et al., 2007), technology space (Boschma et al., 2015), industry space (Neffke et al., 2011), and skill space (Alabdulkareem et al., 2018; Buyukyazici et al., 2024; Buyukyazici, 2023). In this paper, we combine these measures to use as a method to unveil the skill requirements of industries.

The RSR can be summarised in five main steps. Firstly, the main data set is constructed, as described in the Data section, to have a sample of 161 workplace skills, 573 industries and 107 regions for the period 2013–2019. In the second step, the core and enabling CIs are identified as explained in Section 4.1. As the third step, industry-to-skill

[1] The survey is at the five-digit level in the context of the Classificazione delle Professioni (CP), which is the Italian version of ISCO classification.

[2] Importance question: *How important is this competence in carrying out your current profession?* Level question: *Among those indicated below, at what level is this competence necessary for the development of your current profession?* Importance questions are rated on a scale from 1 (not important) to 5 (extremely important), while complexity-level questions are rated on a scale from 1 (least complex) to 7 (most complex). Then they are rescaled to be between 0 and 100.

[3] Hereafter, we use the term *skill* to address each of 275 questions and competencies available in the ICP survey.

[4] The ICP 2007 uses CP 2001 classification, while the ICP 2013 uses CP 2011.

($573x161$) input matrices whose each cell indicates the skill intensity score of skill s for industry i are created for each region (107) and year (7) that sum up to 749 input matrices. In the fourth step, we apply the RSA, skill relatedness, and skill complexity measures, described in detail below, to the input matrices to construct the skill spaces of the CIs. The skill spaces function as networks that embed and illustrate rich information on the skill requirements by which we identify the essential and complementary skills required by the CIs. As the last step, we identify the essential and complementary skills of the core and enabling CIs as well as their CE elements. The essential skills are defined based on the non-binary RSA matrices. On the other hand, the complementary skills are identified using the intra-edges average weighted degree (AWD) measure. All of the mentioned methods are described in the respective sections below.

4.1. Defining circular industries

The CE is a heterogeneous and developing concept with roots in many industries and occupations. Hence, defining a widely accepted set of industries and occupations related to the CE is challenging. Regarding industries, two primary identification strategies are put forth from the policy and academic spheres. The European Commission (EC), as a policy sphere, identifies CE-related economic activities as a part of the commission's agenda to support the move to a more CE. Accordingly, the EC defines the CE-related goods and services by providing a list of CPA (the statistical classification of products by activity) and PRODCOM (community production) codes alongside the industrial classification, i.e. NACE codes, in which the CE-related goods and services are produced.[5] The EC's identification strategy is centred on CE-related goods and services – which draws on the definition of environmental goods and services (Eurostat, 2016) – rather than defining a set of CIs. Therefore, the CE industrial classification provided by the EC manuals and documents is broad and includes also non-circular goods and services. For instance, *tubes and pipes for sewage system* is defined as a CE good under the industry category *casting iron* with NACE code 2451, constituting a share of the casting iron industry alongside other non-circular goods. Therefore, estimating the share of circular goods in broad industry categories requires input–output tables and related methods.

On the other hand, the academic literature on the CE draws on the CE strategies, which can be commonly found in many CE-related works, to identify the CIs. In this regard, Burger et al. (2019) defines four core (*Use Waste as a Resource, Rethink the Business Model, Prioritise Regenerative Resources,* and *Preserve and Extend What is Already Made*) and three enabling (*Incorporate Digital Technology, Design for the Future,* and *Collaborate to Create Joint Value*) CE strategies that are essential to increase the overall circularity of economies. The core strategies account for primary circular practices such as recycle, reuse, recover, repair, and remanufacture that are known as R frameworks (Kirchherr et al., 2017); while enabling strategies allow for easier circular practices and mediate further diffusion of circular practices in the economy.

Given the two above-mentioned identification strategies, we follow Burger et al. (2019). Table 1 documents the core CIs classified by the four CE elements.[6] In this regard, the element *Use Waste as a Resource* is related to 9 NACE four-digit industries, *Rethink the Business Model* is to 12, *Prioritise Regenerative Resources* is to 1, and *Preserve and Extend What is Already Made* is to 15, summing up to 37 core CIs. Regarding the enabling CIs presented in Table 2, the CE element *Incorporate Digital Technology* is related to 13 industries, *Design for the Future* is to 4, and *Collaborate to Create Joint Value* is to 2, summing up to 19 enabling CIs. However, it should be acknowledged that the enabling CIs, despite being crucial, partially contribute to the CE as they also serve the non-CE. For instance, the *Specialised Design Activities* (7410) may design products to ease circular practices, yet, not all design activities are conducted for circular practices.

4.2. Relative skill advantage

RSA is a measure that assesses the relative significance of a skill for an industry with respect to other industries. The RSA measure is structurally identical to the Balassa index, alternatively referred to as the location quotient (LQ) and revealed comparative advantage (RCA) which has been widely used in the EEG and regional economics literature. In contrast to LQ and RCA, which rely on employment figures, RSA utilises skill intensity scores as input data. Accordingly, RSA represents the proportion of the relative significance of skill $s \in S$ to industry $i \in I$ (the numerator) compared to the relative significance of skill s across all industries I (the denominator) in region p at time t as presented in Eq. (1).

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

where $icp(i,s)$ is the skill intensity score of skill s for industry i in region p at time t and is obtained from the ICP and ILFS data sets as described above. Correspondingly, industry i has a relative advantage in skill s if its RSA takes a value greater than 1. In other words, skill s is effectively used by industry i if its RSA is greater than 1. At this point, it is important to underline that the RSA scores are expected to be highly dynamic and subject to evolve with technological change which we aim to account for by providing an industry-region-time level measure.

The RSA formula serves two main objectives in our method. Firstly, the resulting binary RSA matrices, i.e. effective use matrices, are used as input matrices to compute skill relatedness and skill complexity values. For this objective, the RSA formula is applied to the 749 input matrices ($573x161$) and 749 binary RSA matrices obtained. Secondly, non-binary RSA matrices are used to identify the essential skill sets of the core and enabling CIs and the corresponding CE elements. In doing so, the RSA formula is applied to the 749 input matrices and 749 non-binary RSA matrices are obtained. Then their element-wise average is computed to have one global non-binary industry-to-skill ($573x161$) RSA matrix. As the last step, 9 subset matrices for the CIs – core ($37x161$) and enabling ($19x161$) – and their elements – *Use* ($9x161$), *Rethink* ($12x161$), *Prioritise* ($1x161$), *Preserve* ($15x161$), *Incorporate* ($13x161$), *Design* ($4x161$), *Collaborate* ($2x161$) – are created and averaged on the skills to obtain the final non-binary RSA scores which represent the importance of a particular skill s for the core and enabling CIs and their CE elements.

4.3. Skill relatedness

The relatedness[7] measure (Hidalgo et al., 2007) has been widely used to capture the inter-dependencies between a variety of entities including technologies (Boschma et al., 2015), industries (Neffke

[5] The list of the CE-related goods and services with CPA, PRODCOM, and NACE codes can be reached from the following link: https://ec.europa.eu/eurostat/cache/metadata/en/cei_cie011_esmsip2.htm.

[6] Burger et al. (2019) use the USA data, thus, the industry classification system is The North American Industry Classification System (NAICS) in their work. We transform the industry classification from NAICS to NACE rev. 2 to comply with the Italian data. The descriptions of NAICS can be reached via this link: https://www.census.gov/naics/?58967?yearbck=2012. The correspondence between NAICS and NACE is presented in Table A1 in Appendix A.

[7] Relatedness as a concept has a long history. As Neffke and Henning (2013) pointed out, there are three different approaches to relatedness: (1) hierarchical measure based on standard industry classification systems such as NACE and SIC (Chang, 1981-89; Farjoun, 1998; Lee and Lieberman, 2010), (2) resource-based measures such as technological resources (Breschi et al., 0000) and human-capital resources (Farjoun, 1994), and (3) outcome-based co-occurrence methods as in the works of Hidalgo et al. (2007) and Neffke and Svensson Henning (2008). In the present work, we refer to the relatedness measure based on the minimum of conditional probabilities that is introduced by Hidalgo et al. (2007).

Table 1
Core Circular Economy Sectors.

NACE	NACE Description	Circular Economy Elements
3600	Water collection, treatment and supply	Use Waste as a Resource
3700	Sewerage	Use Waste as a Resource
3811	Collection of non-hazardous waste	Use Waste as a Resource
3812	Collection of hazardous waste	Use Waste as a Resource
3821	Treatment and disposal of non-hazardous waste	Use Waste as a Resource
3822	Treatment and disposal of hazardous waste	Use Waste as a Resource
3831	Dismantling of wrecks	Use Waste as a Resource
3832	Recovery of sorted materials	Use Waste as a Resource
3900	Remediation activities and other waste management services	Use Waste as a Resource
7711	Renting and leasing of cars and light motor vehicles	Rethink the Business Model
7712	Renting and leasing of trucks	Rethink the Business Model
7721	Renting and leasing of recreational and sports goods	Rethink the Business Model
7722	Renting of video tapes and disks	Rethink the Business Model
7729	Renting and leasing of other personal and household goods	Rethink the Business Model
7731	Renting and leasing of agricultural machinery and equipment	Rethink the Business Model
7732	Renting and leasing of construction and civil engineering machinery and equipment	Rethink the Business Model
7733	Renting and leasing of office machinery and equipment (including computers)	Rethink the Business Model
7734	Renting and leasing of water transport equipment	Rethink the Business Model
7735	Renting and leasing of air transport equipment	Rethink the Business Model
7739	Renting and leasing of other machinery, equipment and tangible goods n.e.c.	Rethink the Business Model
7740	Leasing of intellectual property and similar products, except copyrighted works	Rethink the Business Model
3511	Production of electricity	Prioritise Regenerative Resources
4779	Retail sale of second-hand goods in stores	Preserve and Extend What's Already Made
4520	Maintenance and repair of motor vehicles	Preserve and Extend What's Already Made
3313	Repair of electronic and optical equipment	Preserve and Extend What's Already Made
3314	Repair of electrical equipment	Preserve and Extend What's Already Made
9511	Repair of computers and peripheral equipment	Preserve and Extend What's Already Made
9512	Repair of communication equipment	Preserve and Extend What's Already Made
9521	Repair of consumer electronics	Preserve and Extend What's Already Made
3311	Repair of fabricated metal products	Preserve and Extend What's Already Made
3312	Repair and maintenance of machinery	Preserve and Extend What's Already Made
3319	Repair of other equipment	Preserve and Extend What's Already Made
9522	Repair of household appliances and home and garden equipment	Preserve and Extend What's Already Made
9523	Repair of footwear and leather goods	Preserve and Extend What's Already Made
9524	Repair of furniture and home furnishings	Preserve and Extend What's Already Made
9525	Repair of watches, clocks and jewellery	Preserve and Extend What's Already Made
9529	Repair of other personal and household goods	Preserve and Extend What's Already Made

Authors' elaboration based on Burger et al. (2019).

Table 2
Enabling Circular Economy Sectors.

NACE	NACE Description	Circular Economy Elements
6110	Wired telecommunications activities	Incorporate Digital Technology
6120	Wireless telecommunications activities	Incorporate Digital Technology
6130	Satellite telecommunications activities	Incorporate Digital Technology
6190	Other telecommunication activities	Incorporate Digital Technology
6311	Data processing, hosting and related activities	Incorporate Digital Technology
6312	Web portals	Incorporate Digital Technology
6391	News agency activities	Incorporate Digital Technology
6399	Other information service activities n.e.c	Incorporate Digital Technology
9101	Library and archives activities	Incorporate Digital Technology
6201	Computer programming activities	Incorporate Digital Technology
6202	Computer consultancy activities	Incorporate Digital Technology
6203	Computer facilities management activities	Incorporate Digital Technology
6209	Other information technology and computer service activities	Incorporate Digital Technology
7111	Architectural activities	Design for the Future
7112	Engineering activities and related technical consultancy	Design for the Future
7120	Technical testing and analysis	Design for the Future
7410	Specialised design activities	Design for the Future
9499	Activities of other membership organisations n.e.c.	Collaborate to Create Joint Value
9420	Trade union activities	Collaborate to Create Joint Value

Authors' elaboration based on Burger et al. (2019).

et al., 2011), occupations (Muneepeerakul et al., 2013) and skills (Alabdulkareem et al., 2018; Buyukyazici et al., 2024). Similarly, we employ a skill relatedness measure, based on Hidalgo et al. (2007) and Buyukyazici et al. (2024), to analyse the skill interdependencies within the CIs. In this regard, the skill relatedness between each pair of skills is defined as the minimum conditional probability of their co-occurrences in terms of effective use ($RSA > 1$) in industry classes as formulated below.

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

where effective use of skills denoted as $e(i,s) = 1$ if $RSA > 1$, and $e(i,s) = 0$ otherwise. The resulting matrix is the skill relatedness index of n industries located in region p at time t which contains proximities between all skill types. Each cell (s,s') indicates the probability that the industries located in region p at time t effectively use skill $s(s')$ when it also effectively utilises skill $s'(s)$. In other words, the skill relatedness score indicates which skills are more likely to be used together by industries.

In our method, skill relatedness is used to display and analyse the interdependencies between different skill types in terms of their usage by the core and enabling CIs. In doing so, we create two subsets of the binary RSA matrices ($573x161$), i.e. effective use matrices, for the core ($37x161$) and enabling ($19x161$) CIs by considering the related rows.[8] Then the skill relatedness formula is applied to the effective use matrices. As a result, we obtain 749+ 749 skill relatedness indexes for the core and enabling CIs each of which displays the skill interdependencies of them in region r at time t. One may conduct region-level analyses by using these matrices. For the global level analyses to construct the skill spaces of the CIs, we take element-wise averages of the skill relatedness matrices.[9]

4.4. Skill complexity

The economic complexity measure (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 have defined many varieties of economic complexity indices by using different data sources including trade flows, patents, employment numbers, and skills that serve various branches of the literature (Hidalgo, 2023). In the present study, we aim to assess the sophisticatedness level of the skills required by the CIs as a part of the method, thus, we employ a skill complexity measure based on Hidalgo and Hausmann (2009) and Buyukyazici et al. (2024).

Skill complexity is characterised by two components: diversity and ubiquity. In our measure, diversity ($K_{i,0}$) is the number of skills effectively used ($RSA > 1$) by industry i located in region p at time t. Ubiquity ($K_{s,0}$) is the number of industries within region p at time t that effectively use a particular skill s.

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

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

where $M_{i,s}$ is the effective use matrix, i.e. an adjacency matrix of industries and skills, resulting from the RSA formula as described above. Once defined, diversity and ubiquity are sequentially combined for $N \geq 1$ steps by iteratively calculating the average value of the properties at the previous level which is called the method of reflections (MOR). Accordingly, a skill has a high complexity score if it is effectively used by a relatively large number of industries (diversity) that effectively use a relatively rare set of skills (ubiquity).

Skill complexity accounts for the sophisticatedness level of skills in our method and is defined at the global level for all industries in the sample. In other words, the complexity value of skill s does not change across industries within a region in a specific time. Accordingly, skill complexity is computed by applying the MOR to 749 binary RSA matrices which yields a vector (1x161) of skill complexity for each region and year, summing up to 749 vectors. These vectors can be used for the region-level analyses. For the global level analyses, element-wise average is taken to define one global skill complexity vector which is displayed in Figure A1 in Appendix A.

5. Results

5.1. Preliminary insights from raw skills data

We first evaluate the skill usage patterns of the CIs by exploiting the raw skills data. Figs. 1 and 2 display the skill distributions of the CIs and non-CIs averaged for the observation period 2013–2019. The figures demonstrate 161 skill types available in the sample with the identification labels that can be traced in Table A2 in Appendix A. Since prior research has shown that workplace skills form two main clusters into technical-physical and cognitive-social skills (Alabdulkareem et al., 2018; Buyukyazici et al., 2024), the figures are sorted by those clusters to enhance the readability. Accordingly, the left-hand side of the figures displays the social-cognitive skill cluster while the right-hand side indicates the technical-physical skill cluster. Both clusters are unfolded in Table A3 in Appendix A. In addition, the skill scores are rescaled in each figure to be between 0 and 100 to better highlight the skill differences and to increase the comparability of the elements in the figure. Accordingly, the minimum (maximum) value in each figure demonstrates the minimum (maximum) skill score available in that figure.

The skill differences between the CIs – include both core and enabling CIs – and non-CIs are demonstrated in Fig. 1(a). The skill intensity scores of the CIs are represented with the blue line while those of the non-CIs are displayed with the red line. The left-hand side of the figure shows that the CIs have significantly higher values on social-cognitive skills. Especially, *(G19) Interacting With Computers* and *(B9) IT and Electronics* constitute the largest skill gap in favour of the CIs, followed by *(C17) Complex Problem Solving* and *(G12) Updating and Using Relevant Knowledge*. The right-hand side of the figure indicates that the CIs also have higher scores for technical and system skills such as *(C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C22) Programming*, and *(C29) Systems Analysis*. On the other hand, the non-CIs display higher scores on psychomotor and physical skills such as *(D23) Manual Dexterity, (D27) Response Orientation*, and *(D34) Dynamic Strength*.

Fig. 1(b) displays the skill differences between the core and enabling CIs. Given that the core and enabling CIs are based on different production activities that address different elements of circularity, it is expected to observe skill differences between them. Indeed, Fig. 1(b) exhibits larger differences between the core and enabling CIs than those of the CIs and non-CIs displayed in Fig. 1(a). Especially, the social-cognitive skills represented on the left-hand side of the figure are substantially higher for the enabling CIs. The largest skill differences are found for *(G19) Interacting With Computers, (B9) IT and Electronics, (C1) Reading Comprehension, (D4) Written Expression, (C8) Active Learning*, and *(G12) Updating and Using Relevant Knowledge* respectively. Regarding the technical-physical skill cluster presented on the right-hand side, the enabling CIs have higher scores for the majority of knowledge and technical skills while the core CIs are advantageable on the psychomotor and physical skills. Consequently, the preliminary analyses suggest that the enabling CIs are more knowledge-intensive than the core CIs and they rely on mostly social-cognitive skills and technical knowledge. In order to unpack these differences and better observe the skill usage patterns of the core and enabling CIs, we map their raw skill cores for each CE element. Fig. 2 displays the results.

Fig. 2(a) represents the four CE elements that compose the core CIs: *Use Waste as a Resource, Rethink the Business Model, Prioritise*

[8] One may question why we create the binary RSA matrices for the core and enabling CIs by subsetting the full binary RSA matrices which include all industries in the sample. The reason is that the RSA measure, as the name befits, is a relative measure that reveals skill advantages for an industry by taking into account the skill advantages of other industries in data. This is to say when we compute RSA values of the CIs together with all industries in the sample, we can make sure that the importance of skill s for a CI is calculated with respect to all other industries.

[9] Alternatively, one could take the element-wise averages of the input matrices to create one input matrix at the global level and apply the RSA and skill relatedness formulas to the global level input matrix to ease the computation process. Nevertheless, this alternative provides less precision than our method. Moreover, our method provides region-level information on the skill usage patterns and skill interdependencies within the CIs that pave the way for further region-level analyses.

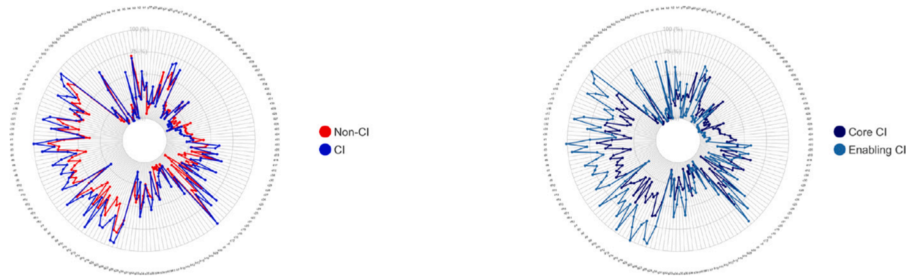
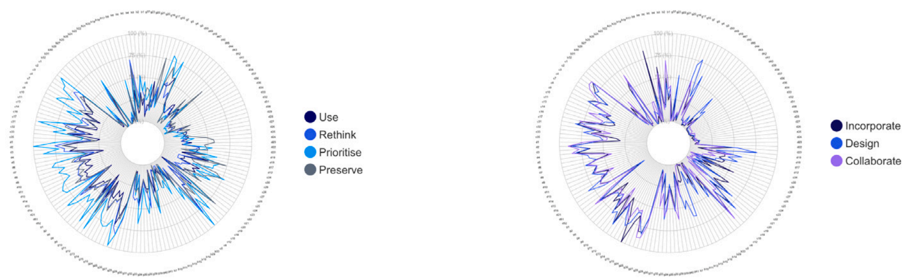


Fig. 1. **Distributions of Average Skill Intensity Scores by Non-circular and Circular Industries (2013–2019).** Fig. 1(a) shows the skill differences between non-circular (Non-CI) and circular industries (CI). Fig. 1(b) displays the differences between core circular industries (Core CI) and enabling circular industries (Enabling CI). Each dot and label on the charts represents a particular skill type that can be traced in Table A2 in Appendix A.



(a) (b)

Fig. 2. **Distributions of Average Skill Intensity Scores by the Elements of Core and Enabling Circular Industries (2013–2019).** Fig. 2(a) shows the skill differences among the four elements of core circular industries: *Use Waste as a Resource, Rethink the Business Model, Prioritise Regenerative Resources, Preserve and Extend What is Already Made*. Fig. 2(b) displays the differences among the three elements of enabling circular industries: *Incorporate Digital Technology, Design for the Future, Collaborate to Create Joint Value*. Each chart label represents a particular skill type that can be traced in Table A2.

Regenerative Resources, and *Preserve and Extend What is Already Made*. It is noticeable at first glance that the element *Prioritise Regenerative Resources*, represented with the light-blue line, has much higher scores for the majority of social-cognitive skills. It also has higher skill scores, though with less difference, for some portion of technical-physical skills such as technical knowledge. Correspondingly, *Prioritise Regenerative Resources* seems to be the most skill-intensive core CE element. The largest differences are, respectively, in the skills *(G19) Interacting With Computers, (G7) Evaluating Information to Determine Compliance with Standards*, and *(C17) Complex Problem Solving*. In contrast, the CE element *Use Waste as a Resource*, represented with the navy line, has the lowest skill scores almost for half of the skills available in the sample. However, it has higher scores for psychomotor, psychical, and sensory skills such as *(D28) Rate Control, (D29) Reaction Time*, and *(D34) Dynamic Strength,* while the largest skill differences with respect to other elements are for *(G20) Operating Vehicles, Mechanised Devices, or Equipment, (D18) Spatial Orientation,* and *(B33) Transportation* respectively. The core CE element *Rethink the Business Model*, which is represented with the blue line, has higher scores for some of the interacting skills such as *(G28) Establishing and Maintaining Interpersonal Relationships,* and *(G30) Selling or Influencing Others* while the highest skill differences compared to other elements are respectively for *(G39) Performing Administrative Activities, (G32) Performing for or Working in Directly with the Public,* and *(B4) Sales and Marketing.* When it comes to the last core CE element *Preserve and Extend What is Already Made*, represented with the grey line, it is advantageous in the technical-physical skill cluster on the right-hand side of the figure. It has higher scores on most of the technical and psychomotor skills and some of the physical skills while the highest scores with respect to other elements are respectively for the skills *(G17) Handling and Moving Objects, (C28) Repairing,* and *(D24) Finger Dexterity*.

Fig. 2(b) performs the same analysis for three elements of the enabling CIs: *Incorporate Digital Technology, Design for the Future,* and *Collaborate to Create Joint Value*. The figure indicates that the enabling CE elements have fewer human capital differences among them compared to the core CE elements. The obvious reason is the industry composition of the CE elements. As displayed in Tables 1 and 2, the core CIs are composed of a variety of sectors from a large spectrum of manufacturing and service industries while the enabling CIs are relatively homogeneous from service industries. Notwithstanding, several sharp differences are visible in Fig. 2(b). *Incorporate Digital Technology*, represented with the navy line, unsurprisingly has higher scores in technical and system skills. It has substantially higher scores for *(C22) Programming, (B9) IT and Electronics*, and *(G19) Interacting With Computers* with respect to other enabling CE elements. On the other hand, *Design for the Future*, represented by the blue line, scores higher in cognitive and resource management skills with the highest values for *(B12) Building and Construction, (D19) Visualisation,* and *(B11) Technical Design*. Lastly, *Collaborate to Create Joint Value*, represented with the purple line, exhibits higher values for the social-cognitive skill cluster with the highest comparative scores for *(C11) Social Perceptiveness, (G29) Assisting and Caring for Others,* and *(B2) Office Work.*

Overall, in line with previous empirical literature on green skills (Popp et al., 2020; Popp et al., 2024; Vona et al., 2015; Saussay et al., 2022), Figs. 1 and 2 signal that the CIs, both core and enabling, consist of diverse sectors that have heterogeneous human capital requirements. These preliminary findings are also supported by the exploratory regressions presented in Tables B1, B2, and B3 in Appendix A. Accordingly, the results suggest a more micro approach to different elements of circularity and underline the importance of granular analyses as an input to policies aiming at contrasting the adverse effects of the CE transition on labour markets. Nevertheless, the results presented in this section are rather descriptive and based on average raw skill scores. In what follows, we employ network methods and various metrics to unpack the skill content of the CIs to better document human capital differences of circularity.

Table 3
Top 20 Most Important Skills for Circular Industries.

Core CIs			Enabling CIs		
Skill	ICP Descriptor	Non-Bin. RSA	Skill	ICP Descriptor	Non-Bin. RSA
(B13) Mechanical	Knowledge	3.63	(C22) Programming	Technical Skills	3.95
(G22) Repairing and Maintaining Mechanical Equipment	Work Output	3.62	(B10) Engineering and Technology	Knowledge	3.71
(C28) Repairing	Technical Skills	3.47	(B11) Technical Design	Knowledge	3.60
(G23) Repairing and Maintaining Electronic Equipment	Work Output	3.42	(B15) Physics	Knowledge	2.70
(C26) Equipment Maintenance	Technical Skills	2.48	(G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment,	Work Output	2.66
(C27) Troubleshooting	Technical Skills	2.22	(C19) Technology Design	Technical Skills	2.62
(D25) Control Precision	Psychomotor	2.10	(B9) IT and Electronics	Knowledge	2.42
(G18) Controlling Machines and Processes	Work Output	2.07	(B12) Building and Construction	Knowledge	2.27
(C25) Operation and Control	Technical Skills	2.02	(C6) Science	Technical Skills	2.05
(G20) Operating Vehicles, Mechanised Devices, or Equipment	Work Output	2.00	(C30) Systems Evaluation	Technical Skills	1.99
(C21) Installation	Technical Skills	1.97	(C21) Installation	Technical Skills	1.91
(G4) Inspecting Equipment, Structures or Materials	Work Output	1.95	(B31) Telecommunications	Knowledge	1.91
(C24) Operation Monitoring	Technical Skills	1.85	(C18) Operations Analysis	Technical Skills	1.88
(D24) Finger Dexterity	Psychomotor	1.84	(C23) Quality Control Analysis	Technical Skills	1.88
(D41) Near Vision	Sensory	1.79	(C29) Systems Analysis	Technical Skills	1.85
(B15) Physics	Knowledge	1.76	(D12) Math Reasoning	Cognitive	1.82
(G3) Monitor Processes, Materials or Surroundings	Information Input	1.71	(C31) Judgement and Decision Making	Technical Skills	1.81
(C34) Management of Material Resources	Technical Skills	1.70	(G19) Interacting With Computers	Work Output	1.78
(D32) Static Strength	Psychical	1.64	(B14) Mathematics	Knowledge	1.71
(C29) Systems Analysis	Technical Skills	1.62	(G38) Provide Consultation and Advice to Others	Work Output	1.69

Note: The table reports the highest non-binary RSA scores as the most important skills for the core and enabling CIs.

5.2. Essential circular skills

The preliminary analyses above signal substantial differences between the skill requirements of the core and enabling CIs, thus, we conduct empirical analyses separately for them. We start by identifying the most important, i.e. effectively used, skills for the CIs based on the RSA approach defined in Section 4.2. Table 3 presents the results. The table is divided into two panels for the core and enabling CIs and each panel reports the top 20 most important skill types which are identified by considering the skills in which the respective CI has the highest non-binary RSA scores. A full list of workplace skills with the non-binary RSA scores by the CIs is provided in Table A4 in Appendix A. Regarding the core CIs, displayed in the first panel of the table, mechanical knowledge and related technical, psychomotor, and work output skills are the most important ones. On the other hand, the enabling CIs, presented in the second panel, display a more knowledge-intensive picture with various knowledge types including engineering, technical design, physics, and telecommunication which are supported by related technical skills.

Despite some skill types being more crucial to specific industries than other skills, every industry requires a skills spectrum that complements its essential skills. In this regard, every industry has a skill space formalising its unique skills spectrum. Industrial skill spaces embed important information on the skill usage patterns of industries, especially on the complementarity of skill pairs. Accordingly, it is useful to construct and analyse the skill spaces to unveil and document the skill requirements of the CIs. In the present study, we use skill relatedness (Section 4.3) and skill complexity (Section 4.4) measures to build the skill spaces of the core and enabling CIs. As defined above, skill relatedness quantifies the skill interdependencies between skill pairs by drawing on their effective usage patterns by industries. On the other hand, skill complexity uses dimension reduction techniques to quantify the sophisticatedness level of a skill based on its industrial usage patterns. These two metrics can be formalised as a one-mode skills network, which is called skill space, on which one can apply further analyses.

Fig. 3(a) maps the skill space of the core CIs for the period 2013–2019. Each node represents a particular skill type in the sample that is identified with a node label. Nodes are coloured by ICP descriptors that are unfolded in Table A2 in Appendix A. Edge lengths indicate skill relatedness between node pairs based on their usage by the core CIs. Accordingly, nodes closer to each other indicate a high degree of relatedness and signal that the core CIs are more likely to use those skills together. For visualisation purposes, the network is thresholded

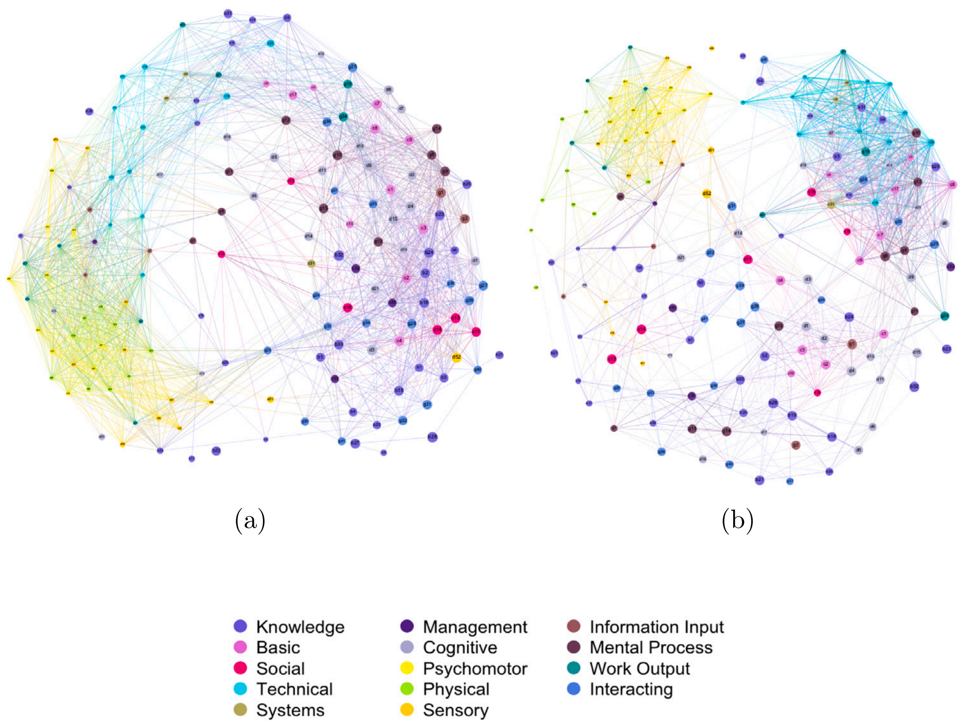


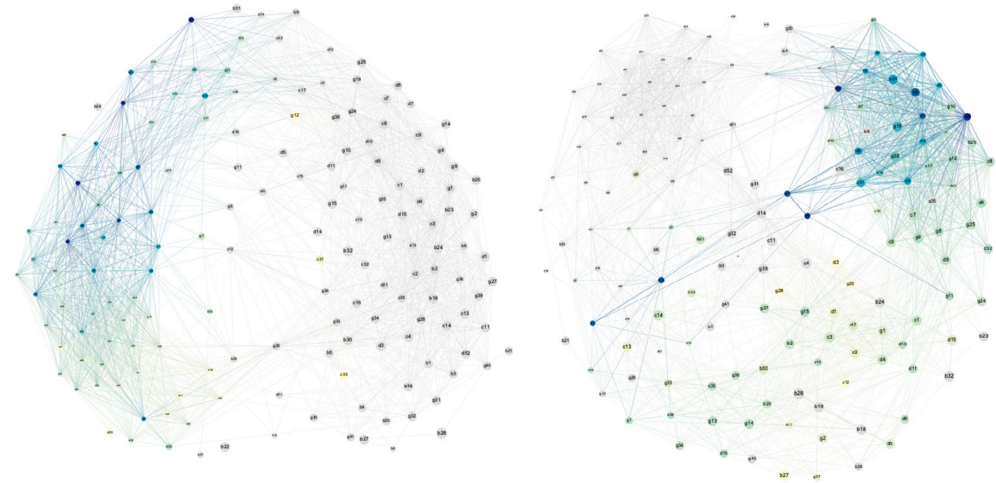
Fig. 3. The Skill Spaces of the Core (a) Enabling (b) Circular Industries (2013–2019). Nodes represent skills. The size of each node is proportional to the complexity level of the skill the node represents. Nodes are coloured to the subcategories of skills. Edge lengths show the degree of relatedness between skill pairs.

by keeping the edge weights higher than or equal to 0.55. Node sizes represent the complexity level of skills. Smaller nodes represent lower skill complexity while larger nodes indicate higher skill complexity. Based on this setting, Fig. 3(a) summarises the skill usage patterns of the core CIs. It is evident at first glance that skills tend to polarise into two clusters. On the left-hand side, physical, psychomotor, sensory, systems and technical skills are located with some knowledge components, coloured with purple, such as *(B7) Production and Processing, (B12) Building and Construction* and *(B33) Transportation*. This is to say that these skills tend to be used together by the core CIs. The right-hand side, on the other hand, locates a higher concentration of basic, social, management, interacting, knowledge and cognitive skills. These two clusters are bridged by some knowledge, technical, and cognitive skills that are highly related to both clusters such as *(B9) IT and Electronics, (B10) Engineering and Technology, (B31) Telecommunications, (C22) Programming, (C17) Complex Problem Solving, (D6) Originality* and *(D12) Math Reasoning*. The evidence of skills polarisation in the core CIs seems therefore to reinforce the observed trend featuring the digital transformation and, to a lower extent, the green transition (Autor et al., 2003; Consoli et al., 2016).

In order to complete the picture, Fig. 4(a) projects the skills in which the core CIs have skill advantage ($RSA > 1$) into the skill space of the core CIs by using coloured nodes while other skills are coloured grey. The non-binary RSA scores are used in the graphs to provide information on the gradual importance of skills to the CIs. In other words, the importance of skills for the respective CIs increases from light-coloured to dark-coloured nodes. The full ranking of the non-binary RSA scores is provided in Table A4 in Appendix A. Accordingly, the core CIs effectively use the skills on the left-hand side of the skill space, mostly belonging to the technical-physical skill cluster. These skills are also less complex than the ones on the right-hand side. If we look at the skills which each core CI element effectively uses, a more heterogeneous picture arises. Fig. 5 demonstrates that elements *Use Waste as a Resource* and *Preserve and Extend What is Already Made* effectively use the skills on the technical-physical skill cluster. In contrast, *Rethink the Business Model* and *Prioritise Regenerative Resources* differ. *Rethink the Business Model* effectively uses psychomotor and physical skills on the left-hand side alongside social and interacting skills related to *(B1) Administration and Management, (B2) Office Work,* and *(B3) Economics and Accounting* knowledge on the right-hand side. *Prioritise Regenerative Resources* effectively uses knowledge components such as *(B9) IT and Electronics, (B10) Engineering and Technology,* and *(B14) Mathematics* together with closely related cognitive (*(D8) Deductive Reasoning, (D12) Math Reasoning*), technical (*(C18) Operations Analysis, (C22) Programming*), and work output (*(G19) Interacting With Computers*) skills. The skill usage patterns of the core CIs summarised here are also reflected in the skill communities detected by the Louvain method (Blondel et al., 2008) as demonstrated in Figure A2 and unfolded in Table A5 in Appendix A.

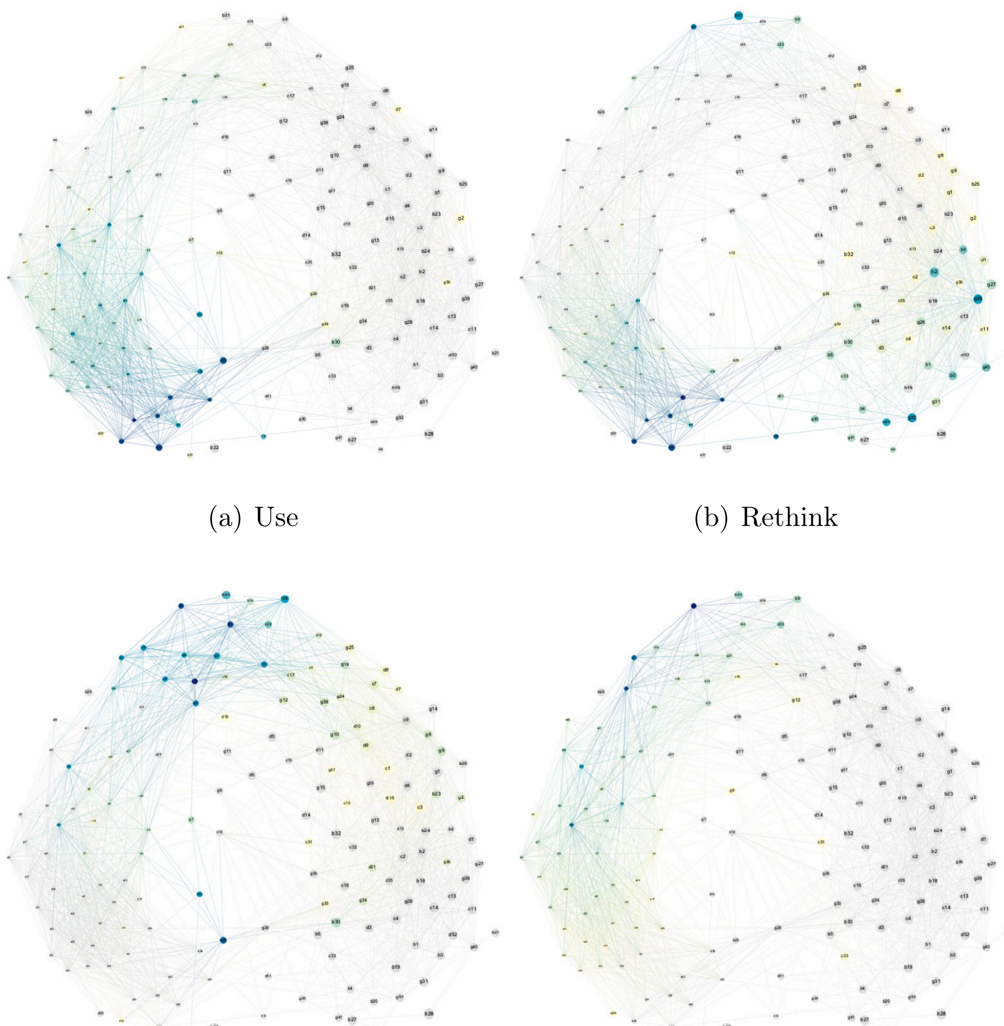
Fig. 3(b) maps the skill space of enabling CIs for the period 2013–2019 by using the same methodological setting as Fig. 3(a). Differently from the core CIs, the skill space of enabling CIs does not form two polarised skill clusters into social-cognitive and technical-physical skills. For instance, technical skills are not closely used with physical and psychomotor skills as in the core CIs skill space. Technical skills are effectively used together with system and mental process skills alongside the knowledge on *(B5) Services to Customers, (B9) IT and Electronics, (B10) Engineering and Technology, (B14) Mathematics,* and *(B31) Telecommunications* that form a somewhat isolated cluster on the top-right part of the network. This result suggests that the enabling CIs are more complex and knowledge-intensive than the core CIs. Fig. 4(b) supports this argument by showing that enabling CIs effectively use more complex skills and a high share of knowledge types that are generally located on the right-hand side of the network.

Fig. 6 displays the skills in which the elements of the enabling CIs have RSA. Each of the three elements effectively uses a large share of complex and knowledge-intensive skills that are mostly located on the right-hand side of the skill space. Nevertheless, the elements *Design for the Future* and *Collaborate to Create Joint Value* effectively use knowledge components that are less technical than the element *Incorporate Digital Technology*. These patterns are also reflected in the detected skill communities presented in Figure A3 and Table A.6 in Appendix A.



(a) (b)

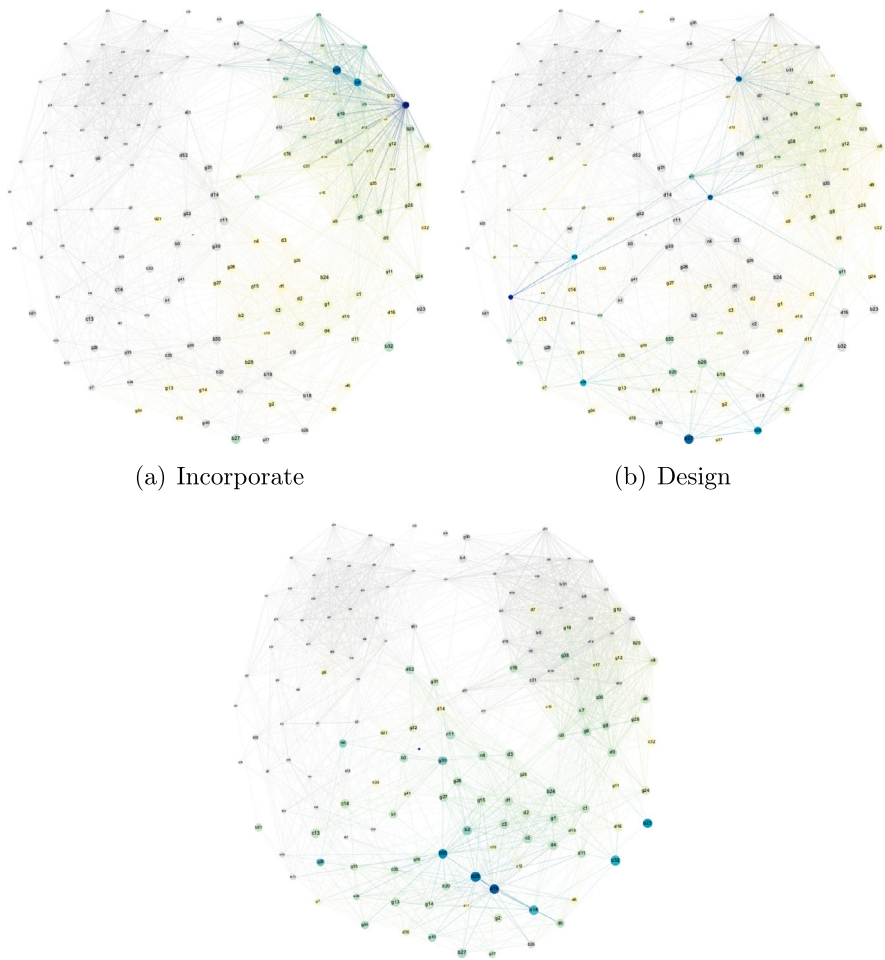
Fig. 4. Skills in which Core (a) and Enabling (b) Circular Industries have Relative Advantage. Coloured nodes indicate the essential skills ($RSA > 1$) while the grey nodes indicate other skills ($RSA \leq 1$). The importance of skills for the respective CIs increases from light-coloured to dark-coloured nodes.



(a) Use (b) Rethink

(c) Prioritise (d) Preserve

Fig. 5. Skills in which the elements of core circular industries have relative advantage.



(a) Incorporate (b) Design

(c) Collaborate

Fig. 6. Skills in which the elements of enabling circular industries have relative advantage.

5.3. Complementary circular skills

The skill composition of industries roughly consists of (1) essential skills required to perform basic production activities, i.e. the most important skills for the industry or the skills in which the industry has RSA, and (2) complementary skills the industry requires to accompany its essential skills. The identification of complementary skills highlights the intricate relationship between essential and complementary skills, emphasising the need for a holistic skill spectrum to effectively operate within the CE.

Complementary skills are expected to be a mix of industry-specific skills and generic skills such as soft skills and digital skills. The exact composition of complementary skills for a specific industry, just as essential skills, can only be identified by employing an industry-specific approach since each industry has a unique spectrum of diverse occupations and tasks that demand particular skill portfolios. In this regard, we employ a data-driven approach to identify complementary skills of the core and enabling CIs by also considering their CE elements. As a first step, we depart from the skill spaces of the core (Fig. 3(a)) and enabling (Fig. 3(b)) CIs and define two skill groups as *essential skills*, i.e. the skills in which the CIs have RSA, and *other skills* as highlighted in Fig. 4. In the second step, we calculate the average weighted degree (AWD) of each node, i.e. skill, by considering intra-edges between the identified two skill groups. AWD is a useful indicator to assess the complementarity of a particular skill since it is simply the sum of the edge weights of a node. In our case, the AWD of a node is the sum of the skill relatedness values between the skill the node represents and the rest of the skills that belong to the opposite skill group. If a skill has a high AWD, it means that the skill is effectively used together with many skills, signalling high complementarity. An important aspect of our methodology is that we calculate AWD by considering intra-edges between essential skills and other skills because we are mainly interested in identifying the skills that complement the essential skills. Intra-edges are simply the skill relatedness values between essential and other skills without considering the skill relatedness values within the groups of essential and other skills. For instance, the skill relatedness value between a skill pair that belongs to the other skills group is not considered since the industry does not have RSA in any of these skills.

As the third step, we rank the AWD scores of skills to identify the skills with the highest AWD as complementary skills. Lastly, we exclude the complementary skills that belong to the essential skills group to identify the skills that are complementary only to the essential skills. The reason behind the last step is that since we consider intra-edges to calculate AWD, the complementary score of an essential skill indicates its usage patterns with the other skills group. In this case, that essential skill is complementary to the other skills group. This four-step methodology is separately applied to the core and enabling CIs as well as to their seven CE elements by considering their essential skills that are displayed in Figs. 4, 5, 6.

Based on the above-mentioned methodology, Table 4 presents the top five complementary skills for the core (panel 1) and enabling (panel 2) CIs as well as for their CE elements. The complementary skills for each industry are ranked by their AWD values. The full ranking of complementary skills by their AWD values is presented in Tables A7

Table 4
Complementary Skills for Core and Enabling Circular Industries.

Core CIs		Enabling CIs	
CE Element	Complementary Skills	CE Element	Complementary Skills
All	(D36) Stamina, (D42) Far Vision, (B29) Civil Protection and Public Safety, (C18) Operations Analysis, (D51) Speech Recognition	All	(C16) Service Orientation, (G35) Training and Teaching Others, (B5) Services to Customers, (D14) Memorisation, (B19) Sociology and Anthropology
Use	(D30) Wrist-Finger Speed, (C20) Equipment Selection, (B7) Production and Processing, (G29) Assisting and Caring for Others, (D22) Arms-Hand Steadiness	Incorporate	(D13) Number Facility, (D14) Memorisation, (C25) Operation and Control, (B30) Legislation and Institutions, (B19) Sociology and Anthropology
Rethink	(G29) Assisting and Caring for Others, (D4) Written Expression, (G16) Performing General Physical Activities, (D15) Speed of Closure, (B24) Italian Language	Design	(C16) Service Orientation, (G35) Training and Teaching Others, (C15) Instructing, (B5) Services to Customers, (D14) Memorisation
Prioritise	(C15) Instructing, (D2) Written Comprehension, (D4) Written Expression, (C9) Learning Strategies, (G35) Training and Teaching Others	Collaborate	(B5) Services to Customers, (D51) Speech Recognition, (D13) Number Facility, (D32) Static Strength, (D20) Selective Attention
Preserve	(D33) Explosive Strength, (D36) Stamina, (D16) Flexibility of Closure, (C15) Instructing, (C5) Mathematics		

and A8 in Appendix A. The results show that physical and sensory skills constitute a substantial part of the complementary skills for the core CIs. Inspecting the complementary skills in Fig. 4(a) affirms that they are in a very close relationship with the essential skills cluster. Regarding the CE elements, *Prioritise Regenerative Resources* significantly differs from other core CE elements as it requires cognitive and basic skills related to instructing, learning, and training. The primary reason might be that on-the-job training is more important for *Prioritise Regenerative Resources* than for other CE sectors and the rest of the economy as shown by Burger et al. (2019). Hence, the skills related to vocational training become preeminent as complementary skills. Regarding the complementary skills for the enabling CIs, service-related skills, such as *(C16) Service Orientation* and *(B5) Services to Customers*, come forward alongside cognitive skills such as *(D14) Memorisation, (D13) Number Facility*, and *(D20) Selective Attention*.

6. Discussion and concluding remarks

Enhancing the understanding of the skills required by the CIs is crucial to harnessing the job creation potential associated with the CE transition as well as aligning the workforce with the evolving needs of these industries, fostering economic growth, innovation, and sustainable employment within national and regional economies. In this regard, the present study introduces a bottom-up and data-driven methodology based on the RSA, skill relatedness, and skill complexity measures to identify the essential and complementary skills of the core and enabling CIs as well as their elements.

The results, briefly summarised in Table 5, provide valuable insights into the skill landscape of the CIs, highlighting the diverse skill requirements and emphasising the importance of human capital in driving the CE transitions. One of the most salient observations throughout the analysis is the heterogeneity of the skill requirements within the CIs. Since the CE is a concept that refers to various economic activities, it relates to diverse industries that demand different human capital and skills. Therefore, our analysis emphasises the inadequacy of holistic approaches and underscores the importance of a nuanced approach to understanding human capital dynamics within the CE.

Overall, the analyses above reveal that the core CIs prioritise mechanical proficiency and physical and psychomotor skills, reflecting the labour-intensive composition of waste management, repair, and maintenance activities. The reliance of the core CIs on relatively less complex and ubiquitous skills provides an opportunity for low-skilled displaced workers due to recent advancements in automation and digitalisation. With not much up-skilling and re-skilling,[10] these workers can be transferred to waste management, re-use, and repair sectors which are expected to create more jobs in the near future (European Commission, 2018; International Labour Office, 2018). The RSR method provided in this paper can also be used to define the skill sets to be acquired for such a transfer by comparing the essential skills of the prior industry and the next industry. Moreover, the regional analysis shows that low-income regions can possess a workforce highly endowed with core circular skills. Accordingly, these regions may easily specialise in the core CIs with guided policy-making since they possess the required capabilities, presenting a prospective development path. However, it should be kept in mind that the recent advancements in automation and robotics may change the near-future labour intensities, thereby, the skill sets of the CIs. Therefore, the skill content of the CIs should be monitored across years with dynamic models to meet the requirements of the CE transition as well as to ensure well-informed industrial and regional policy-making.

In contrast to the core CIs, the enabling CIs place greater emphasis on knowledge-intensive highly complex skills, aligning with their role in facilitating circular processes and innovation. These differences are also visible in the regional distribution of their skills. The divergence between the skill requirements of the core and enabling CIs reflects their distinct roles in the CE. The core CIs are responsible for conducting the circular activities, such as collect, recycle, repair, reuse and maintain, while the enabling CIs design and create the circular knowledge. In this regard, in a circular body metaphor, the core CIs would be the arms while the enabling CIs are the head. Hence, policymakers and stakeholders must ensure the coordination between these two organs to facilitate the transition to a more CE. Moreover, adequate support to the enabling CIs to create the circular knowledge that facilitates circular activities would also induce a higher circularity in the non-CIs in terms of their waste management, material use, and

[10] The grey and the academic literature largely agrees on the fact that the circular transition would require less re-skilling and up-skilling than other ongoing transitions such as automation and digitalisation (European Commission, 2018; International Labour Office, 2018; Vona, 2023; Popp et al., 2024).

Table 5
Circular Skills: Summary of Key Findings.

• The CIs consist of diverse economic activities that require heterogeneous skill sets (see Tables 1 and 2). Therefore, highly granular analyses are needed.
• The CIs, overall, are more dependent on social-cognitive skills than the non-CIs. Especially, *(G19) Interacting With Computers* and *(B9) IT and Electronics* constitute the largest skill gap in favour of the CIs, followed by *(C17) Complex Problem Solving* and *(G12) Updating and Using Relevant Knowledge* (see Fig. 1(a) and Tables B2 and B3 in the Appendix).
• The CIs also have higher scores than the non-CIs for technical and system skills such as *(C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C22) Programming*, and *(C29) Systems Analysis* (see Fig. 1(a) and Tables B2 and B3 in the Appendix).
• The diversity of the CIs is reflected in the skill requirements of the core and enabling CIs. The core CIs mostly require technical-physical skills (such as mechanical knowledge and related technical, psychomotor, and work output skills) while the enabling CIs rely on social-cognitive skills (i.e., various knowledge types including engineering, technical design, physics, and telecommunication which are supported by related technical skills) (see Table 3 and Fig. 4). These patterns do not change according to the income level of regions (see Table B3 in the Appendix).
• The enabling CIs are more skill-complex and knowledge-intensive than the core CIs as they use various sophisticated skills together (see Fig. 4).
• The defined skill set of the core CIs is highly correlated with the technical-physical skill cluster (0.988) while negatively correlated with social-cognitive skills (−0.219). Conversely, the skill set of the enabling CIs is strongly correlated with social-cognitive skills (0.926) and weakly correlated with technical-physical skills (0.160) (see Table B1 in the Appendix).
• Another layer of heterogeneity is unveiled with consideration of the CE elements that compose the core (*Use, Rethink, Prioritise,* and *Preserve*) and enabling (*Incorporate, Design,* and *Collaborate*) CIs. The defined skill set of each CE element is unique, underlining the inadequacy of holistic approaches to the CE (see Figs. 5, 6 and Tables B2, B3 in the Appendix).

equipment maintenance which might result in increased demand for the core CIs. This process might create an important development path for low-income and left-behind regions that possess sufficient levels of core circular skills.

Analysing the skill requirements of the CIs with a reproducible and dynamic empirical method conveys substantial policy implications. Having a clear understanding of the skills required in the CIs can guide the development of supportive policies, such as subsidies for training programs or tax incentives for sustainable businesses. Furthermore, identifying the skills required in the CIs may facilitate collaboration among industries, educational institutions, training providers, civil society, and government agencies. It allows to development of targeted training and initiatives that can efficiently meet industry needs, thus, helping to take necessary measures, by re-skilling and up-skilling, to mitigate job losses in resource-intensive sectors and to bridge the skill gap of workforce to transfer to the CIs.

The present study, like any other, is not free from limitations. Due to methodological and data limitations, we consider the CE from a production point of view by using industry codes defined as *circular*. However, the transition from a linear economy to a CE is expected to have implications and impacts on all industries given that the transition process is not confined to particular industries. The CE concept entails a more general philosophy that covers also private and industrial consumption patterns. For instance, we do not possess any data or method to analyse what types of skills are required for individuals and firms to adopt more circular practices regarding their waste management and material use. Hence, we follow the existing practice (Burger et al., 2019) and define some industries more *circular* than others if they produce goods and services for the circular practices of households and other industries. Second significant limitation is that the latest date the skills data (ICP survey) is available is 2013. Hence, we create the main dataset by using the changes in the occupational distributions within industries and regions across years. However, the skill content of occupations might have been changed during our time frame since the last decade has witnessed significant technological change including industry 4.0, digital and green transition. Due to unavailability of recent skills data, we are not able to quantify this aspect and have to leave it to a further study. Another possible limitation is that the present study is based on one country, Italy. It should be kept in mind that the required circular skills might change across years from country to country depending on the general development level, technological endowments, industrial portfolio, and the level of CE transition. Correspondingly, a cross-country study is needed to validate the results.

CRediT authorship contribution statement

Duygu Buyukyazici: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Quatraro:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organisation or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing Arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Appendix A. Additional tables and figures

See Tables A.6–A.13 and Figs. A.7–A.9.

Appendix B. Skill differences between circular and non-circular industries

The present study analyses the skill requirements of the CIs and defines their skill sets. Another useful practice is looking deeper at the skill differences between the CIs and non-CIs to better portray the skill requirements of the CIs. Descriptive analyses in Section 5.1 signal that there might be significant skill differences between them, yet

Table A.6
Circular Industries: Correspondence Table.

NAICS	NAICS Description	NACE	NACE Description
221300	Water, sewage and other systems	3600	Water collection, treatment and supply
		3700	Sewerage
562100	Waste collection	3811	Collection of non-hazardous waste
		3812	Collection of hazardous waste
562200	Waste treatment and disposal	3821	Treatment and disposal of non-hazardous waste
		3822	Treatment and disposal of hazardous waste
		3831	Dismantling of wrecks
		3832	Recovery of sorted materials
562900	Remediation and other waste management services	3900	Remediation activities and other waste management services
532100	Automotive equipment rental and leasing	7711	Renting and leasing of cars and light motor vehicles
		7712	Renting and leasing of trucks
532200	Consumer goods rental	7721	Renting and leasing of recreational and sports goods
		7722	Renting of video tapes and disks
		7729	Renting and leasing of other personal and household goods
532300	General rental centres		No correspondence
532400	Commercial and industrial machinery and equipment rental and leasing	7731	Renting and leasing of agricultural machinery and equipment
		7732	Renting and leasing of construction and civil engineering machinery and equipment
		7733	Renting and leasing of office machinery and equipment (including computers)
		7734	Renting and leasing of water transport equipment
		7735	Renting and leasing of air transport equipment
		7739	Renting and leasing of other machinery, equipment and tangible goods n.e.c.
533000	Lessors of nonfinancial intangible assets (except copyrighted works)	7740	Leasing of intellectual property and similar products, except copyrighted works
22110X	Electric power generation: hydroelectric, wind, solar, biomass and geothermal	3511	Production of electricity
453300	Used merchandise stores	4779	Retail sale of second-hand goods in stores
811110	Automotive mechanical and electrical repair and maintenance	4520	Maintenance and repair of motor vehicles
811120	Automotive body, paint, interior, and glass repair	4520	Maintenance and repair of motor vehicles
811190	Other automotive repair and maintenance	4520	Maintenance and repair of motor vehicles
811200	Electronic and precision equipment repair and maintenance	3313	Repair of electronic and optical equipment
		3314	Repair of electrical equipment
		9511	Repair of computers and peripheral equipment
		9512	Repair of communication equipment
		9521	Repair of consumer electronics
811300	Commercial and industrial machinery and equipment repair and maintenance	3311	Repair of fabricated metal products
		3312	Repair and maintenance of machinery
		3319	Repair of other equipment

Continuation of Table A1

NAICS	NAICS Description	NACE	NACE Description
811400	Personal and household goods repair and maintenance	9522	Repair of household appliances and home and garden equipment
		9523	Repair of footwear and leather goods
		9524	Repair of furniture and home furnishings
		9525	Repair of watches, clocks and jewellery
		9529	Repair of other personal and household goods
517100	Wired telecommunications carriers	6110	Wired telecommunications activities
517200	Wireless telecommunications carriers (except satellite)	6120	Wireless telecommunications activities
517400	Satellite telecommunications	6130	Satellite telecommunications activities
517900	Other telecommunications	6190	Other telecommunication activities
518000	Data processing, hosting and related services	6311	Data processing, hosting and related activities
		6312	Web portals
519000	Other information services	6391	News agency activities
		6399	Other information service activities n.e.c
		9101	Library and archives activities
541500	Computer systems design and related services	6201	Computer programming activities
		6202	Computer consultancy activities
		6203	Computer facilities management activities
		6209	Other information technology and computer service activities
541330	Architectural and engineering services	7111	Architectural activities
		7112	Engineering activities and related technical consultancy
541380	Testing laboratories	7120	Technical testing and analysis
541400	Specialised design services	7410	Specialised design activities
813300	Social advocacy organisations	9499	Activities of other membership organisations n.e.c.
813400	Civic and social organisations	9499	Activities of other membership organisations n.e.c.
813930	Labor unions and similar labour organisations	9420	Trade union activities

Note: Authors' elaboration based on Burger et al. (2019).

Table A.7
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

Author's own elaboration on ICP 2013 and O*NET data descriptors.

they are based on aggregated sums which might hinder some granular information. Therefore, further exploration by also incorporating the regional dimension may be useful to complement our analyses. In doing so, we consider the technical-physical and social-cognitive skill clusters (Table A.8), as we do in Section 5.1, since the existing literature shows that workplace skills form these main clusters in terms of their usage patterns by industries (Buyukyazici et al., 2024). In addition, the core and enabling circular skill sets are highly correlated to these clusters as shown in Table B.1.

Based on the motivation above, we define two dependent variables to account for technical-physical ($Technical\_Physical_{i,p}$) and social-cognitive ($Social\_Cognitive_{i,p}$) skills level of industries and regions by taking the average of the intensity values of skills belong to each cluster. The CIs and their elements are captured with ten dummy variables (see the vector $\mathbf{X}_{i,p}$ below) that take the value 1 if the industry in question is a CI and take the value zero if the industry is a non-CI. Based on this setting, we estimate the following model with OLS to briefly analyse the main skill differences between the CIs and non-CIs.

$$Y_{i,p} = \beta_0 + \beta_1 \mathbf{X}^{0,1}_{i,p} + \rho_p + \varepsilon_{i,p}$$

Table A.8
Skill Clusters.

Cluster 1: Social-Cognitive	Critical Thinking, Active Learning, Active Listening, Administration and Management, Analysing Data or Information, Assisting and Caring for Others, Category Flexibility, Communicating with Persons Outside Organisation, Communicating with Supervisors, Peers, or Subordinates, Communication and Media, Complex Problem Solving, Coordinating the Work and Activities of Others, Deductive Reasoning, Developing Objectives and Strategies, Developing and Building Teams, Documenting/Recording Information Economics and Accounting, Education and Training, Establishing and Maintaining Interpersonal Relationships, Fine Arts, Flexibility of Closure, Fluency of Ideas, Food Production, Foreign Language, Geography, Getting Information, Guiding, Directing, and Motivating Subordinates, History and Archaeology, Human Resources Management, IT and Electronics, Identifying Objects, Actions, and Events, Inductive Reasoning, Information Ordering, Instructing, Interacting with Computers, Interpreting the Meaning of the Information for Others, Italian Language, Judging the Qualities of Things, Services or People, Judgement and Decision Making, Learning Strategies, Legislation and Institutions, Making Decisions and Solving Problems, Management of Financial Resources, Management of Personnel Resources, Medicine and Dentistry, Memorisation, Monitoring, Monitoring and Controlling Resources, Negotiation, Number Facility, Office Work, Oral Comprehension, Oral Expression, Organising, Planning, and Prioritising Work, Originality, Performing Administrative Activities, Performing for or Working in Directly with the Public, Persuasion, Philosophy and Theology, Problem Sensitivity, Processing Information, Provide Consultation and Advice to Others, Psychology, Reading Comprehension, Resolving Conflicts and Negotiating with Others, Sales and Marketing, Scheduling Work and Activities, Selling or Influencing Others, Service Orientation, Services to Customers, Social Perceptiveness, Sociology and Anthropology, Speaking, Speech Clarity, Speech Recognition, Speed of Closure, Staffing Organisational Units, Telecommunications, Therapy and Counseling, Thinking Creatively, Time Management, Time Sharing, Training and Teaching Others, Updating and Using Relevant Knowledge, Writing, Written Comprehension, Written expression
Cluster 2: Technical-Physical	Mathematics, Science, Biology, Building and Construction, Arms-Hand Steadiness, Auditory Attention, Chemistry, Civil Protection and Public Safety, Control Precision, Controlling Machines and Processes, Coordination, Depth Perception, Drafting, Laying Out, and Specifying Technical Devices Parts and Equipment, Dynamic Flexibility, Dynamic Strength, Engineering and Technology, Equipment Maintenance, Equipment Selection, Estimate the Quantifiable Characteristics of Products, Events or Information, Evaluating Information to Determine Compliance with Standards, Explosive Strength, Extent Flexibility, Far Vision, Finger Dexterity, Glare Sensitivity, Gross Balance Body Equilibrium, Gross Body Coordination, Handling and Moving Objects, Hearing Sensitivity, Inspecting Equipment, Structures or Material, Installation, Management of Material Resources, Manual Dexterity, Math Reasoning, Mathematics, Mechanics, Monitor Processes, Materials or Surroundings, Multilimb Coordination, Near Vision, Night Vision, Operating Vehicles, Mechanised Devices, or Equipment, Operation Monitoring, Operation and Control, Operations Analysis, Perceptual Speed, Performing General Physical Activities, Peripheral Vision, Physics, Production and Processing, Programming, Quality Control Analysis, Rate Control, Reaction Time, Repairing, Repairing and Maintaining Electronic Equipment, Repairing and Maintaining Mechanical Equipment, Response Orientation, Selective Attention, Sound Localisation, Spatial Orientation, Speed of Limb Movement, Stamina, Static Strength, Systems Analysis, Systems Evaluation, Technical Design, Technology Design, Train and Nurture Other People, Transportation, Troubleshooting, Trunk Strength, Visual Colour Discrimination, Visualisation, Wrist-Finger Speed

Notes: Detected skill clusters, by the Louvain algorithm, of industrial skill usage patterns. Based on Buyukyazici et al. (2024).

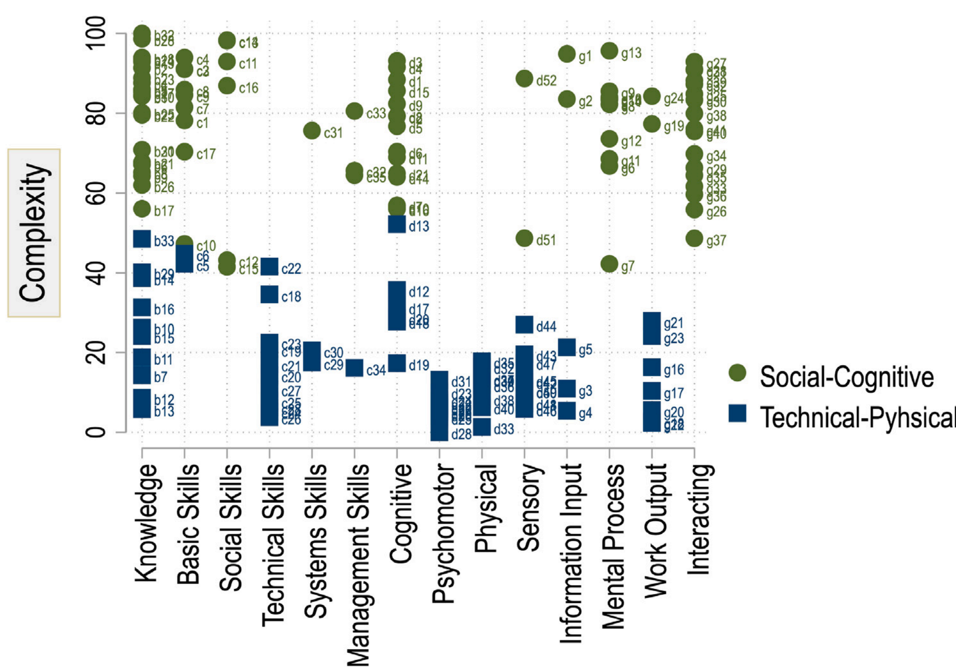

Fig. A.7. Complexity scores of skills.

$$Y_{i,p} = [Technical\_Physical_{i,p},\ Social\_Cognitive_{i,p}]$$

$$\mathbf{X}_{i,p} = [Circular_{i,p},\ Core_{i,p},\ Enabling_{i,p},\ Use_{i,p},\ Rethink_{i,p},\ Prioritise_{i,p},\ Preserve_{i,p},\ Incorporate_{i,p},\ Design_{i,p},\ Collaborate_{i,p}]$$

where i represents industry, p is region, and ρ_p is region fixed effects. We start with industry-level analysis by eliminating the regional dimension to observe industries' global tendencies and provide a benchmark to the industry-region level analyses. Table B.2 displays the results. The first four columns report the analyses for the technical-physical skill cluster while the last four columns present the social-cognitive skill cluster. Columns 1 and 5 signal that the CIs have higher skill intensity values than the non-CIs for both skill clusters. The picture changes when we look at the core and enabling CIs separately in Columns 2 and 6. The core CIs have higher skill intensity values for the technical-physical skills and less for the social-cognitive skills than the rest of the economy. This pattern more or less holds when we look at the

Table A.9
Non-Binary RSA Scores of Skills by Circular Industries.

Skill	Core	Enabling	Use	Rethink	Prioritise	Preserve	Incorporate	Design	Collaborate
B1	.	.	.	1.24	.	.	.	.	1.35
B2	.	1.24	.	1.33	.	.	1.20	.	1.83
B3	.	.	.	1.30	.	.	.	.	1.54
B4	.	.	.	1.24	.	.	.	.	.
B5	.	.	.	1.25	.	.	1.04	.	.
B6	.	.	.	1.30	.	.	.	.	1.82
B7	1.59	1.21	.	.	.	1.09	.	1.06	.
B8	.	.	.	1.19	.	.	.	.	.
B9	.	2.42	.	1.19	1.76	1.75	4.06	1.32	.
B10	1.26	3.72	1.13	.	2.84	1.66	2.59	4.51	.
B11	1.35	3.60	.	.	2.05	1.80	1.71	4.90	.
B12	.	2.27	1.64	1.66	.	.	.	8.79	.
B13	3.63	.	1.23	.	1.81	2.28	.	.	.
B14	.	1.71	.	.	1.28	.	1.21	1.54	.
B15	1.76	2.70	1.52	.	3.55	1.52	.	3.51	.
B16	1.25	1.34	1.78	.	1.81	.	.	1.91	.
B17	.	.	1.11	.	.	.	.	1.71	.
B18	.	.	.	.	.	.	.	.	2.01
B19	.	.	.	.	.	.	.	1.44	3.35
B20	.	1.23	.	1.37	.	.	.	2.39	1.44
B21	.	.	.	.	.	.	.	.	1.33
B22	.	.	.	.	.	.	.	.	4.75
B23	.	.	.	.	1.15	.	.	.	2.17
B24	.	.	.	.	.	.	1.24	.	1.52
B25	.	1.43	.	1.03	.	.	1.68	1.27	1.22
B26	.	.	.	.	.	.	.	3.36	.
B27	.	1.06	.	.	.	.	2.00	4.66	1.69
B28	.	.	.	.	.	.	1.23	1.63	2.61
B29	.	1.56	2.30	1.06	2.20	.	.	3.16	1.47
B30	.	1.13	1.26	1.15	1.35	.	.	1.70	2.35
B31	.	1.91	.	1.44	1.65	1.92	4.70	.	.
B32	.	.	.	1.01	.	.	1.97	.	2.07
B33	1.39	.	2.85	1.87	.	.	.	.	.
C1	.	1.24	.	.	1.01	.	1.24	1.09	1.36
C2	.	1.13	.	1.02	.	.	1.24	.	1.49
C3	.	1.22	.	1.01	1.02	.	1.25	1.11	1.48
C4	.	.	.	1.01	.	.	1.04	.	1.48
C5	.	1.52	.	.	1.09	.	1.14	1.20	.
C6	.	2.05	1.10	.	1.87	1.03	1.53	2.14	.
C7	.	1.35	.	.	1.11	.	1.37	1.17	1.33
C8	.	1.40	.	.	1.08	.	1.36	1.19	1.25
C9	.	1.23	.	.	.	.	1.21	1.07	1.33
C10	.	1.32	.	.	1.00	.	1.01	1.07	1.16
C11	.	.	.	1.02	.	.	.	.	1.59
C12	.	1.05	1.09	1.02	.	.	.	.	1.20
C13	.	1.10	.	.	.	.	.	1.05	1.35
C14	.	1.22	.	1.04	.	.	.	1.04	1.30
C15	.	1.15	.	.	.	.	1.10	.	1.10
C16	.	.	.	1.11	.	.	1.23	.	1.38
C17	.	1.55	.	.	1.15	.	1.31	1.19	1.21
C18	.	1.88	.	.	1.15	1.02	1.36	1.37	.
C19	1.40	2.62	.	.	1.83	1.72	2.51	1.90	.
C20	1.57	1.58	.	.	1.11	1.47	1.21	1.14	.
C21	1.97	1.91	1.01	1.13	1.87	2.97	2.73	.	.
C22	.	3.95	.	1.26	1.57	1.92	9.50	1.32	.
C23	1.43	1.88	.	.	.	1.35	1.49	1.02	.
C24	1.85	.	1.64	.	1.25	1.14	.	.	.
C25	2.02	.	1.41	.	1.28	1.38	.	.	.
C26	2.48	.	1.76	1.04	1.23	2.11	.	.	.
C27	2.22	1.34	1.39	.	1.48	1.78	1.44	.	.
C28	3.47	.	1.51	1.15	1.62	3.71	.	.	.
C29	1.62	1.85	1.22	.	1.78	1.41	1.57	1.10	.

(*continued on next page*)

CE elements of the core CIs in Columns 3 and 7. *Use, Prioritise,* and *Preserve* have higher values for the technical-physical skills than the non-CIs. *Use* and *Preserve* have lower values for the social-cognitive skills while *Prioritise* has higher values. *Rethink* is insignificant for both clusters. Columns 4 and 8 consider the CE elements of the enabling CIs. All elements have higher skill intensity values for the social-cognitive skills and lower values for the technical-physical skills than the non-CIs, except for *Design* which has higher values for both skill clusters.

Table B.3 reports the same model with regional dimensions. The first three columns display the results for the technical-physical skill cluster while the last three columns show the social-cognitive skill cluster. All specifications are estimated separately for all (Columns 1 and 4), lagging (Columns 2 and 5), and leading (Columns 3 and 6) regions. Panel 1 shows that the CIs overall have higher skill intensity

Table A.9 (*continued*).

Continuation of Table A4

Skill	Core	Enabling	Use	Rethink	Prioritise	Preserve	Incorporate	Design	Collaborate
C30	1.58	1.99	1.22	.	1.85	1.32	1.74	1.15	.
C31	1.07	1.81	.	.	1.04	1.06	1.17	1.19	.
C32	.	1.50	.	.	.	.	1.03	1.07	1.07
C33	1.01	1.16	.	1.13	.	1.04	.	1.11	1.12
C34	1.70	.	1.23	.	1.03	1.48	.	1.03	.
C35	.	1.34	.	1.04	.	.	.	1.29	1.42
D1	.	1.11	.	1.06	.	.	1.09	.	1.39
D2	.	1.17	.	1.01	.	.	1.17	1.00	1.29
D3	.	1.01	.	1.06	.	.	1.06	.	1.40
D4	.	1.22	.	.	.	.	1.22	1.11	1.41
D5	.	1.17	.	.	.	.	1.08	1.31	1.36
D6	.	1.24	.	.	.	.	1.15	1.51	1.11
D7	.	1.46	1.01	.	1.07	.	1.13	.	1.16
D8	.	1.43	.	1.00	1.06	.	1.24	1.13	1.31
D9	.	1.27	.	.	1.08	.	1.30	1.16	1.38
D10	.	1.32	.	.	1.10	.	1.26	1.08	1.29
D11	.	1.35	.	.	.	.	1.30	1.19	1.35
D12	.	1.82	.	.	1.15	.	1.45	1.39	.
D13	.	1.22	.	1.05	.	.	.	1.01	.
D14	.	.	.	.	.	.	.	.	1.11
D15	.	1.14	.	.	1.03	.	1.12	.	1.16
D16	.	1.36	.	.	1.00	.	1.08	1.23	1.17
D17	.	1.10	.	.	.	.	.	1.17	1.09
D18	1.04	.	1.88	1.27	.	.	.	1.10	.
D19	1.19	1.21	1.18	.	.	1.17	.	1.71	.
D20	1.03	1.25	1.05	.	.	1.03	1.12	1.10	.
D21	.	1.25	.	.	1.14	.	1.05	1.09	1.15
D22	1.43	.	.	.	.	1.73	.	.	.
D23	1.46	.	1.05	.	.	1.53	.	.	.
D24	1.84	.	.	.	.	1.99	.	.	.
D25	2.10	.	1.16	.	.	1.72	.	.	.
D26	1.33	.	1.43	1.14	.	1.34	.	.	.
D27	1.31	.	1.26	1.25	.	1.14	.	.	.
D28	1.50	.	1.53	1.21	.	1.12	.	.	.
D29	1.32	.	1.60	1.16	.	1.03	.	.	.
D30	1.38	.	.	.	.	1.50	.	.	.
D31	1.04	.	1.21	1.07	.	1.05	.	.	.
D32	1.64	.	1.69	1.07	.	1.36	.	.	.
D33	1.11	.	1.66	1.20	.	.	.	.	.
D34	1.50	.	1.57	.	.	1.17	.	.	.
D35	1.16	.	1.33	1.05	.	1.13	.	.	.
D36	.	.	1.38	1.11	.	.	.	.	.
D37	1.53	.	1.37	1.08	.	1.49	.	.	.
D38	1.51	.	1.65	1.07	.	1.35	.	.	.
D39	1.22	.	1.43	1.06	.	1.17	.	.	.
D40	1.17	.	1.45	1.33	.	1.21	.	.	.
D41	1.79	.	.	.	.	1.70	.	.	.
D42	.	.	1.76	1.34	.	.	.	1.00	.
D43	1.15	.	.	.	.	1.33	.	1.27	.
D44	1.20	.	2.78	1.86	1.02	.	.	.	.
D45	1.04	.	2.49	1.84	.	.	.	.	.
D46	1.13	.	2.32	1.78	.	.	.	.	.
D47	1.02	.	2.47	2.35	.	.	.	.	.
D48	1.29	.	1.59	1.34	1.03	1.12	.	.	.
D49	1.17	.	1.55	1.28	.	1.05	.	.	.
D50	1.31	.	1.65	1.35	.	1.14	.	.	.
D51	.	.	.	1.17	.	.	.	.	.
D52	.	.	.	.	.	.	.	.	1.43
G1	.	1.15	.	1.04	.	.	1.20	1.08	1.44
G2	.	1.13	1.02	1.00	1.14	.	1.15	1.09	1.29
G3	1.71	1.22	1.44	.	1.29	1.15	.	1.16	.
G4	1.95	.	1.57	.	1.17	1.46	.	.	.
G5	1.55	1.47	1.00	.	1.12	1.26	.	1.34	.

(*continued on next page*)

Table A.9 (*continued*).

Continuation of Table A4

Skill	Core	Enabling	Use	Rethink	Prioritise	Preserve	Incorporate	Design	Collaborate
G6	.	1.18	.	.	.	1.01	.	1.10	1.14
G7	1.20	1.44	1.17	.	1.28	.	.	1.31	1.14
G8	.	1.45	.	1.01	1.16	.	1.56	1.20	1.36
G9	.	1.50	.	1.03	1.18	.	1.60	1.24	1.50
G10	.	1.53	.	.	1.16	.	1.25	1.20	1.20
G11	.	1.42	.	.	.	.	1.38	1.86	1.13
G12	1.02	1.58	.	.	1.13	1.07	1.39	1.26	1.14
G13	.	1.37	.	.	.	.	1.15	1.21	1.44
G14	.	1.40	.	.	.	.	1.06	1.18	1.34
G15	.	1.45	.	.	.	.	1.15	1.24	1.34
G16	1.17	.	1.38	.	.	1.06	.	.	.
G17	1.61	.	1.02	.	.	1.51	.	.	.
G18	2.07	.	1.17	.	.	1.20	.	.	.
G19	.	1.78	.	1.02	1.26	.	2.14	1.41	1.27
G20	2.00	.	3.52	1.75	.	.	.	.	.
G21	1.52	2.66	1.21	.	1.80	1.48	1.47	2.63	.
G22	3.62	.	1.83	1.05	1.71	2.78	.	.	.
G23	3.42	1.46	1.02	1.53	2.77	5.61	2.48	.	.
G24	.	1.23	.	.	1.11	.	1.41	1.03	1.22
G25	.	1.27	.	.	1.05	.	1.33	1.11	1.26
G26	.	1.03	1.10	1.04	.	.	1.07	.	1.26
G27	.	1.23	.	1.23	.	.	1.16	1.05	1.35
G28	.	1.02	.	1.12	.	.	1.09	.	1.36
G29	.	.	.	.	.	.	.	.	1.94
G30	.	.	.	1.27	.	.	.	.	.
G31	.	.	.	1.08	.	.	.	.	1.31
G32	.	.	.	1.44	.	.	.	.	1.22
G33	.	1.18	1.06	1.01	1.03	.	.	1.14	1.31
G34	.	1.23	.	.	1.14	.	1.03	1.12	1.58
G35	.	.	.	.	.	.	1.08	.	1.37
G36	.	1.26	1.01	1.01	1.11	.	.	1.12	1.36
G37	.	1.11	.	.	1.03	.	.	1.04	1.33
G38	.	1.69	.	.	1.16	.	1.43	1.31	1.49
G39	.	.	.	1.44	.	.	.	.	1.87
G40	.	.	.	1.31	.	.	.	.	1.71
G41	.	.	.	1.20	.	.	.	.	1.24

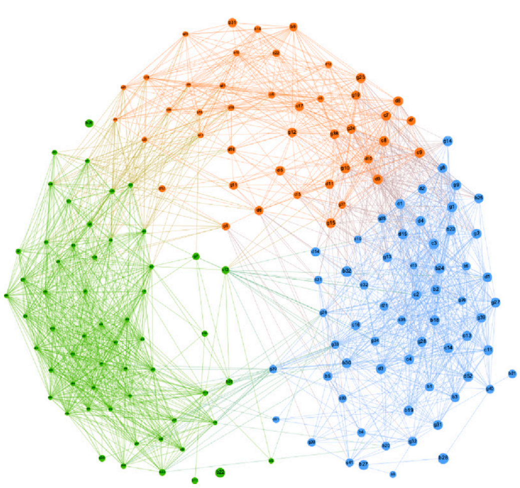

Fig. A.8. Detected skill communities of the core circular industries.

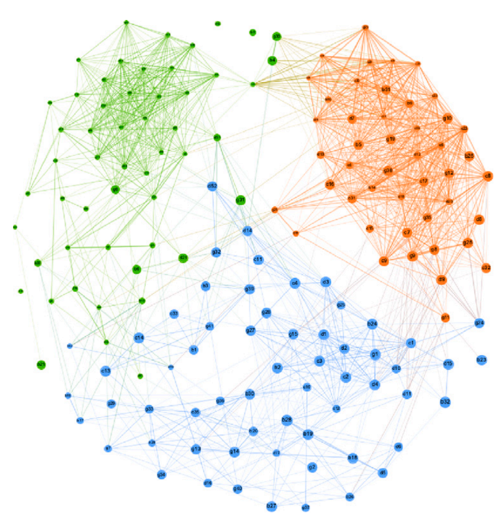

Fig. A.9. Detected skill communities of the enabling circular industries.

values in every type of region for both skill clusters. Panel 2 considers the core and enabling CIs separately. The core CIs have higher values for technical-physical skills and lower values for social-cognitive skills in every type of region. Differently from Table B.2, the enabling CIs have higher values than the rest of the economy for technical-physical skills in lagging regions while no difference is captured for leading regions. They have higher values for social-cognitive skills in every type of region. Panel 3 reports the CE elements of the core CIs and Panel 4 exhibits the CE elements of the enabling CIs. The overall results are similar to Table B.2. *Use* and *Preserve* have higher values for technical-physical skills and lower values for the social-cognitive skills while *Prioritise* has higher values for both clusters and *Rethink* is not significantly different from the rest of the economy in every type of region. Regarding the CE elements of the enabling CIs, *Incorporate* and *Collaborate* have higher skill intensities for social-cognitive skills and lower values for technical-physical skills while *Design* has higher values for both skill clusters in every type of region. These results suggest that

Table A.10
Skill Communities of the Core Circular Industries.

Community 1:	(B1) Administration and Management, (B2) Office Work, (B3) Economics and Accounting, (B4) Sales and Marketing, (B5) Services to Customers, (B6) Human Resources Management, (B8) Food Production, (B18) Psychology, (B19) Sociology and Anthropology, (B20) Geography, (B21) Medicine and Dentistry, (B23) Education and Training, (B24) Italian Language, (B25) Foreign Language, (B27) History and Archaeology, (B28) Philosophy and Theology, (B30) Legislation and Institutions, (B32) Communication and Media, (C1) Reading Comprehension, (C2) Active Listening, (C3) Writing, (C4) Speaking, (C10) Monitoring, (C11) Social Perceptiveness, (C13) Persuasion, (C14) Negotiation, (C16) Service Orientation, (C31) Judgement and Decision Making (C32) Time Management, (C33) Management of Financial Resources, (C35) Management of Personnel Resources (D1) Oral Comprehension, (D2) Written Comprehension, (D3) Oral Expression, (D4) Written Expression, (D13) Number Facility, (D14) Memorisation, (D15) Speed of Closure, (D21) Time Sharing, (D51) Speech Recognition, (D52) Speech Clarity, (G1) Getting Information, (G2) Identifying Objects, Actions, and Events, (G8) Processing Information, (G9) Analysing Data or Information, (G13) Developing Objectives and Strategies, (G14) Scheduling Work and Activities, (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, (G39) Performing Administrative Activities, (G40) Staffing Organisational Units, (G41) Monitoring and Controlling Resources
Community 2:	(B9) IT and Electronics, (B10) Engineering and Technology, (B11) Technical Design, (B14) Mathematics, (B15) Physics, (B31) Telecommunications, (C5) Mathematics, (C6) Science, (C7) Critical Thinking, (C8) Active Learning, (C9) Learning Strategies, (C15) Instructing, (C17) Complex Problem Solving, (C18) Operations Analysis, (C19) Technology Design, (C21) Installation, (C22) Programming, (C23) Quality Control Analysis, (C28) Repairing, (C29) Systems Analysis, (C30) Systems Evaluation, (D5) Fluency of Ideas, (D6) Originality, (D7) Problem Sensitivity, (D8) Deductive Reasoning, (D9) Inductive Reasoning, (D10) Information Ordering, (D11) Category Flexibility, (D12) Math Reasoning, (D16) Flexibility of Closure, (D17) Perceptual Speed, (G6) Judging the Qualities of Things, Services or People, (G10) Making Decisions and Solving Problems, (G11) Thinking Creatively, (G12) Updating and Using Relevant Knowledge, (G15) Organising, Planning, and Prioritising Work, (G19) Interacting With Computers, (G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment, (G23) Repairing and Maintaining Electronic Equipment, (G24) Documenting/Recording Information, (G25) Interpreting the Meaning of the Information for Others, (G37) Train and Nurture Other People, (G38) Provide Consultation and Advice to Others
Community 3	(B7) Production and Processing, (B12) Building and Construction, (B13) Mechanical, (B16) Chemistry, (B17) Biology, (B22) Therapy and Counseling, (B26) Fine Arts, (B29) Civil Protection and Public Safety, (B33) Transportation, (C12) Coordination, (C20) Equipment Selection, (C22) Programming, (C24) Operation Monitoring, (C25) Operation and Control, (C27) Troubleshooting, (C34) Management of Material Resources, (D18) Spatial Orientation, (D19) Visualisation, (D20)Selective Attention, (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, (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 (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, (G3) Monitor Processes, Materials or Surroundings, (G4) Inspecting Equipment, Structures or Material, (G5) Estimate the Quantifiable Characteristics of Products, Events, or Information, (G7) Evaluating Information to Determine Compliance with Standards, (G16) Performing General Physical Activities, (G17) Handling and Moving Objects, (G18) Controlling Machines and Processes, (G20) Operating Vehicles, Mechanised Devices, or Equipment, (G22) Repairing and Maintaining Mechanical Equipment

sectoral heterogeneity should be considered by differentiating different elements of the CE when analysing their skill requirements. However, once sectoral heterogeneity is accounted for, general skill patterns mostly hold in every type of region. At this point, it is important to underline that the analyses in this section are very preliminary and must be interpreted as mere correlations. Future studies should develop more parsimonious models to account for endogeneity and further confounding factors.

Appendix C. A regional perspective

The skill requirements of the CIs have a strong regional aspect that has hardly been addressed in the literature so far, mainly due to the lack of adequate data and methods (Bianchi et al., 2023). As underlined above, the method proposed in this study paves the way to empirically assess regional circular skills. Nevertheless, here we only explore the regional distribution of the essential circular skills and leave further regional analyses to future studies for the sake of brevity. Fig. C.10 presents the essential skills distribution of the core C.10(a) and enabling C.10(b) circular skills. Regional circular skills' level indicates the weighted average – by industry employment – value of the essential circular skills available in the region's industry mix for the period 2013–2019. The figures show that regions have a high value either in the core or enabling skills. On the other hand, some upper central and northern regions can have medium-level values in both core and enabling circular skills. Given that core circular skills are mostly low-complex technical-physical skills, they are found in abundance in many of the Italian regions some of which are known as low-income regions. Contrastingly, the enabling circular skills are accumulated mostly in high-income regions such as Rome, Milan, Bologna and northern Italy since they are relatively more complex and knowledge-intensive.

In order to empirically validate these findings, we perform a brief regression analysis presented in Table B.4. The dependent variables are the average core and enabling circular skills level of industry-region pairs for the period 2013–2019. The independent variable (*Leading*) is a dummy indicating the high-income and low-income regions in Italy. The regions that have GDP per capita on the third and fourth quartiles of income distribution are defined as leading regions (*Leading*= 1); while the ones on the first and second quartiles are lagging regions (*Leading*= 0). Column 1 reports the differences in core circular skills within regional industry mixes of leading and lagging regions. Column 2 presents the same analyses for enabling circular skills. The results

Table A.11
Skill Communities of the Enabling Circular Industries.

Community 1:	(B1) Administration and Management, (B2) Office Work, (B3) Economics and Accounting, (B12) Building and Construction, (B16) Chemistry, (B17) Biology, (B18) Psychology, (B19) Sociology and Anthropology, (B20) Geography, (B22) Therapy and Counseling, (B23) Education and Training, (B24) Italian Language, (B26) Fine Arts, (B27) History and Archaeology, (B28) Philosophy and Theology, (B29) Civil Protection and Public Safety, (B30) Legislation and Institutions, (B32) Communication and Media, (C1) Reading Comprehension, (C2) Active Listening, (C3) Writing, (C4) Speaking, (C10) Monitoring, (C11) Social Perceptiveness, (C12) Coordination, (C13) Persuasion, (C14) Negotiation, (C33) Management of Financial Resources, (C35) Management of Personnel Resources, (D1) Oral Comprehension, (D2) Written Comprehension, (D3) Oral Expression, (D4) Written Expression, (D5) Fluency of Ideas, (D6) Originality, (D10) Information Ordering, (D11) Category Flexibility, (D14) Memorisation, (D15) Speed of Closure, (D16) Flexibility of Closure, (D17) Perceptual Speed, (D19) Visualisation, (D52) Speech Clarity, (G1) Getting Information, (G2) Identifying Objects, Actions, and Events, (G7) Evaluating Information to Determine Compliance with Standards, (G13) Developing Objectives and Strategies, (G14) Scheduling Work and Activities, (G15) Organising, Planning, and Prioritising Work, (G24) Documenting/Recording Information, (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, (G32) Performing for or Working in Directly with the Public, (G33) Coordinating the Work and Activities of Others, (G34) Developing and Building Teams, (G36) Guiding, Directing, and Motivating Subordinates, (G37) Train and Nurture Other People, (G39) Performing Administrative Activities, (G40) Staffing Organisational Units, (G41) Monitoring and Controlling Resources
Community 2:	(B4) Sales and Marketing, (B6) Human Resources Management, (B7) Production and Processing, (B8) Food Production, (B13) Mechanical, (B15) Physics, (B21) Medicine and Dentistry, (B33) Transportation, (C24) Operation Monitoring, (C34) Management of Material Resources, (D18) Spatial Orientation, (D21) Time Sharing, (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 (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 (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, (G3) Monitor Processes, Materials or Surroundings, (G4) Inspecting Equipment, Structures or Material, (G5) Estimate the Quantifiable Characteristics of Products, Events, or Information (G6) Judging the Qualities of Things, Services or People, (G16) Performing General Physical Activities, (G17) Handling and Moving Objects, (G18) Controlling Machines and Processes, (G20) Operating Vehicles, Mechanised Devices, or Equipment, (G22) Repairing and Maintaining Mechanical Equipment, (G30) Selling or Influencing Others, (G31) Resolving Conflicts and Negotiating with Others
Community 3	(B5) Services to Customers, (B9) IT and Electronics, (B10) Engineering and Technology, (B11) Technical Design, (B14) Mathematics, (B25) Foreign Language, (B31) Telecommunications, (C5) Mathematics, (C6) Science, (C7) Critical Thinking, (C8) Active Learning, (C9) Learning Strategies, (C15) Instructing, (C16) Service Orientation (C17) Complex Problem Solving, (C18) Operations Analysis, (C19) Technology Design, (C20) Equipment Selection, (C21) Installation, (C22) Programming, (C23) Quality Control Analysis, (C25) Operation and Control, (C26) Equipment Maintenance, (C27) Troubleshooting, (C28) Repairing, (C29) Systems Analysis, (C30) Systems Evaluation, (C31) Judgement and Decision Making (C32) Time Management, (D7) Problem Sensitivity, (D8) Deductive Reasoning, (D9) Inductive Reasoning, (D12) Math Reasoning, (D13) Number Facility, (D20) Selective Attention, (G8) Processing Information, (G9) Analysing Data or Information, (G10) Making Decisions and Solving Problems, (G11) Thinking Creatively, (G12) Updating and Using Relevant Knowledge, (G19) Interacting With Computers, (G21) Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment, (G23) Repairing and Maintaining Electronic Equipment, (G25) Interpreting the Meaning of the Information for Others, (G35) Training and Teaching Others, (G38) Provide Consultation and Advice to Others, (G39) Performing Administrative Activities

Table A.12
Complementary Skills of the Core Circular Industries.

Core CIs		Use		Rethink		Prioritise		Preserve	
Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD
D36	34.35	D30	29.27	G29	35.88	C15	30.9	D33	29.25
D42	27	C20	28.9	D4	34.34	D2	29.62	D36	29.04
B29	25.72	B7	28.17	G16	33.98	D4	28.98	D16	25.14
C18	25.58	G29	27.83	D15	33.86	C9	28.64	C15	23.15
D51	24.76	D22	27.63	B24	33.65	G35	28.54	C5	23.01
C12	24.38	D51	26.38	D21	33.37	G1	27.84	D18	22.93
G6	24	D24	24.85	B18	33.27	G15	27.36	B16	22.8
D16	23.84	D41	24.79	C1	33.04	C23	27.28	G7	22.58
C15	23.7	B22	24.43	B23	32.87	G14	26.75	D14	21.99
C6	23.67	G37	24.26	B19	32.64	D11	26.54	D12	21.79
G29	23.35	C15	24.21	G34	32.61	D14	26.4	D51	21.65
G37	22.71	G34	24.08	D34	32.46	B25	26.17	G37	21.42
C5	22.44	C10	23.84	G35	31.94	C2	25.67	B14	21.4
D14	22.13	D4	23.72	C32	31.78	D5	25.52	D17	21.37
D7	21.98	D3	23.52	C13	31.46	C12	25.29	D7	21.27
G33	21.78	C3	23.15	C10	31.45	C32	25.25	B29	21.11
B17	21.77	B11	23.03	D52	31.07	B24	25.25	C17	21
D17	21.48	C2	22.9	C24	30.12	D13	25.12	D42	20.81
B22	21.38	C18	22.86	D14	30.07	G13	25.03	C12	20.79
C10	21.12	C23	22.7	D9	29.75	G26	24.79	G11	20.49
G26	21.07	C35	22.65	G37	29.67	D6	24.63	D6	20.24
D12	20.95	C19	22.59	G10	28.98	B2	24.53	G24	20.23
C32	20.72	D21	22.47	B22	28.73	G11	24.41	D45	20.07
D4	20.4	C32	22.25	G24	28.69	C35	24.41	D47	19.79
B14	20.25	C1	22.25	D19	28.55	D1	24.26	G20	19.42
B12	20.22	D15	22.22	C15	28.48	B6	24.09	D10	19.4
D15	20.14	G35	22.14	G3	28.47	B18	23.67	C10	19.35
G35	19.88	C5	21.83	C25	28.35	D25	23.52	D15	19.28
D3	19.84	D2	21.67	G4	28.26	D41	23.44	G10	19.26
C2	19.84	C4	21.34	G14	28.25	G16	23.15	C32	19.09
B30	19.68	B23	21.25	C31	28.05	D50	22.7	G15	19.05
D10	19.56	D43	21.19	C9	27.95	C16	22.63	D46	18.94
G34	19.53	D14	21.03	D10	27.94	B32	22.56	C16	18.83
G24	19.52	D16	20.87	G13	27.81	D3	21.85	D5	18.8
C3	19.26	D10	20.8	D20	27.81	G27	21.84	B33	18.62
C16	19.16	D1	20.73	C5	27.44	D35	21.84	G35	18.46
C17	19.14	B2	20.56	D23	27.39	G39	21.79	G29	18.39
C1	18.94	D12	20.53	B28	27.36	D40	21.61	D4	18.31
C35	18.36	G24	20.34	B16	26.91	C4	21.59	G14	18.28
D2	18.35	B19	20.29	G7	26.76	G18	21.52	D44	18.25
G11	18.27	G6	20.25	G15	26.63	G28	21.49	D11	18.2
B23	18.21	B20	20.02	G18	26.54	G6	21.46	B17	18.12
D21	18.19	G31	19.96	C7	26.35	D33	21.45	G33	17.87
G14	18.17	B14	19.95	D7	26.3	D24	21.44	D8	17.84
G2	18.15	D52	19.66	G5	26.17	G29	21.38	B22	17.8
D6	18.1	G39	19.31	B17	25.72	D51	21.29	C2	17.76
G10	18.04	B18	19.25	C8	25.41	C13	21.14	G25	17.52
G36	17.93	B24	19.11	G17	25.35	D49	21.06	C7	17.46
G15	17.92	B6	19.08	D11	25.3	C14	20.95	C1	17.42
D1	17.56	C16	18.66	G6	25.28	D32	20.92	G26	17.26
C4	17.3	C11	18.63	C6	25.11	D52	20.68	C9	17.05
G31	17.29	C9	18.62	G12	24.74	D27	20.66	D2	16.97
D8	17.26	C31	18.58	C27	24.64	C11	20.53	C3	16.89
C9	17.08	D17	18.55	D12	24.63	D18	20.42	C8	16.62
D5	17.07	C17	18.52	G25	24.46	D26	20.29	D9	16.62
D52	17.02	D8	18.34	D25	24.43	D37	20.26	G2	16.58

(*continued on next page*)

Table A.12 (*continued*).

Continuation of Table A7

Core CIs		**Use**		**Rethink**		**Prioritise**		**Preserve**	
Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD
B2	16.92	G8	18.26	C34	24.34	D38	20.26	D3	16.56
B19	16.84	G12	18.24	D16	24.29	B7	20.2	B12	16.49
D11	16.54	G14	18.2	G38	24.14	D31	20.08	B23	16.49
C7	16.45	G10	17.62	C29	24.04	B17	20.06	B5	16.26
B28	16.45	G1	17.58	B21	23.58	B5	20.03	G34	16.02
B9	16.43	D13	17.3	C17	23.47	D39	19.91	B30	16
B18	16.37	D9	17.21	B15	23.33	D29	19.87	G19	15.97
G25	16.24	C7	17.08	D6	23.25	B12	19.82	D1	15.65
B24	16.13	B3	16.94	C30	22.65	B19	19.7	D13	15.35
B6	16.02	G9	16.89	G21	22.65	D17	19.65	C35	15.25
D9	16.02	B28	16.84	D5	22.49	D36	19.56	G28	15.24
G39	15.95	G25	16.72	B14	22.45	D22	19.49	B26	15.21
B5	15.89	G15	16.66	C20	22.07	G40	19.3	G38	15.09
D13	15.86	C13	16.3	B7	22.06	G31	19.2	G41	15.04
G28	15.84	G28	16.29	B27	21.98	D23	19.09	D21	15.01
B20	15.77	G27	16.11	D17	21.86	D20	19.08	G36	14.88
G41	15.53	C8	15.78	C18	21.42	G17	18.97	G8	14.88
G8	15.33	G40	15.47	D22	21.33	D28	18.94	B28	14.85
C8	15.32	C14	15.22	B10	21.04	B3	18.87	B2	14.8
B26	15.19	B25	15.18	B13	20.91	D34	18.83	B24	14.75
C11	14.97	C33	15.05	C23	20.79	D19	18.37	B25	14.64
G30	14.96	D11	15	G11	20.69	B22	18.09	G31	14.6
B4	14.76	B21	14.74	D30	20.55	D43	17.73	B18	14.6
G40	14.64	D5	14.66	C19	20.13	B1	17.55	D52	14.55
B27	14.56	G19	14.65	B11	19.82	B33	17.08	G30	14.44
G1	14.52	D6	14.55	D43	18.65	B20	16.99	B32	14.42
B25	14.38	G11	14.52	D41	17.68	D46	16.91	B6	14.3
C13	14.35	B32	14.35	D24	17.1	D45	16.77	C4	14.2
G19	14.33	B9	14.32	B26	11.13	D47	16.75	B4	14.05
B32	14.3	B5	14.25			D30	16.73	B27	13.97
G27	14.18	G41	14.15			D42	16.67	B19	13.9
C14	13.98	B27	14.13			C33	16.49	G40	13.82
G9	13.8	G13	13.82			B28	16.4	G1	13.74
B3	13.71	B4	13.69			B21	15.91	G13	13.68
G13	13.22	G38	13.41			B27	15.62	G39	13.66
G38	13.22	G30	13.27			G41	15.49	C14	13.36
C22	12.9	B1	13.25			B4	15.24	C13	13.22
B21	12.31	G32	12.19			G20	14.66	G9	13.13
B31	12.23	B8	11.96			G32	14.01	G27	13.1
G32	12.22	B26	11.57			G30	12.99	C11	12.47
B1	12.21	C22	11.13			B8	10.95	B20	11.84
B8	11.43	B31	10.29			B26	9.19	G32	11.44
								B1	11.32
								B3	11.31
								B21	10.34
								B8	9.94

Table A.13
Complementary Skills of the Enabling Circular Industries.

Enabling CIs		Incorporate		Design		Collaborate	
Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD
C16	41.13	D13	33.06	C16	36.65	B5	33.75
G35	39.08	D14	31.00	G35	34.99	D51	30.08
B5	38.02	C25	29.74	C15	34.33	D13	29.22
D14	33.88	B30	27.74	B5	32.86	D32	28.78
B19	32.18	B19	27.09	D14	30.36	D20	28.39
B28	32.18	C12	26.68	G26	29.32	D44	27.38
B24	32.12	C28	26.28	B1	28.89	D47	26.87
B1	31.13	C26	26.28	B24	28.70	C31	26.02
C25	30.85	G36	25.60	D7	28.00	C18	25.84
G39	30.38	G39	25.28	G28	27.93	D36	25.58
C4	30.17	B18	24.37	C12	27.92	D35	25.58
D2	29.22	B1	24.35	G39	27.70	D37	25.51
G41	28.91	B20	24.25	C27	27.68	B14	25.24
B18	28.59	C35	24.20	B18	27.61	D49	25.17
B6	28.32	D52	24.00	G40	27.45	B33	24.96
G40	28.09	C11	23.71	B31	27.01	B26	24.89
B23	27.94	B23	23.63	C25	26.87	C19	24.77

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Table A.13 (*continued*).

Enabling CIs		Incorporate		Design		Collaborate	
Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD
C28	27.92	G41	23.62	G41	26.83	D39	24.31
C26	27.92	D17	23.46	B6	26.82	G22	24.27
D52	27.09	B4	23.40	D1	26.09	B16	23.96
C11	26.92	G30	23.40	B23	25.90	B17	23.96
G32	26.75	G32	23.30	C4	25.86	D12	23.78
D44	26.37	G40	23.23	D3	25.63	C5	23.78
C34	26.32	G31	23.21	C2	25.59	D18	23.54
D18	26.09	B3	22.29	D46	25.31	D42	23.54
B33	26.02	B6	22.02	C21	25.18	B9	23.04
D42	25.92	G33	22.00	D15	25.16	C27	23.04
D32	25.88	D32	21.73	D44	25.16	B31	22.98
B26	25.68	D51	21.65	D47	25.16	D45	22.73
G31	25.56	C33	21.60	B33	25.16	G30	22.37
B3	25.12	G6	21.54	D32	24.38	B4	22.37
B32	25.07	B26	21.49	B2	24.19	C23	22.35
G30	24.66	B29	21.38	B13	23.70	C22	22.27
B4	24.66	C14	21.26	C28	23.68	G3	22.20
B17	24.55	G37	21.02	C26	23.68	C20	22.07
G29	24.51	D44	20.92	G4	23.58	D33	21.85
D47	24.34	G29	20.01	G32	23.58	D34	21.85
D51	24.32	C13	19.72	D52	23.44	D40	21.82
D45	23.59	D49	19.18	C11	23.36	G17	21.76
G4	23.42	C24	19.10	D40	23.12	C6	21.63
D37	22.83	C34	18.84	G29	23.02	D38	21.39
D46	22.77	D37	18.83	D45	22.75	C34	21.30
D41	22.76	B33	18.74	D41	22.42	G18	21.17
D40	22.51	G22	18.31	B32	22.31	D27	21.17
D49	22.43	G7	18.19	D37	22.02	D24	21.17
B13	22.42	D47	18.12	B4	22.00	D30	21.17
D36	22.25	D45	18.02	G30	22.00	D31	21.17
D35	22.25	D35	17.82	D39	21.79	D23	21.17
G17	21.51	D36	17.82	G23	21.74	D28	21.17
G22	21.50	D18	17.70	D36	21.56	D29	21.17
D39	21.44	G17	17.24	D35	21.56	G16	20.67
C24	21.27	G3	17.20	B3	21.16	C30	20.18
D43	20.99	D41	17.19	G31	21.12	C25	20.18
G18	20.91	D27	17.07	D51	20.51	C29	20.18
D31	20.91	D31	17.07	G17	20.08	B10	20.11
D29	20.91	G18	17.07	G16	19.71	D50	20.01
D27	20.91	D23	17.07	D49	19.70	D48	20.01
D23	20.91	D30	17.07	D34	19.33	D41	19.83

Continuation of Table A8

Enabling CIs		**Incorporate**		**Design**		**Collaborate**	
Skill	AWD	Skill	AWD	Skill	AWD	Skill	AWD
D28	20.91	D24	17.07	G22	19.29	D19	19.51
D30	20.91	D28	17.07	D27	19.17	C21	19.46
D24	20.91	D29	17.07	D28	19.17	D46	18.94
D34	20.59	D34	16.76	G18	19.17	G21	18.87
G16	20.53	D42	16.67	D23	19.17	G20	18.81
D38	19.59	D39	16.65	D29	19.17	C28	17.58
D25	19.23	D40	16.51	D30	19.17	C26	17.58
D48	19.21	G16	16.26	D31	19.17	D22	17.53
D50	19.21	B16	16.12	D24	19.17	D26	17.53
D33	18.61	B17	16.12	D33	18.90	D25	17.42
D26	18.28	G4	16.10	D38	18.78	G4	17.08
D22	18.28	D38	15.99	C24	17.90	B11	16.95
G20	18.10	D25	15.98	D25	17.58	G23	16.69
B21	16.64	D50	15.96	D26	16.80	B7	16.60
B8	13.36	D48	15.96	D22	16.80	B13	15.65
B22	0.00	D43	15.90	D48	16.76	D43	15.56
		D19	15.46	D50	16.76	G5	15.14
		G20	14.90	G20	16.22	C24	14.56
		D26	14.38	B21	16.14	B8	14.14
		D22	14.38	B8	12.84	B15	12.52
		B13	14.35	B22	0.00	B12	11.63
		B7	14.26				
		D33	14.16				
		D46	13.43				
		G5	13.05				
		B21	12.83				
		B15	10.42				
		B12	9.85				
		B8	9.12				
		B22	0.00				

Table B.1
Correlation Matrix of Skill Measures at the Industry-Region Level.

	Core circular	Enabling circular	Technical-physical	Social-cognitive
Core Circular	1.000			
Enabling Circular	0.062	1.000		
Technical-Physical	0.988	0.160	1.000	
Social-Cognitive	−0.219	0.926	−0.137	1.000

Table B.2
Skill Differences between Circular and Non-Circular Industries.

	Technical-Physical				Social-Cognitive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Circular	2.585**				2.841**			
	(1.025)				(1.407)			
Core		4.399***				−2.495*		
		(1.248)				(1.355)		
Enabling		−0.947				13.23***		
		(1.343)				(0.943)		
Use			2.179***				−8.297***	
			(0.744)				(2.006)	
Rethink			0.944				0.637	
			(2.352)				(2.462)	
Prioritise			10.10***				8.120***	
			(0.329)				(0.435)	
Preserve			8.197***				−3.386**	
			(1.827)				(1.639)	
Incorporate				−2.153*				12.81***
				(1.238)				(0.806)
Design				5.307**				13.93***
				(2.100)				(2.396)
Collaborate				−8.405***				16.18***
				(1.900)				(3.961)
Constant	21.20***	21.20***	21.17***	21.50***	27.98***	27.98***	28.45***	27.81***
	(0.336)	(0.337)	(0.329)	(0.328)	(0.435)	(0.435)	(0.435)	(0.416)
N	573	573	573	573	573	573	573	573
Adj. R^2	0.008	0.017	0.027	0.004	0.005	0.059	0.008	0.054

Heteroskedasticity-robust standard errors are displayed in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table B.3
Regional Skill Differences between Circular and Non-Circular Industries.

	Technical-Physical			Social-Cognitive		
	All (1)	Lagging (2)	Leading (3)	All (4)	Lagging (5)	Leading (6)
Panel 1						
Circular	1.946***	1.957***	1.936***	2.329***	2.342***	2.317***
	(0.100)	(0.148)	(0.135)	(0.156)	(0.237)	(0.206)
Constant	12.59***	12.55***	12.59***	23.03***	21.68***	23.04***
	(0.258)	(0.295)	(0.258)	(0.400)	(0.472)	(0.400)
Adj. R^2	0.010	0.010	0.010	0.012	0.009	0.012
Panel 2						
Core	3.191***	3.163***	3.214***	−2.321***	−2.620***	−2.079***
	(0.135)	(0.198)	(0.183)	(0.180)	(0.271)	(0.240)
Enabling	0.221*	0.368*	0.090	8.767***	8.876***	8.668***
	(0.124)	(0.190)	(0.162)	(0.152)	(0.238)	(0.195)
Constant	12.58***	12.56***	12.58***	23.08***	21.67***	23.07***
	(0.256)	(0.294)	(0.257)	(0.394)	(0.464)	(0.394)
Adj. R^2	0.016	0.015	0.016	0.044	0.044	0.042
Panel 3						
Use	1.688***	1.620***	1.750***	−5.270***	−5.639***	−4.935***
	(0.161)	(0.223)	(0.232)	(0.310)	(0.450)	(0.426)
Rethink	0.007	−0.331	0.217	−0.921*	−1.157	−0.773
	(0.409)	(0.681)	(0.510)	(0.536)	(0.881)	(0.674)
Prioritise	6.532***	7.755***	5.383***	5.876***	5.490***	6.236***
	(0.769)	(1.223)	(0.922)	(0.581)	(0.921)	(0.719)
Preserve	5.074***	4.920***	5.198***	−2.187***	−2.347***	−2.058***
	(0.186)	(0.268)	(0.258)	(0.205)	(0.310)	(0.274)

(*continued on next page*)

Table B.3 (*continued*).

Constant	12.60***	12.56***	12.59***	23.43***	22.04***	23.42***
	(0.253)	(0.292)	(0.253)	(0.398)	(0.472)	(0.398)
Adj. R^2	0.023	0.022	0.023	0.014	0.013	0.014
Panel 4						
Incorporate	−0.735***	−0.729***	−0.740***	8.308***	8.385***	8.244***
	(0.147)	(0.223)	(0.194)	(0.181)	(0.284)	(0.232)
Design	3.769***	4.117***	3.424***	9.528***	9.792***	9.266***
	(0.157)	(0.233)	(0.208)	(0.226)	(0.358)	(0.275)
Collaborate	−4.126***	−4.156***	−4.096***	10.47***	10.31***	10.62***
	(0.261)	(0.419)	(0.317)	(0.581)	(0.890)	(0.752)
Constant	12.79***	12.72***	12.80***	22.93***	21.53***	22.93***
	(0.258)	(0.295)	(0.258)	(0.395)	(0.465)	(0.395)
Adj. R^2	0.008	0.009	0.006	0.041	0.040	0.040
N	37,790	16,760	21,030	37,790	16,760	21,030

Heteroskedasticity-robust standard errors are displayed in parentheses.
All models include fixed effects for region. * p<0.1, ** p<0.05, *** p<0.01

Table B.4
Regional Variation of Core and Enabling Circular Skills.

	Core circular skills (1)	Enabling circular skills (2)
Leading	−0.530	2.249***
	(0.525)	(0.667)
Constant	13.11***	21.31***
	(0.447)	(0.547)
N	37,790	37,790
Adj. R^2	0.001	0.008

Heteroskedasticity-robust standard errors are displayed in parentheses.
Fixed effects for region are included. * p<0.1, ** p<0.05, *** p<0.01

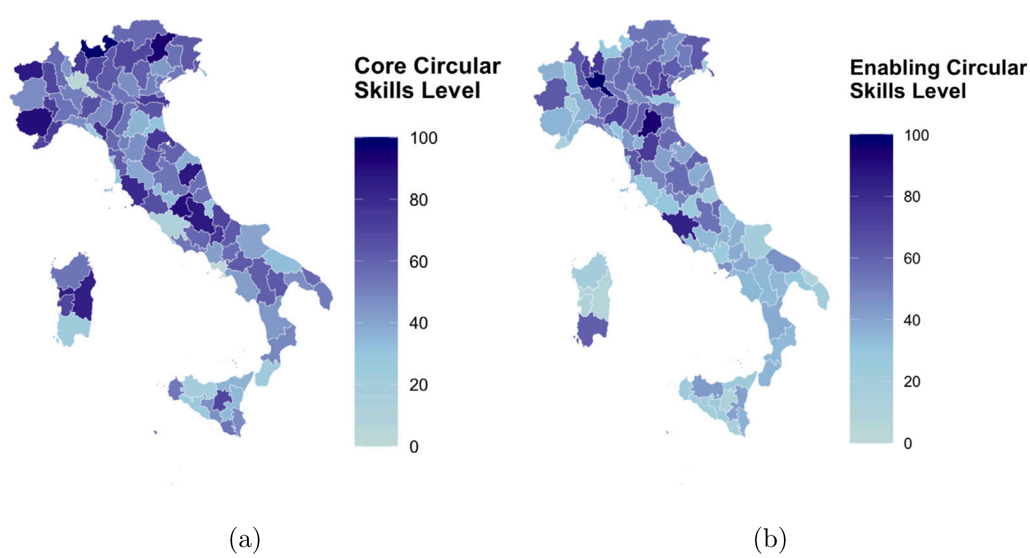

Fig. C.10. Regional distribution of the core (a) and Enabling (b) Circular skills for the period 2013–2019.

show that leading regions have significantly higher levels of enabling circular skills than lagging regions. On the other hand, lagging regions seem to have higher levels of core circular skills as signalled by the negative coefficient in Column 1 which is statistically insignificant. The insignificant coefficient does not come as a surprise given that Fig. C.10(a) displays that core circular skills are relatively in abundance in many north, central, and south regions.

Data availability

The authors do not have permission to share data.

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